WHEN ALL DATA IS CREDIT DATA

Consumer Credit Markets, Technological Development,
and Distributive Justice

Nikita Aggarwal
Brasenose College
University of Oxford

A thesis submitted for the degree of
Doctor of Philosophy
Hilary 2023

ABSTRACT

This thesis examines how advances in predictive technology influence the distributional outcomes due to consumer credit markets, using 'alternative' consumer credit scoring as a case study. The thesis contributes the first scholarly analysis of the distributional effects due to alternative credit scoring in the UK, and the role of legal, technological, political, and market forces in shaping these effects. It also contributes to the deeper and broader analysis of the economic and social outcomes due to consumer credit markets, and the boundaries of 'fair' credit.

Alternative credit scoring—the use of alternative data and machine learning techniques in consumer credit decisions—has been heralded with the implicitly distributional promise of improving access to credit for marginalized consumers, particularly lower-income consumers. Leveraging theoretical and empirical insights, the thesis argues that this promise is credible but strictly bounded. First, due to the limits of consumer credit, particularly unsecured credit, as a mechanism for reducing poverty and inequality. Second, due to the potential *negative* distributional effects of alternative credit scoring—whether resulting from more precise, data-driven price discrimination targeted at lower-income consumers, or the expansion of affordable credit to higher-income consumers.

Further empirical investigation is needed to estimate the distributional outcomes due to alternative credit scoring, and advances in predictive credit technology more broadly, as well as the mechanisms producing these outcomes, particularly in the UK. To the extent that regressive outcomes are at least plausible, the thesis sketches the contours of policy interventions that could more effectively limit these outcomes and foster more progressive outcomes due to technological development in consumer credit markets.

ACKNOWLEDGMENTS

There are many people to whom I am indebted for this thesis. I extend a special thank you to Professor Hugh Collins, who encouraged me along this path to begin with and offered continuing support. For extensive and valuable feedback on innumerable drafts of the thesis, I thank my advisors, and contributors, Professors John Armour, Horst Eidenmüller, and Thomas Melham. For examining the thesis and providing valuable feedback at various stages, I thank Professors Jeremias Adams-Prassl, Dan Awrey, Bettina Lange, Orla Lynskey, and William Magnuson. For fruitful collaboration and inspiration, I thank Professor Luciano Floridi and the members of the Digital Ethics Lab at the Oxford Internet Institute. I am grateful to the Harvard Kennedy School's Carr Center for Human Rights Policy and the UCLA School of Law for providing both support and latitude while I was in the final stages of writing up the thesis. And I am grateful to the many scholars, organizers of, and participants in, workshops and conferences who offered feedback during my journey towards this thesis. Finally, it must be acknowledged that, as much as the PhD is a highly rewarding endeavour, it is also a highly demanding one. I am therefore especially grateful to my friends, family, and colleagues who provided support, and respite, during this time.

CONTENTS

TABLE OF ABBREVIATIONS

annual percentage rate	APR
anti-money laundering and counter-terrorism financing	AML/CFT
Application Programming Interface	API
area under the curve	AUC
artificial general intelligence	AGI
artificial intelligence	AI
artificial neural networks	ANNs
artificial specific intelligence	ASI
buy now, pay later	BNPL
Consumer Credit Directive 2008	CCD 2008
Consumer Credit Directive 2021	CCD 2021
Consumer Credit Sourcebook	CONC
Consumer Financial Protection Bureau	CFPB
Council of Europe	CoE
Credit Account Information Sharing	CAIS
Credit Reference Agency Information Notice	CRAIN
credit reporting agency	CRA
current account turnover	CATO
Data Protection Act 1984	DPA 1984
Data Protection Act 1998	DPA 1998
Data Protection Act 2018	DPA 2018
Data Protection Directive 1995	DPD 1995
data protection impact assessment	DPIA
deep learning	DL
Fair Credit Reporting Act	FCRA
Financial Conduct Authority	FCA
Financial Ombudsman Service	FOS
Financial Policy Committee	FPC
Financial Services Authority	FSA
Financial Services Compensation Scheme	FSCS
General Data Protection Regulation	GDPR
Global Financial Crisis	GFC
Gross Domestic Product	GDP
high-cost short-term credit	HCSTC
loss given default	LGD
machine learning	ML
Office for Budget Responsibility	OBR
Office for National Statistics	ONS
Office of Fair Trading	OFT
Organisation for Economic Cooperation and Development	OECD
peer-to-peer	p2p
privacy-enhancing technologies	PETs
probability of default	PD
Prudential Regulation Authority	PRA

risk-weighted assets	RWA
support vector machines	SVMs
United Kingdom	UK
United States	US

TABLE OF CASES

Case	Page
Tournier v National Union and Provincial Bank of England [1924] 1 KB 461	95, 96
Judgment of the German Constitutional Court of December 15, 1983, 1 BvR 209/83, BVerfG 65	100
Attorney-General v. Guardian Newspapers Ltd. (No. 2) [1990] 1 AC 109 (HL)	96
Bodnar v Townsend [2003] TASSC 148	96
Lloyd v Google Inc [2021] UKSC 50	244
Request for a preliminary ruling from the Verwaltungsgericht Wiesbaden (Germany) lodged on 15 October 2021 – OQ v Land Hesse, Case C-634/21-1	215

TABLE OF STATUTES

Statute	Page
United Kingdom	
Consumer Credit Act 1974	31, 89, 91, 92, 93, 113, 126
Data Protection Act 1984	100, 122, 218
Data Protection Act 1998	122, 123, 124, 209, 210
Unfair Terms in Consumer Contracts Regulations 1999, SI 1999/2083	93
Human Rights Act 2000	97
Financial Services and Markets Act 2000	97, 113, 118, 120
FSMA 2000 (Regulated Activities) Order 2001	128
Crime (International Cooperation) Act 2003	97
Equality Act 2010	91, 233
Child Poverty Act 2010	46
Financial Services Act 2012	113
Financial Services (Banking Reform) Act 2013	120
FSMA 2000 (Regulated Activities) (Amendment) (No.2) Order 2013	128
The Capital Requirements (Capital Buffers and Macro-prudential Measures) Regulations 2014, SI 2014/894	114
Consumer Rights Act 2015	93, 120
Data Protection Act 2018	122, 125, 207, 208, 209, 211, 212, 213, 215, 218, 219, 220, 221, 224
European Union (Withdrawal) Act 2018	19
European Union / Council of Europe	
Convention for the Protection of Human Rights and Fundamental Freedoms 1953	98
Convention for the Protection of Individuals with Regard to Automatic Processing of Personal Data 1981	100
Directive 87/102/EEC of 22 December 1986 for the Approximation of the Laws, Regulations and Administrative Provisions of the Member States Concerning Consumer Credit [1986] OJ L42/48	93
Directive 90/88/EEC of 22 February 1990 Amending Directive 87/102/EEC [1990] OJ L61/14	93
Directive 93/13/EEC on Unfair Terms in Consumer Contracts [1993] OJ L95/29	93
European Parliament and Council Directive 95/46/EC of 24 October 1995 on the Protection of Individuals Regarding the Processing of Personal Data and on the Free Movement of Such Data [1995] OJ L281/23	122, 124, 209, 210, 211, 212

2001 Protocol to the EU Convention on Mutual Assistance in Criminal Matters [2001] OJ C326/1	97
Treaty of Lisbon Amending the Treaty on European Union and the Treaty Establishing the European Community [2007] OJ C306/1	210
Directive (EC) No 2008/48/EC of the European Parliament and of the Council of 23 April 2008 on Credit Agreements for Consumers and Repealing Council Directive 87/102/EEC [2008] OJ L133/66	117, 126
Treaty on the Functioning of the European Union [2012] OJ C326/47	124, 210
Charter of Fundamental Rights of the European Union [2012] OJ C326/391	124, 210
Directive 2015/2366 on Payment Services in the Internal Market [2015] OJ L337/35	70
Regulation (EU) No 2016/679 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data [2016] OJ L119/1	122, 123, 124, 125, 127, 182, 207, 208, 209, 210, 211, 212, 213, 214, 217, 218, 219, 220, 221, 222, 223, 224, 244
Regulation (EU) 2018/1807 of the European Parliament and of the Council of 14 November 2018 on a Framework for the Free Flow of Non-Personal Data in the European Union [2018] OJ L303/59	220
Proposal for a Directive of the European Parliament and of the Council on Consumer Credits COM/2021/347 final	164, 214
United States	
Fair Credit Reporting Act (1970)	39, 126
Equal Credit Opportunity Act (1974)	41, 73
Community Reinvestment Act (1977)	236
Dodd-Frank Wall Street Reform and Consumer Protection Act (2010)	119
California Civil Code (2023)	74, 100
International	
Universal Declaration of Human Rights (adopted 10 December 1948 UNGA Res 217 A(III)	98

TABLE OF DIAGRAMS AND TABLES

1 INTRODUCTION

Consumer credit is a core engine of the modern economy. From buying a home, to going to university and purchasing everyday items, most of us will rely on credit during our lifetimes. This central role of consumer credit in the modern economy did not come about by happenstance. Over the last fifty years, successive governments—in the United Kingdom (UK), as well as in other credit-driven economies such as the United States (US)—actively encouraged the growth of consumer credit markets to boost household consumption and imperfectly privatize the functions of the welfare state, thereby satisfying their short-term political goals.[1]

As consumer credit markets have become increasingly central to the economy, levels of inequality and poverty—of consumption, income, and wealth—have also risen. These trends are not unrelated but partly causal of each other.[2] Their perverse, cumulative effect has been to make access to credit a key site in the fight to reduce poverty and inequality and thereby support distributive justice.[3] If access to credit, on favourable terms, enables us to

[1] *See further* text to n 42 et seq, in ch 2. Note that the information in this thesis is accurate as of February 26 2023, the time of writing and submission for examination.

[2] *See further* n 51 and 98 et seq, and associated text in ch 2, and Appendix 1 – Poverty, Inequality, and Credit (examining poverty, inequality, and credit usage in the UK).

[3] This thesis takes a nonideal approach to distributive justice. That is, it does not pursue any one ideal theory of distributive justice but rather takes as its point of departure the manifest and widely recognized distributive injustice in the UK due to high levels of inequality and relative poverty, of consumption, income, and wealth, and asks how this injustice might be ameliorated. *See e.g.* Amartya K Sen, *The Idea of Justice* (HUP 2009)

smooth consumption and grow our income and wealth through investment, it follows that a lack of credit access on favourable terms, or access on unfavourable terms—especially for lower income consumers—will limit these opportunities, potentially exacerbating poverty and inequality and undermining distributive justice.[4]

In recent years, developments in credit scoring technology[5]—commonly referred to as 'alternative credit scoring'—have been promoted as a new weapon in the fight for 'fair' credit. Lenders and policymakers frequently posit that, by using more sophisticated credit scoring models developed using 'alternative data' and 'machine learning' (ML) techniques, alternative credit scoring could improve access to credit for consumers historically excluded from credit markets, particularly 'credit invisible' consumers excluded due to a lack of conventional credit data such as a credit history, and consumers with blemished credit files.[6]

(distinguishing non-ideal 'realization-focused' theories of justice that focus on removing manifest injustice from the world as it is, from ideal 'transcendental', 'arrangement-focused', 'perfect' theories of justice in the vein of Rawls and others); Anthony B Atkinson, *Inequality: What Can Be Done?* (HUP 2015), 9 ('I am not seeking to eliminate all differences in economic outcomes…Rather, the goal is to *reduce* inequality below its current level, in the belief that the present level of equality is excessive.' Emphasis added). *See further* n 100 et seq and associated text in ch 2 (discussing poverty and inequality reduction as public policy goals); ch 5, section 5.1 (discussing poverty and inequality, of consumption, income, and wealth, as benchmarks of applied distributive justice); Appendix 1 (discussing levels of poverty and inequality in the UK, and credit usage by low-income households). On the terminology of a 'site' of distributive justice, *see* G.A. Cohen, 'Where the Action Is: On the Site of Distributive Justice' (1997) 26(1) Philosophy and Public Affairs 3 (arguing that the principles of distributive justice should also apply to the private sphere, i.e. individual choices not regulated by the law, or 'the personal is political' cf. John Rawls, *A Theory of Justice* (Belknap 1971), focusing on the just arrangement of society's 'basic structure' i.e. the main economic and social, public and private institutions, as the main locations of application of principles of distributive justice).

4 *See further* ch 5 (examining the functions and distributional effects of consumer credit). Note that the distributional analysis in this thesis will refer broadly to 'low(er)' and 'higher' income groups, while acknowledging that this stratification is coarse and stylized. More detailed future analysis should include additional income and wealth strata, and distinguish, for example, 'upper-tail' and 'lower-tail' inequality.

5 'Technological development' includes invention (e.g. the development of new statistical methods for credit scoring), innovation (e.g., the commercial adoption and application of inventions as new products or processes), and their diffusion in the economy. *See generally* Joseph Schumpeter, *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process* (McGraw-Hill 1939); W Rupert McLaurin, 'The Sequence From Invention to Innovation and its Relation to Economic Growth' (1953) 67(1) The Quarterly Journal of Economics 97, 98 (breaking down the process of technological development into: 1) the propensity to develop pure science; 2) the propensity to invent; 3) the propensity to innovate; 4) the propensity to finance innovation; and 5) the propensity to accept innovation).

6 *See e.g.* Equifax, 'Equifax Partners With Rent Reporting Innovator CreditLadder to Improve Tenants' Access to Credit', <https://www.equifax.co.uk/about-equifax/press-releases/en_gb/-/blog/equifax-partners-with-rent-reporting-innovator-creditladder-to-improve-tenants-access-to-credit/> ('The inclusion of rental data in credit assessments is a huge lift to improve financial inclusion and fairer access to the right financial products.');

Implicit in this rhetoric is the promise of smoother consumption and greater income and wealth through better access to credit, particularly for less well-off credit-marginalized consumers.[7] To the extent that alternative credit scoring thereby offers to reduce current high levels of poverty and inequality, it offers to support distributive justice. I refer to this as the 'distributional promise' of alternative credit scoring.[8]

The early exuberance for alternative credit scoring, and its distributional promise, is captured vividly in the following 2012 quote from Doug Merrill, CEO of Zest AI, an early pioneer of alternative credit scoring in the US. It also inspires the title of this thesis:

> *'It turns out that there are hundreds of sources of data, trivially available on the net. And thousands if you include things like web-crawls etc. And if your view is that all data is credit data, you build a piece of mathematics, or in our case a whole bunch of mathematics, that consumes thousands of data points. And of those thousands many are missing, many are wrong, etc., but regardless you build a score. And suddenly you*

Christopher Woolard (former CEO of the Financial Conduct Authority [FCA]), 'The FCA and Innovation' (May 22, 2015) <https://www.fca.org.uk/news/speeches/fca-and-innovation> (describing how the FCA, through its 'Innovation Hub', helped launched the alternative credit-score provider, Aire). *See further* text to n 125 et seq; section 3.1 (examining credit invisibility).

7 On the assumption that consumers with good credit scores and credit market access, who are also more likely to be well-off, are less likely to benefit from alternative credit scoring. *See* Experian and Oliver Wyman, 'Financial Inclusion and Access to Credit' (January 2022) <https://www.businesswire.com/news/home/20220112005355/en/Experian-and-Oliver-Wyman-Find-Expanded-Data-and-Advanced-Analytics-Can-Improve-Access-to-Credit-for-Nearly-50-Million-Credit-Invisible-and-Unscoreable-Americans> ('Access to fair and affordable credit can help consumers get a college degree, buy a car or home, start or expand a business and ultimately help establish careers, build wealth and achieve greater financial success.'); *see generally* Saule T. Omarova, 'New Tech v. New Deal: Fintech as a Systemic Phenomenon' (2019) 36 Yale Journal on Regulation 735, 737 ("the fintech narrative has distinct undertones of a social revolution in its broader aspirations to rebuild financial markets on principles of mutuality, cooperation, and inclusiveness").

8 Note, this thesis focuses on the *distributional* rhetoric and reality of alternative credit scoring. Of course, alternative credit scoring also carries an *interpersonal* or *individual* promise of fairer individual terms of credit, for example based on a more accurate assessment of the borrower's risk (also referred to as 'actuarial fairness' – *see* n 235). This does not necessarily imply a (progressive) distributional promise, to the extent that it is agnostic to the effects of changes in credit access on the levels of income, wealth, and consumption levels of different socio-economic groups, in both relative and absolute terms. In this sense, there is a broader *fairness* promise of alternative credit scoring, which has overlapping interpersonal and distributional dimensions. *See also* n 3 (discussing non-ideal theory) and further chapters 5 and 6, *infra*.

build a score that allows you to figure out people who are maybe not quite good enough to get a subprime credit card, but are a way better credit risk than the payday loan guys. So instead of offering them a 700% APR borrowing [sic], you can offer them something in between".[9]

Policymakers have encouraged the development of alternative credit scoring—and 'fintech' innovation more broadly[10]—in an effort to boost competition in financial markets and increase 'financial inclusion'.[11] This rhetoric has been amplified by the news media. The following is an excerpt from a 2011 Forbes article profiling Wonga, the infamous UK-based online 'payday' lender, and its founder, Errol Damelin:[12]

---

[9] As cited in Joe Deville and Lonneke van der Velden, 'Seeing the Invisible Algorithm: The Practical Politics of Tracking the Credit Trackers' in Louise Amoore and Volha Piotukh (eds), *Algorithmic Life: Calculative Devices in the Age of Big Data* (Routledge 2016). *See also* Rob Aitken, 'All Data is Credit Data: Constituting the Unbanked' (2017) 21(4) Competition and Change 274; Mikella Hurley and Julius Adebayo, 'Credit Scoring in the Era of Big Data' (2016) 18 Yale Journal of Law and Technology 148, 168-183 (describing ZestFinance's patent for using machine learning to build an alternative credit scoring model); John Lippert, 'ZestFinance Issues Small, High-Rate Loans, Uses Big Data to Weed Out Deadbeats' *Washington Post* (11 Oct 2014) <https://wapo.st/2J6ugVc>.

[10] *See e.g.* Woolard, n 6; FCA, 'Loan-based ('Peer-to-Peer') and Investment-based Crowdfunding Platforms: Feedback on our Post-implementation Review and Proposed Changes to the Regulatory Framework' (Consultation paper CP 18/20, July 2018), 6 (motivating the initial light-touch regulation of p2p platforms 'as a proportionate framework to give investors appropriate protection without preventing innovation and growth.'). Fintech is an abbreviation of 'financial technology' and generally refers to the application of digital technology in financial services. *See* Marc Hochstein, 'Fintech (the Word, That Is) Evolves' *American Banker* (5 October 2015) <https://www.americanbanker.com/opinion/fintech-the-word-that-is-evolves>. *See further* ch 3 (examining the technological drivers of alternative credit scoring) and Appendix 3 (discussing the fintech credit ecosystem in the UK).

[11] FCA, ibid; *see further* n 125 and associated text.

[12] Parmy Olson, 'The Algorithm That Beats Your Bank Manager' *Forbes* (March 15, 2011) <https://www.forbes.com/sites/parmyolson/2011/03/15/the-algorithm-that-beats-your-bank-manager/?sh=606b2ef61ae9>. *See also* Hagerty et al (Wonga Technology Limited), 'Loan Automation System' (2015), Patent no. US 2015/0278941 A1 <https://patentimages.storage.googleapis.com/9c/8c/f5/facd568aeb068c/US20150278941A1.pdf>, 3-4 (describing Wonga's patent for automatic credit scoring and lending using extensive behavioural monitoring of users, including checking 'social media, browsing history and other online information'); and Joe Deville, 'Leaky Data: How Wonga Makes Lending Decisions' *Estudios de la Economia* (May 20 2013) <https://perma.cc/D9SB-TXDX> (describing Wonga's extensive use of consumer data in lending decisions). Wonga collapsed into administration in 2018. *See* n 130.

'Wonga.com is a short-term lending Web site that uses an algorithm and thousands of pieces of information about its customers in the public domain, to decide in a few seconds whether to grant a short-term loan. Not to be dismissed as another loan shark dressed in Web 2.0 clothing, Wonga makes money by being highly selective and keeping its default rate low, and is starting to disrupt the space dominated by credit card companies and banks.

….

Damlin (sic) defends the computer as decision maker to the hilt, not only because they're accurate but because taking humans out of the equation nixes the risk of manipulation by borrowers. "We felt that we could make more responsible decisions if we kept it objective," he says. "We want to build a business that's still here in a hundred years (sic) time."

Clearly, the distributional promise of alternative credit scoring is economically, socially, and politically salient. It remains unclear, however, whether and to what extent it can or will be delivered. This thesis unpacks and critically evaluates the distributional promise of alternative credit scoring, as a case study in the distributional effects due to advances in predictive technology in consumer credit markets. It contributes the first scholarly analysis of the distributional effects due to alternative credit scoring in the UK, and the role of legal, technological, political, and market forces in shaping these effects.[13] To do so, it necessarily unpacks the distributional promise of consumer credit itself—thus contributing, additionally,

[13] Some scholars and consumer advocates, particularly in the US, have in recent years begun to question the distributional effects of alternative credit scoring, and fintech (credit) more generally. *See e.g.* Chi Chi Wu, 'Credit Invisibility and Alternative Data: Promises and Perils' (National Consumer Law Center, July 2019) <https://www.nclc.org/wp-content/uploads/2022/08/ib-credit-invisib-alt-data-july19.pdf>; Ratna Sahay et al, 'The Promise of Fintech: Financial Inclusion in the Post Covid-19 era' (IMF Working Paper No. 20/09, 2020) <https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2020/06/29/The-Promise-of-Fintech-Financial-Inclusion-in-the-Post-COVID-19-Era-48623>; Pamela Foohey and Nathalie Martin, 'Fintech's Role in Exacerbating or Reducing the Wealth Gap' (2021) University of Illinois Law Review 459; Christopher K Odinet, 'Predatory Fintech and the Politics of Banking' (2021) 106 Iowa Law Review 1739; Pamela Foohey and Sara Greene, 'Credit Scoring Duality' (2022) 85 Law and Contemporary Problems 101; Lindsay Sain-Jones and Goldburn P Maynard Jr , 'Unfulfilled Promises of the Fintech Revolution' (2023) 111 California Law Review (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4031044>.

to the deeper and broader analysis of the economic and social outcomes due to consumer credit markets, and the boundaries of 'fair' credit.[14]

The thesis will argue that the distributional promise of alternative credit scoring is credible, yet strictly bounded—first, due to the limits of consumer credit itself as a mechanism for supporting distributive justice; and second, due to the potential regressive distributional effects of alternative credit scoring. To the extent that regressive outcomes due to advances in predictive technology are at least plausible, the thesis sketches the contours of policy reforms that could more effectively limit these outcomes, as well as foster more progressive outcomes due to technological development in consumer credit markets.[15] The thesis acknowledges, however, that further empirical investigation is needed to estimate the distributional effects due to alternative credit scoring and the mechanisms producing them, particularly in the UK, and to develop policy interventions accordingly. The thesis thus concludes by setting out an agenda for further research.

The primary jurisdictional focus of the thesis is the UK, and English law. The thesis analyses EU law to the extent that it continues to be relevant to the regulation of consumer

[14] *See* ch 5 (Unpacking the Credit Promise). The thesis focuses primarily on *unsecured* consumer credit markets in order to narrow the scope of inquiry and facilitate analysis, and based on the observation that low-income households rely on unsecured credit more than high-income households (*see* Appendix 1, Figure 8), as well as the hypothesis that the allocation and pricing of unsecured credit is more likely to be sensitive to the use of alternative data and alternative statistical methods due to lenders' lack of collateral to mitigate credit risk (*see* Itzhak Ben-David, Mark J Johnson, Jason Lee, and Vincent Yao, 'Fintech Lending with Lowtech Pricing' (2022) <https://cpb-us-w2.wpmucdn.com/u.osu.edu/dist/d/7877/files/2022/07/Ben_David__Johnson__Lee__Yao__FinTech.pdf; Leonardo Gambacorta, Yiping Huang, Zhenhua Li, Han Qiu, Shu Chen, 'Data vs Collateral', BIS Working Paper No. 881 (Sept. 01, 2020), https://www.bis.org/publ/work881.htm). Collectively, these conditions make the distributional promise of alternative credit scoring potentially more potent and relevant in unsecured consumer credit markets. Consumers are thus taken to be individuals transacting in their personal capacity, typically dealing with relatively modest sums of money borrowed for short periods of time. The terms 'consumer', 'borrower', and 'household' will be used interchangeably. Likewise, the terms 'lender' and 'credit provider' will be used interchangeably. Alternative credit scoring is, however, still relevant to secured consumer credit markets and the distributional effects of consumer credit markets, and will be included in future extensions of the analysis in this thesis.

[15] The question of whether policymakers ought to pursue distributional goals, particularly through the avenues discussed, and whether these avenues would be politically feasible if pursued, are beyond the scope of this thesis.

credit markets in the UK following Brexit,[16] with a focus on EU consumer credit and data protection law. The thesis also draws theoretical and empirical insights from the US given strong similarities between the structure of consumer credit markets in both countries, including their regulation and digitization. More specifically, there are strong interconnections between the development of statistical credit scoring in consumer credit markets in the UK and US, including, in recent years, the rise of alternative credit scoring. Furthermore, both countries have relatively permissive credit regimes and restrictive social welfare regimes, with policymakers sharing similar expectations of consumer credit markets, and technological developments therein, to support the achievement of distributional goals. The analysis and conclusions of this thesis will thus also be relevant to other jurisdictions, such as the US, for which the aforementioned conditions for external validity are satisfied.[17]

1.1 Overview

The thesis is organized into two parts. **Part One** examines the legal, technological, and socio-political drivers of alternative credit scoring and its distributional promise. It demonstrates that alternative credit scoring, and its distributional promise, have been constructed by the co-evolution of credit markets, technology, law, social norms, and the political economy over the course of the last half a century. More particularly, they have been constructed through symbiotic technology and credit cycles—a process that this thesis refers to as the 'technology-credit cycle', a species of broader 'fintech cycles'. Advances in credit scoring technology, and digital technology more generally, play an important role in

[16] European Union (Withdrawal) Act 2018, s 3 (incorporating into English law Direct EU legislation that is operative immediately prior to Exit Day).

[17] Whilst acknowledging that there are various institutional differences that limit the generalizability of results to and from other jurisdictions—including but not only between the UK and US. *See further* chs 6 and 8.

driving the periodic expansionary and contractionary gyrations of the credit cycle.[18] At the same time, the credit cycle catalyses investment in, and the development of, digital technology, including but not limited to credit and financial markets.[19]

Various structural factors, including changes in law and regulation, contributed towards shaping successive technology-credit cycles.[20] Beginning in the 1970s, policymakers, faced with globalization, a weak macroeconomic environment, and rising levels of poverty and inequality, and combined with an ideological turn towards managerial, neoliberal government, promoted liberal monetary and credit market policies with the objective of boosting economic growth through consumer borrowing and consumption, and partially transferring the state's redistributive functions to the private sector.[21]

The liberalization of, and increased competition in, consumer credit markets increased the commercial incentives for lenders to manage credit risk more cost-effectively and thereby grow their loan portfolios and market share. Statistical credit scoring systems ('credit scoring 1.0')—enabled by broader advances in computing technology—played a key role in enabling lenders to better manage credit risk and grow their loan portfolios.[22] During the latter part of the twentieth century, broader technological development, particularly the wider diffusion of the Internet, enabled the further growth of consumer credit markets. The technologically enabled expansion of consumer credit markets was, in turn, enabled by

---

[18] *See* Sahay et al, n 13, 37 ('The small size of fintech credit limits the potential impact of a *fintech credit cycle* on the economy. But fintech lending is growing rapidly, in part because the automation of credit decisions makes credit extension more frequent and much faster.' Emphasis added.).

[19] As discussed further *infra* (*see* n 91 in ch 2 and associated text, and ch 8, section 8.2.1), the term 'technology-credit cycle' seeks to capture the reciprocal interaction between technological development and credit cycles, not limited to fintech or financial markets, and is thus broader than a 'fintech credit cycle'.

[20] *See* ch 4.

[21] *See* ch 2.

[22] *See* section 2.1.

permissive financial and information laws, the latter facilitating the sharing, collection, and storage of personal data.[23]

Reflecting both the myopia of political cycles as well as regulatory capture by an increasingly powerful financial services industry, policymakers regularly de-prioritized the potential regressive and welfare-diminishing effects of expansionary credit policies and household overindebtedness. The rapid growth of subprime credit in the latter part of the twentieth century would lead to a credit-housing bubble and once-in-a-lifetime global financial crisis (GFC), which began to unfold with the collapse of Northern Rock, in September 2007, and the collapse of Lehman Brothers in September 2008. Overconfidence in the market mechanism and innovative credit risk management techniques were key determinants of the GFC, and the Great Recession that followed. Lower-income groups would be hardest hit by the economic fallout from the crisis.

Paradoxically—or, perhaps, inevitably—the GFC was also a key driver of alternative credit scoring ('credit scoring 2.0').[24] In the wake of the crisis, banks tightened credit underwriting standards and reduced lending to higher-risk (lower income) borrowers. Stricter prudential regulation further restricted the scope for lending by banks and other traditional credit providers, particularly to high-risk borrowers. The 2008 crisis was a stark reminder that, in the absence of regulation, consumer credit markets will tend to over-produce unaffordable debt and generate financially unstable—as well as distributionally regressive—outcomes.

The post-2008 credit crunch, austerity policies, and broader socio-economic poverty and inequality—combined with stricter bank regulation and a low-interest environment as central banks, globally, sought to stimulate demand—created a commercial opportunity for

---

[23] *See* ch 4.

[24] *See* section 2.2.

less regulated, non-bank fintech entrepreneurs to tap unmet demand for credit. They were enabled by advances in digital technology—particularly data-driven, ML techniques—as well as relatively permissive data protection and non-bank financial laws. They were also encouraged by policymakers, who embraced alternative credit scoring, and developments in fintech more broadly, for their promise to increase competition and financial inclusion.[25] In a symbiotic manner, the credit industry leveraged the financial inclusion policy agenda to promote the distributional promise of alternative credit scoring. In particular, they appealed to 'credit invisible' consumers excluded from mainstream credit markets due to a lack of conventional credit data, such as a credit history.

Part Two critically examines the distributional promise of alternative credit scoring. It begins by unpacking the relationship between consumer credit allocation and distributive justice, and thus the distributional promise of consumer credit itself.[26] It argues that consumer credit can produce both positive as well as negative distributional effects. Key determinants of these effects are the *affordability* of credit—that is, the ability of individual borrowers to repay credit in a sustainable manner—as well as the relative effects of credit access on the levels of consumption, income, and wealth of higher and lower-income consumers, respectively. *Unaffordable* borrowing, particularly by low-income consumers, will generally be distributionally regressive due to the income- and wealth-diminishing costs of servicing debt. Conversely, *affordable* borrowing by low-income consumers can produce positive distributional outcomes—by enabling those consumers to smooth consumption and, under much more stringent conditions, increase their income and wealth.[27] Importantly,

---

[25] *See* text to n 125 et seq.

[26] *See* ch 5.

[27] However, an increase in affordable borrowing by *high-income* households (only) is likely to be distributionally regressive. *See* ch 5.

the distributional effects due to consumer credit flow through both micro- as well as macro-economic channels.

Building on the distributional analysis of consumer credit allocation, the thesis examines the distributional effects due to alternative credit scoring.[28] Leveraging theoretical and empirical insights, it argues that that the distributional promise of alternative credit scoring is credible yet strictly bounded. By enabling certain lenders to estimate consumer creditworthiness and price credit more accurately—and more broadly by reducing the cost of extending (small value) credit—alternative credit scoring enables an improvement in access to credit for consumers who were previously marginalized from mainstream credit markets, particularly 'credit invisible' consumers. To the extent that this entails the expansion of *affordable* credit to low-income, marginalized consumers, alternative credit scoring could mitigate the existing, regressive distributional effects due to unaffordable borrowing by these consumers—as well as enable positive distributional outcomes due to more affordable borrowing.

These positive distributional outcomes are, however, contingent. First, due to the limits of consumer credit itself as a mechanism for supporting distributive justice. Although greater access to affordable credit due to alternative credit scoring can increase the lifetime utility of low-income consumers through consumption smoothing, the conditions under which borrowing—especially short-term, unsecured, small value borrowing—will enable these consumers to increase their income and/or wealth are highly stringent. Second, due to the potential *negative* distributional effects of alternative credit scoring. Notably, by enabling the *over*-expansion of credit—including too rapid credit expansion—and *un*affordable

[28] *See* ch 6.

borrowing, particularly by low-income consumers, alternative credit scoring will tend to produce regressive distributional effects, rendering its distributional promise illusory.[29]

Among other things, unaffordable borrowing and consumer overindebtedness could result from lenders intentionally exploiting the misperceptions of myopic consumers, leveraging the improved observability of borrowers' characteristics through the use of alternative credit scoring. In turn, due to cognitive and behavioural limitations, consumers—particularly lower income, less financially sophisticated 'vulnerable' consumers—are often inclined to take on more debt than is individually, and often socially, optimal. They are also less likely to be able to assess the affordability of debt before entering into a loan agreement, to the extent that affordability is even foreseeable. Given their thinner financial safety nets, these consumers are more susceptible to unexpected income shocks that can make their debts unaffordable ex post.

In the absence of strong redistribution through social policy (tax and transfer) or markets (wages), the expansion of credit to *high-income* consumers as a result of alternative credit scoring will also likely have regressive effects, due to consumption smoothing and income and wealth accretion. Importantly, given their lower consumption needs, the conditions under which high-income consumers can grow their income and wealth through borrowing and investment are less stringent than for low-income consumers.[30] High-income consumers are also more likely to participate through investment in the profits generated by lending firms, including profits from lending to low-income consumers. Furthermore, more personalized credit pricing due to alternative credit scoring reduces the cross-subsidization

[29] There are further distributional effects due to price discrimination by firms, within the boundaries of affordable lending, i.e., greater extraction of consumer surplus based on a more precise knowledge of consumers' reservation price (*see* ch 6, section 6.2). Although beyond the scope of this thesis, there are also distributional effects due to the use of credit scores as screening mechanisms in non-credit contexts.

[30] As discussed *infra*, however, the potential regressive distributional effects through this channel are necessarily more limited in the case of unsecured consumer credit, in modest sums (*see further* ch 5).

of credit risk between higher and lower income consumers within credit score 'bins', which is expected to be distributionally regressive.

The distributional promise of alternative credit scoring is thus contingent on how lenders apply their data-driven insights, the resulting cost and affordability of credit for consumers, and the relative effects of credit access on the levels of consumption, income, and wealth of high and low-income consumers, respectively. In turn, these conditions are shaped by various individual and firm-specific factors, such as borrowers' credit risk and relative informedness (myopia), the lender's target profit margin and business model (including whether they 'originate to distribute', i.e., securitize the debt), and broader structural factors. The latter include market structure (particularly, the level of competition), macroeconomic conditions (particularly, policy interest rates affecting lenders' cost of funds), and regulatory restrictions (particularly, the enforcement of prudential regulations limiting credit exposures, and consumer protection regulations limiting unaffordable lending). Just as the distributional promise of alternative credit scoring was co-constructed by technology, law, markets, social norms, and the political economy, so too are its distributional effects.

Further empirical investigation is needed to understand the mechanisms by which alternative credit scoring influences the distributional outcomes due to consumer credit markets, the individual and structural factors that shape these outcomes, and the magnitude of their influence, particularly in the UK. To that end, the thesis concludes by setting out an agenda for future research, building on the key themes and findings of the thesis.[31] This includes research on longer-term outcomes for borrowers in different income and wealth deciles due to alternative credit scoring and credit access, including both demand and supply-side drivers of these outcomes. The latter includes a deeper examination of the

[31] *See* ch 8, section 8.2.

macroeconomic drivers and effects of fintech lending, including the role of technological development in driving credit cycles, and vice versa.

To the extent that policymakers are concerned to reduce current high levels of poverty and inequality, and alternative credit scoring exacerbates poverty and/or inequality (of consumption, income, and/or wealth), the thesis also sketches—in broad strokes—the contours of policy reforms that could help to mitigate these regressive outcomes, as well as encourage more progressive outcomes.[32] The suitability of the canvassed reforms necessarily depends on the precise mechanisms and factors that shape the distributional effects due to alternative credit scoring. Moreover, the efficacy of any of these interventions would need to be justified relative to the apparent non-efficacy of alternative credit data and ML in achieving distributional goals (in the hands of both lenders as well as borrowers).[33]

Thus, if regressive outcomes due to alternative credit scoring result primarily from the expansion of unaffordable credit, particularly to low-income borrowers, recourse may be found in strengthening regulatory interventions that limit high-cost, unaffordable credit. On the supply-side, this could include strengthening and broadening the scope of application of lenders' duties to test and mitigate unaffordable lending, and/or tightening credit interest rate caps. It could also include tightening, and expanding the perimeter of, prudential regulation, such as capital adequacy requirements.[34]

Rather than restricting the data and technology available to lenders, and thereby running the risk of stifling beneficial technological development and use (in credit markets), interventions based on credit risk management and affordability focus more narrowly on the

[32] *See* ch 8, section 8.1.

[33] *See* ch 6.

[34] Although a detailed examination of bankruptcy and discrimination law (among other legal frameworks) is beyond the scope of this thesis, they could offer additional avenues for mitigating the regressive effects due to unaffordable borrowing.

ways in which lenders use available data and technology, inter alia to support distributional goals, thereby mitigating the harms of technological development without necessarily squandering the benefits. These interventions would need to be balanced by demand-side interventions that reduce the demand for unaffordable credit, as well as the probability that debt becomes unaffordable ex post, particularly in the hands of low-income borrowers. They include interventions that reduce consumer myopia (improve consumer financial literacy), as well as more foundational, structural policy interventions. The thesis emphasises that there are clear limits to the potential progressive distributional effects due to (unsecured) borrowing by low-income consumers, even on highly concessional terms. Policymakers thus need to acknowledge the floor on consumer credit as a mechanism for improving distributive justice and invest in non-credit mechanisms to achieve distributional goals. This includes strengthening the social safety net, encouraging and improving opportunities for household saving and investment, and investing to facilitate improvements in skills, productivity, job stability, and wage earnings.

Likewise, if the primary mechanism by which alternative credit scoring produces regressive effects is the expansion of affordable credit to *high-income* borrowers, traditional consumer credit law interventions—such as limits on high-cost, unaffordable borrowing—are less directly relevant. These regressive effects may, however, strengthen the justification for more progressive redistribution, whether via credit markets or social policy.

1.2 Roadmap

The thesis proceeds as follows. **PART ONE** examines the rise of alternative credit scoring and its distributional promise. **Chapter 2** situates alternative credit scoring, and its distributional promise, as the latest stage in the co-evolution of consumer credit markets, technological change, legal and social norms, and the political economy over the course of the last century. **Chapter 3** examines the main socio-technical drivers of alternative credit scoring—credit invisibility and financial exclusion in the UK, as well as advances in data-driven, predictive technology. **Chapter 4** examines the key legal and regulatory drivers of alternative credit scoring, focusing on consumer credit, banking, and information (data protection and privacy) laws.

PART TWO unpacks and critically assesses the distributional promise of alternative credit scoring. **Chapter 5** unpacks the distributional promise of consumer credit. It examines the economic functions of credit, the key mechanisms by which consumer credit allocation influences distributive justice—as proxied by levels of poverty and inequality, of consumption, income, and wealth—and how existing consumer credit regulation mitigates the regressive distributional effects due to consumer credit. Building on this analysis, **Chapter 6** analyses the distributional effects due to alternative credit scoring, drawing on both theory and available empirical data. **Chapter 7** examines how existing data protection laws could influence the distributional effects due to alternative credit scoring.

Chapter 8 concludes by summarizing the key contributions of the thesis, sketching the contours of regulatory reforms that could help to mitigate potential regressive outcomes due to alternative credit scoring and consumer lending, whilst acknowledging their distributional boundaries, and setting out an agenda for future research. **Appendices 1, 2** and **3** provide further background, respectively, on: (1) poverty, inequality, and consumer credit use in the UK; (2) artificial intelligence (AI) and ML; and (3) fintech credit.

PART ONE

2 THE CREDIT (SCORING) PROMISE

Credit and debt—lending and borrowing money on the promise of repayment—are as old as civilization itself.[35] But, for much of history, credit has received a bad rap. In ancient times, credit was viewed in many cultures as sinful, with lending at interest especially repugnant.[36] A central concern was borrowers becoming enslaved to wealthy, powerful and unscrupulous lenders, who in turn would exploit the poor and powerless through relationships of debt. Religious admonitions against debt played a critical role in shaping these attitudes.[37] Many governments thus sought to restrain the extension of credit, specifically the charging of interest for credit, a practice termed 'usury'.[38]

With the expansion of international trade in the early thirteenth century, commercial credit came to perform an increasingly useful economic function. This helped to shift

---

[35] David Graeber, *Debt: The First 5000 Years* (Melville House 2014), 48ff ('Some of the very first written documents that have come down to us are Mesopotamian tablets recording credits and debits,'); Rosa-Maria Gelpi and Francois Julien-Labroyère, *The History of Consumer Credit: Doctrines and Practices* (Palgrave Macmillan 2000), 1-94.

[36] Alvin E Roth, 'Repugnance as a Constraint on Markets' (2007) 21(3) Journal of Economic Perspectives 37, 39 ('Lending money for interest was once widely repugnant and no longer is').

[37] Graeber, n 35, 105 ('[e]ven the very earliest Vedic poems, composed sometime between 1500 and 1200 BC, evince a constant concern with debt—which is treated as synonymous with guilt and sin.'); 147 ('In the Bible, as in Mesopotamia, "freedom," came to refer above all to release from the effects of debt.').

[38] Edward Chancellor, *The Price of Time: The Real Story of Interest* (Atlantic Monthly Press 2022), 51ff (describing and critiquing historical opposition to usury, as well as attempts to evade usury laws); Geoffrey Crowther, *Report of the Committee on Consumer Credit (Chairman: Lord Crowther)* (Cmnd 4596, 1971), 'Part Two—Consumer Credit in Britain', 31-49 (discussing historical opposition to usury) (hereinafter, 'Crowther, *Consumer Credit*').

attitudes towards credit and usury, and the approach of credit regulation.[39] In England, usury laws were gradually narrowed and eventually repealed in the late nineteenth century, to be replaced by powers for courts to reopen unconscionable credit contracts ex post.[40] Bankruptcy laws became more debtor friendly.[41]

Over the course of the 20th century, and gathering pace in the post-war period, successive British governments liberalized consumer credit markets, particularly unsecured consumer credit markets.[42] This propelled the rise of the consumer and credit society, and the reimagination of credit as essential, productive, and desirable.[43] As **Figure 1** shows, household debt in the UK grew from c. 30 percent of GDP in 1970, to reach a peak of almost 100 percent in 2008 with only a modest decline since. **Figure 2** shows that household

---

[39] Chancellor, ibid, 63 ('the ban on usury proved futile because as trade expanded, both at home and abroad, the demand for credit became overwhelming'); Roth, n 36, 40 (citing Weber); Crowther, *Consumer Credit* (noting that 'equally widespread, under the impulse of the trading instinct, have been the legal fictions and the practical devices used to evade the prohibition').

[40] Where it was stipulated by statute that interest over 48% p.a. was prima facie excessive and the transaction unconscionable. *See* Roy M Goode, 'Usury in English Law' (1982) 1 Arizona Journal of International and Comparative Law 38. Although the nominal 48% interest rate limit was repealed by the 1974 Consumer Credit Act (CCA), restrictions on high-interest credit were reintroduced in 2013 following an impassioned moral campaign led by the Church of England against payday lending companies such as Wonga. *See* Crowther, *Consumer Credit*, 346-365 ('Statutory control of credit terms') and *infra* ch 4, section 4.2.2.2.1. On similar trends in the US, *see e.g.* Louis Hyman, *Borrow: The American Way of Debt* (Vintage Books 2012) (hereinafter, 'Hyman, *Borrow*'), 7; Louis Hyman, 'The Politics of Consumer Debt: U.S. State Policy and the Rise of Investment in Consumer Credit, 1920-2008' (2012) 644 Annals of the American Academy of Political & Social Science 40 (hereinafter, 'Hyman, *Politics of Consumer Debt*'), 41 ('A lack of profits confined lending to the margins of American capitalism in the nineteenth century…usury laws made the lending of cash unprofitable.').

[41] Ian PH Duffy, *Bankruptcy and Insolvency in London During the Industrial Revolution* (Routledge 1985), cited in Paolo di Martino, 'The Historical Evolution of Bankruptcy Law in England, the US and Italy up to 1939: Determinants of Institutional Change and Structural Differences' *in* Karl Gratzer, Dieter Stiefe (eds) *History of Insolvency and Bankruptcy: From an International Perspective* (Huddinge: Södertörns högskola, 2008), 265 ('Modern English bankruptcy legislation has its roots in strict and creditors-supportive medieval laws but began to loose [sic] its punitive nature in the beginning of the eighteenth century'). In the US, *see generally* Teresa A Sullivan, Elizabeth Warren, Jay L Westbrook, *As We Forgive Our Debtors* (Beard Books 1999).

[42] *See further* ch 4, section 4.1.1.

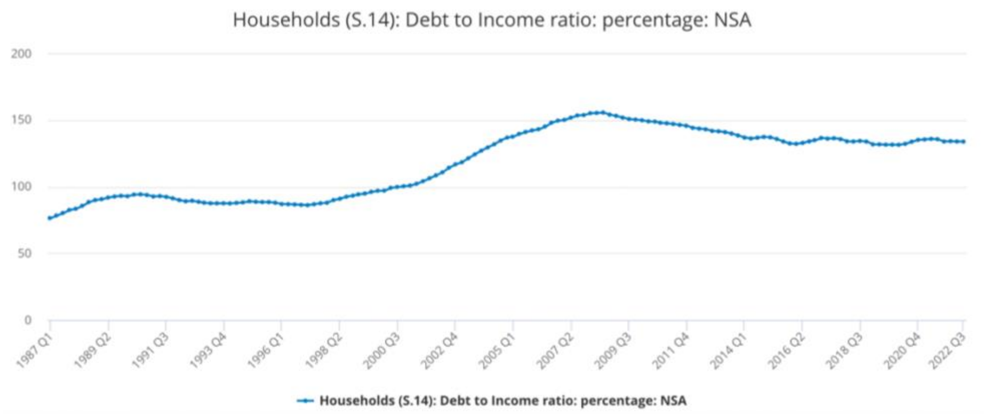
[43] *See generally* Stuart Aveyard, Paul Corthorn and Sean O'Connell, *The Politics of Consumer Credit in the UK, 1938-1992* (OUP 2018) (hereinafter, 'Aveyard et al, *Politics of Consumer Credit*'); Crowther, *Consumer Credit*, 31-108; 366-377; 407-573 (describing the expansion of consumer credit markets before the 1970s and projecting continuing increase); Lyn C Thomas, *Consumer Credit Models: Pricing, Profit, and Portfolios* (OUP 2009) (hereinafter, 'Thomas, *Consumer Credit Models*'), 2-5 (discussing the expansion of consumer credit markets in the US and Europe over the course of the 20th century, particularly unsecured credit markets, and describing consumer credit as 'the driving force behind the economies of most of the leading industrial economies').

debt in the UK as a share of household disposable income grew from c. 75 percent in 1987 to over 150 percent in 2008, again with only a modest decline since.[44]

Figure 1. Household Debt, Loans, and Debt Securities as a Percentage of GDP (1950-2021)—Selected Countries

Source: International Monetary Fund, Global Debt Database[45]

Figure 2. Household Debt to Income Ratio, United Kingdom, 1987 to 2022



[44] *See also* UK Parliament, 'Household Debt: Statistics and Impact on Economy' (Research briefing, 5 December 2022) <https://commonslibrary.parliament.uk/research-briefings/cbp-7584/>; Gunnar Trumbull, 'Credit Access and Social Welfare: The Rise of Consumer Lending in the United States and France' (2012) 40(1) Politics & Society 9, 11; 13 (showing the rapid growth of consumer debt as a share of disposable income in the UK from 1945 to 2005). For the US, *see also* New York Fed, 'Quarterly Report on Household Debt and Credit' (2022) <https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/hhdc_2022q1.pdf>, 3 (showing an increase in US consumer debt over the last twenty years, primarily comprised of mortgage/housing debt).

[45] <https://www.imf.org/external/datamapper/HH_LS@GDD/GBR/USA/DEU/FIN>

Source: Office for National Statistics (ONS)[46]

Various structural changes enabled and encouraged the rapid expansion of (unsecured) consumer credit markets, beginning in the 1970s. The resurgence of neoliberal political ideology favoured 'free' markets, a smaller (welfare) state, and the 'responsibilisation' of citizens as financial consumers.[47] The consumer was reimagined as an independent economic actor—a 'citizen consumer'—a vision that would become more firmly embedded during the 1980s.[48] The elaborate marketing efforts of the credit industry, particularly mail order and credit card companies, further helped to reimagine credit as productive and desirable. A consumer no longer needed to be extremely wealthy to enjoy a luxury lifestyle: she could just charge it to her Mastercard.[49] A growing consumer and labour movement supported access to credit as an economic right.[50] The expansion of consumer

46 <https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/cvzi/ukea?referrer=search&searchTerm=cvzi>

47 Aveyard et al, *Politics of Consumer Credit*, 222; 231-232 ('state's key role in enabling citizens to become consumers'); Niamh Moloney, 'Regulating the Retail Markets' in Niamh Moloney, Eilis Ferran and Jennifer Payne (eds) *The Oxford Handbook of Financial Regulation* (OUP 2015), 743 (identifying a similar ideology in the years leading up to the 2008 financial crisis: 'Retail market regulation came to display 'marketing' and 'responsibilizing' characteristics and to promote the importance of financial independence though long-term market-based savings.').

48 Joseph T Molony, *Report of the Committee on Consumer Protection* (Cmnd 1781, 1962); Aveyard et al, *Politics of Consumer Credit*, 172 (noting that 'Molony set the tone for the circumscribed expansion of the state into consumerism, with the consumer imagined as an individualist.'); Gunnar Trumbull, 'National Varieties of Consumerism,' (2006) 47(1) Jahrbuch für Wirtschaftsgeschichte / Economic History Yearbook 77 (categorizing Britain's national approach to consumerism as 'economic', which [78] 'treated the consumer as an economic actor, with a legal and social status equivalent to suppliers and retailers'); Peter Gurney, 'The Battle of the Consumer in Postwar Britain' (2005) 77(4) Journal of Modern History 976, cited in Aveyard et al, *Politics of Consumer Credit*, 6 (arguing that the 'embrace of the 'individual consumer' by the main political parties undermined the cooperative alternative to mass consumption… the alternative model of thrift (and equitable consumption)'), and at 8 (referring to the 'citizen consumer' and noting that by the time of the Consumer Credit Act in 1974 'a model of the rational, educated shopper dominated approaches to consumer protection.').

49 R B Jack, *Banking Services: Law and Practice. Report by the Review Committee* (Cmnd 622, 1989) (hereinafter, Jack, *Banking Services*), 96-102 (examining the benefits and risks of the rise of payment cards, or 'The Plastic Revolution'). In the US context, *see generally* Robert D Manning, *Credit Card Nation: The Consequences of America's Addiction to Debt* (Basic Books 2000); Ronald J Mann, *Charging Ahead: The Growth and Regulation of Payment Card Markets Around the World* (CUP 2006).

50 Aveyard et al, *Politics of Consumer Credit*, 181ff (discussing the consumer movement for access to credit and against credit discrimination). In the US, *see* Greta R Krippner, 'Democracy of Credit: Ownership and the Politics of Credit Access in Late Twentieth-Century America' (2017) 123 American Journal of Sociology 1, 4

credit markets was also, necessarily, driven by structural changes—including due to technological change and automation[51]—that reduced productivity, employment, and wages (or, changed their distribution), and increased poverty and inequality. Consumer credit supplemented increasingly volatile and declining real incomes.[52]

Via consumer credit market expansion, the state thus sought to partially transfer its redistributive functions to the private (and third) sectors, as 'privatized welfare'.[53] Rather than expanding social provision in response to wage stagnation, an ageing population, and rising poverty and inequality (inter alia), the state encouraged borrowing and consumption,

---

(analysing 'two influential credit movements that mobilized to democratize access to credit beginning in the 1970s.').

51 Daron Acemoglu and Pascual Restrepo, 'Automation and New Tasks: How Technology Displaces and Reinstates Labor' (2019) 33(2) Journal of Economic Perspectives 3 ('automation always reduces the labor share in value added and may reduce labor demand even as it raises productivity. The effects of automation are counterbalanced by the creation of new tasks in which labor has a comparative advantage… Our empirical decomposition suggests that the slower growth of employment over the last three decades is accounted for by an acceleration in the displacement effect, especially in manufacturing, a weaker reinstatement effect, and slower growth of productivity than in previous decades.'); Daron Acemoglu, 'Technical change, Inequality, and the Labor Market' (2002) 40(1) Journal of Economic Literature 7.

52 Dirk Krueger and Fabrizio Perri, 'Does Income Inequality Lead to Consumption Inequality? Evidence and Theory' (2006) 73(1) The Review of Economic Studies 163 (arguing that an increase in inequality causes an expansion in consumer credit markets and a change in the development of financial markets; at 164, 'the structure of the credit markets [sic] in an economy is endogenous and may evolve in response to higher income volatility'); Greta R. Krippner, *The Financialization of the American Economy* (2005) 3 Socio-Economic Review 173 (hereinafter, 'Krippner, *Financialization of the American Economy*'). *See further* Appendix 1 (examining the rise of poverty and inequality in the UK).

53 Andreas Wiedemann, 'A Social Policy Theory of Everyday Borrowing: On the Role of Welfare States and Credit Regimes' (2021) 0(0) American Journal of Political Science 1 (hereinafter, 'Wiedemann, *Social Policy Theory*') (arguing that credit *substitutes* welfare in countries with restrictive social welfare regimes, but *complements* welfare in countries with more permissive social welfare regimes); Jodi Gardner, Mia Gray and Katherine Moser (eds) *Debt and Austerity* (Edward Elgar 2021) (hereinafter, 'Gardner, Gray, and Moser, *Debt and Austerity*'); Aveyard et al, *Politics of Consumer Credit*, 191 (citing research from the Labour Party in 1988 that '74 per cent of families on benefits had to borrow to make ends meet and that 54 per cent had fallen behind on debt repayments.'); Joseph Spooner, *Bankruptcy: The Case for Relief in an Economy of Debt* (CUP 2019); Iain Ramsay, 'Changing Policy Paradigms of EU Consumer Credit and Debt Regulation', in Dorota Leczykiewicz and Stephen Weatherill (eds) *The Images of the Consumer in EU Law: Legislation, Free Movement and Competition Law* (Hart 2016) (hereinafter, 'Ramsay, *Changing Policy Paradigms*'), 178-179; Greta R Krippner, *Capitalizing on Crisis: The Political Origins of the Rise of Finance* (HUP 2011) (arguing that the 'financialization' of the U.S. economy since the 1970s was an inadvertent response to unresolved political distributional dilemmas as post-war growth stalled); Hyman, *Borrow*, 7ff (noting additionally the important role of secondary market trading in facilitating the expansion of credit: 'What ultimately made all this lending possible was that lenders could now, for the first time, resell their debt.'). Of course, the idea of 'credit-as-welfare' predates the 1970s: *see* Trumbull, n 44; Gelpi and Julien-Labroyère, n 35, 95 ('For centuries, the nearest thing to consumer credit, that is the money lender, acted as a social lifebuoy for the poorest families.').

thereby supplementing declining real incomes, whilst boosting aggregate demand and economic growth (as 'privatised Keynesianism').[54] As Raghuram Rajan observes, 'easy credit has been used throughout history as a palliative by governments that are unable to address the deeper anxieties of the middle class directly…'[55]—a policy he terms 'let them eat credit'.[56] Policymakers framed expansionary credit policies with the distinctly distributional promise of 'democratizing access to credit' and creating a 'property-owning democracy', the latter by increasing access to low-cost mortgages and homeownership.[57]

Figures 3 and **4**, below, show that (non-means tested) social welfare spending as a share of GDP has effectively flatlined since the 1970s, failing to keep up with increasing demand for financial support.[58] This trend, and the relationship between poverty, inequality, and credit growth more broadly, are explored further in **Appendix 1**.

---

[54] Colin Crouch, 'Privatized Keynesianism: An Unacknowledged Regime' (2009) 11(3) British Journal of Politics and International Relations 382, cited in Aveyard et al, *Politics of Consumer Credit*, 232; Hyman, *Politics of Consumer Debt*, 45 ('For Great Society policy-makers and promoters, the problem of inequality was framed as a problem of credit access rather than job access.').

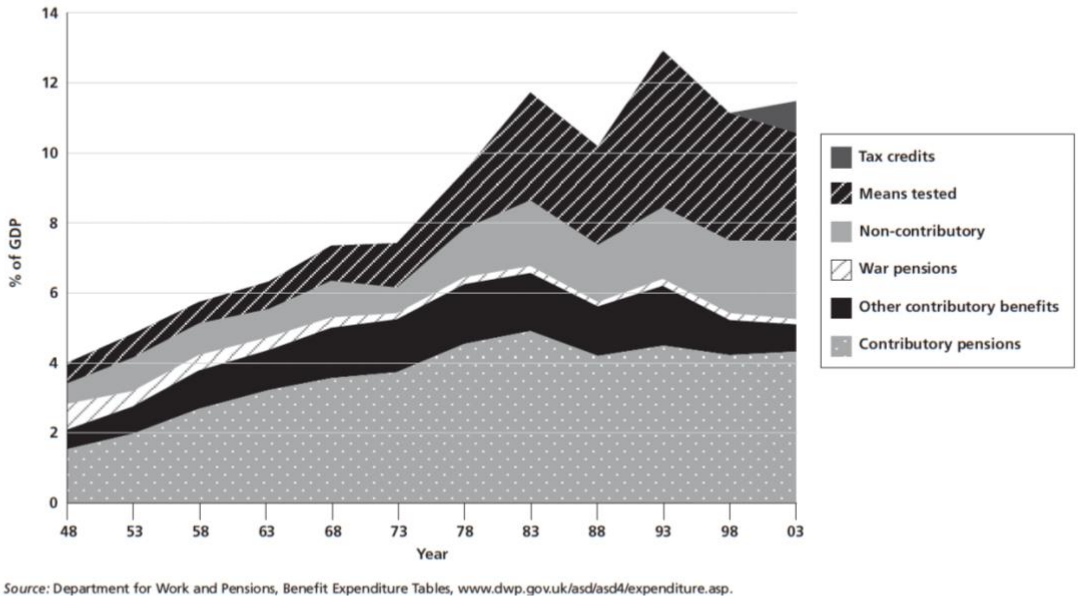
[55] Raghuram Rajan, *Fault Lines: How Hidden Fractures Still Threaten the World Economy* (Princeton 2011) (hereinafter, 'Rajan, *Fault Lines*'), 9 (discussing 'rising inequality in the United States and the political pressure it has created for easy credit.'); 21-45.

[56] Rajan, *Fault Lines*, 19; 21-45.

[57] Although the ideal that 'every man should own a home' has a long cultural and political history, the ideal that everyone should own a home *financed by a mortgage* is of more recent vintage. *See e.g.* Anthony Eden, Speech at 1946 Conservative Party Conference, cited in Aveyard et al, *Politics of Consumer Credit*, 14; 229. In the US, *see e.g.* George W. Bush, 'Remarks by the President at Signing of the American Dream Downpayment Act' *White House Archives* (Dec 16 2003) <https://georgewbush-whitehouse.archives.gov/news/releases/2003/12/20031216-9.html> ('Our government is supporting homeownership because it is good for America, it is good for our families, it is good for our economy.'); Rajan, *Fault Lines*, 9 ('In the United States, the expansion of home ownership—a key element of the American Dream—to low and middle-income households was the defensible linchpin for the broader aims of expanding credit and consumption.'), 21-45; Torben Iversen and Phillip Rehm, 'Information and Financialization: Credit Markets as a New Source of Inequality' (2022) 0(0) Comparative Political Studies 1, 2 ('Owning a home has also become a marker of middle-class success in many countries, and access to mortgage finance is therefore increasingly seen as an important tool for aspirational voters.')

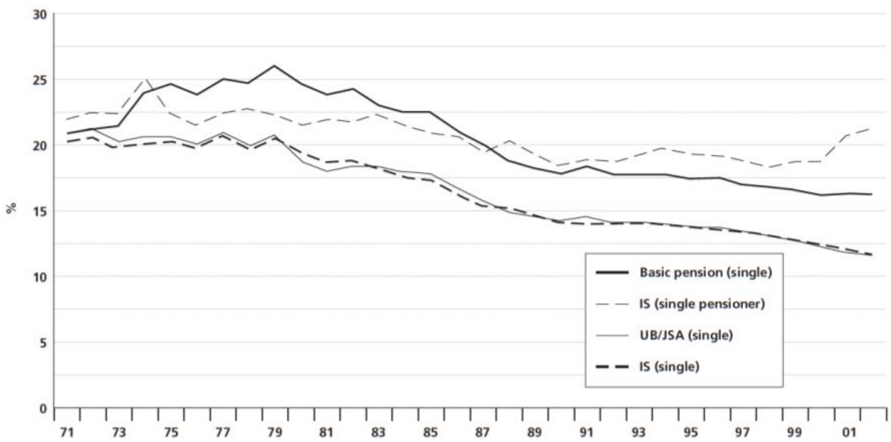
[58] John Hills, 'The Last Quarter Century: From New Right to New Labour' in Howard Glennerster, John Hills, David Piachaud, and Jo Webb, 'One Hundred Years of Poverty' (2004) <https://eprints.lse.ac.uk/3913/1/One_hundred_years_of_poverty.pdf>, 103 ('The comparatively static total [of social spending] results from the collision of two opposing forces: desire to reduce public spending to allow lower taxes, particularly in the 1980s; and the upward pressure on pensions, social services, and healthcare from an ageing population, on social security from higher levels of market inequality, and on almost all of these items from growing affluence.').

Figure 3. Social Security Benefits in the UK as a Percentage of GDP, 1948/49 to 2003/4



Source: Department for Work and Pensions, as reproduced in Glennerster, Hills, Piachaud, and Webb (2004)[59]

Figure 4. Benefits Relative to Average Earnings, 1971 to 2002



Source: Glennerster, Hills, Piachaud, and Webb (2004)[60]

[59] Ibid., 104.

[60] Ibid., 106-108 (showing the fall in the relative value of many benefits).

2.1 Credit scoring 1.0

The expansion of consumer credit markets during this period, particularly unsecured consumer credit markets, could not have occurred, however, but for major advances in information and communications technology, beginning in the late 1960s.[61] As such, technological change and automation not only contributed to the structural drivers of expansionary credit policy and credit demand during the latter part of the twentieth century, as discussed above, but also *enabled* credit market expansion.[62] Crucially, the growth of (unsecured) consumer credit markets depended on the ability of lenders to cost-effectively measure and manage 'credit risk' in their loan portfolios, i.e., the probability that borrowers will default on credit (PD) and the loss to the lender in the event of the borrower's default (LGD).[63] More particularly, it depended on lenders' ability to sort 'good' quality (low credit risk) borrowers from 'bad' quality (high credit risk) borrowers.[64]

---

[61] Andrew Leyshon and Nigel Thrift, 'Lists Come Alive: Electronic Systems of Knowledge and The Rise of Credit Scoring in Retail Banking' (1999) 28(3) Economy and Society 434 (hereinafter, 'Leyshon and Thrift, *Lists Come Alive*'), 436 ('It is the rise of practices based in a new machinic assemblage designed more effectively to overcome information asymmetries which has in large part driven the current transformation in retail banking in Britain.'); Hal R Varian, 'Competition and Market Power' in Hal R Varian, Joseph Farrell, and Carl Shapiro *The Economics of Information Technology: An Introduction* (CUP 2004), 7 (and generally discussing waves or clusters of technological innovation due to combinatorial innovation set off by computing and the Internet, and the greater speed of digital technological revolutions). *See also* Roth n 36, 53 (characterizing moral and social norms as analogous to technological barriers in shaping and constructing markets).

[62] As articulated further below, competition in credit markets itself drove innovation in credit scoring technology.

[63] *See further* ch 4, section 4.2.

[64] Joseph Stiglitz and Andrew Weiss, 'Credit Rationing in Markets with Imperfect Information' (1981) 71(3) The American Economic Review 393; George Akerlof, 'The Market for "Lemons": Quality Uncertainty and the Market Mechanism' (1970) 84(3) Quarterly Journal of Economics 488; Charles W Calomiris, Stanley D Longhofer and Dwight M Jaffee, 'Credit Rationing' in Steven E Durlauf and Lawrence E Blume (Eds) *The New Palgrave Dictionary of Economics* (2nd edition, Palgrave Macmillan 2008), 8 ('The use of risk-based pricing in consumer lending, including credit card loans and mortgages, has become widespread, reflecting the increased ability of lenders to distinguish between borrowers with different risk profiles.'); Thomas, *Consumer Credit Models*; Lyn Thomas, Jonathan Crook, and David Edelman, *Credit Scoring and Its Applications* (Society for Industrial and Applied Mathematics 2017, 2nd edition) (hereinafter, 'Thomas et al, *Credit Scoring*'). *See further* ch 4, section 4.2.

Traditionally, lenders relied on loan officers to gather information from prospective borrowers—in person in bank branches— in order to ascertain their creditworthiness, decide whether to lend, and at what price. This includes 'hard' information, such as the borrower's financial and employment status, along with a wide range of 'soft' (informal, tacit) information.[65] The latter could include anything from whether the borrower went to Church on Sunday, to how they dressed and their family's reputation in the community—relied upon as proxies for a borrower's moral character and therefore their propensity to default on credit.[66]

Due to the high costs of manually acquiring information and evaluating the creditworthiness of large numbers of borrowers from distant locations, as well as the high costs of processing large volumes of (small) loans, the scale and geographical scope of lending was limited to local borrowers, often those whom lenders knew personally.[67] Manual, 'judgmental' credit analysis was, as a result, also highly susceptible to the personal biases of

---

[65] Leyshon and Thrift, *Lists Come Alive*, 440-41. On the distinction between 'hard' and 'soft' information in financial markets *see* José M Liberti and Mitchell A Petersen, 'Information: Hard and Soft' (2019) 8(1) The Review of Corporate Finance Studies 1.

[66] Thomas et al, *Credit Scoring*, 11 ('Traditional credit assessment relied on "gut feel" and an assessment of the prospective borrower's character, ability to repay, and collateral/security.'); Noel Capon, 'Credit Scoring Systems: A Critical Analysis' (1982) 46(2) Journal of Marketing 82, 83 (describing the 'five Cs'—credit, character, capacity, capital, and collateral—as the 'conceptual framework' for judgmental credit decisions). For an articulation of the five Cs of credit analysis *see e.g.* Jean Tirole, *The Theory of Corporate Finance* (Princeton 2006), 103; Cathy O'Neil, *Weapons of Math Destruction* (Crown Books 2016), 177-8.

[67] Stiglitz and Weiss, n 64 (showing that where asymmetric information precludes lenders from effectively screening borrowers and assessing their credit risk, they will ration credit to riskier borrowers to mitigate adverse selection effects); Gunnar Trumbull, 'Regulating for Legitimacy: Consumer Credit Access in France and America' (Harvard Business School BGIE Unit Working Paper, 2010) <https://ssrn.com/abstract=1705550> (hereinafter, 'Trumbull, *Regulating for Legitimacy*'), 7 (arguing, conversely, that the high administrative costs associated with 'writing, tracking, and collecting small loans', rather than concerns about adverse selection due to the riskiness of borrowers, explained the high costs of credit and limits on the size of the credit market in the postwar period); Marco Pagano and Tullio Jappelli, 'Information Sharing in Credit Markets' (1993) XLVIII Journal of Finance 1693; Robert M Hunt, 'What's in the File? The Economics and Law of Consumer Credit Bureaus' (Federal Reserve Bank of Philadelphia Business Review, Second Quarter, 2002), 18 ('When there is a high volume of applications for loans of modest size, lenders cannot afford to invest a lot of resources evaluating each application. A credit bureau can help lenders adopt lower cost techniques for screening applications—such as credit scoring—without incurring an unacceptable rise in overall credit risk.'). Of course, the expansion of consumer credit markets was also limited by other factors, such as government-imposed credit controls. *See* text to n 47 et seq, and text to n 248 et seq.

lending officers, who were disproportionately likely to be White males. This includes explicit bias, particularly against non-Whites and women. It also includes implicit bias: lending officers would have more personal experience of other White males than of women or non-Whites, making their costs of acquisition of soft information about White males lower in relative terms, and leading to implicit bias.[68] As a result, non-White and female borrowers were often denied credit, or offered credit on less favourable terms, compared to White and/or male borrowers.[69]

Advances in computing, beginning in the late 1960s, enabled the collection, processing, storage, and sharing of (consumer) data at a much lower cost, and greater scale, than previously.[70] This enabled the growth of credit databases, the system of 'credit referencing' through credit reference agencies (CRAs),[71] and the development of computerized, statistical 'credit scoring' models.[72] Although statistical credit scoring can

[68] Leyshon and Thrift, *Lists Come Alive*, 448 (describing traditional credit assessment in the UK which 'for the most part involved applicants being vetted by white, middle-class males.')

[69] *See generally* Aveyard et al, *Politics of Consumer Credit*, 181-187. The prevalence of racial and gender-based discrimination in lending was an important driver of anti-discrimination legislation beginning in the late 1960s.

[70] Advances in computing and communications technology also facilitated the expansion of consumer credit markets in other ways. They enabled money to be transferred at a much greater speed and scale, in turn enabling consumer credit markets, as well as other financial markets, to expand and globalize. *See* Thomas et al, *Credit Scoring*, 266 ('[d]uring the 1970s and 1980s several countries reduced the amount of regulation that applied to banks, and at the same time the rapid advance of computer technology enabled funds to be moved between banks in different countries almost instantaneously…financial systems between countries became increasingly interdependent.'). Advances in computing also facilitated the development of magnetic stripe technology, which in turn enabled the development of consumer credit cards. Credit cards were a key driver of the growth in consumer credit and consumption in the latter part of the twentieth century. *See* n 49.

[71] Referred to as '(consumer) credit reporting' in the US. *See* Fair Credit Reporting Act of 1970, Pub. L. No. 91-508 §§ 601-629, 84 Stat. 1128 (1970), codified as amended at 15 U.S.C. §§ 1681 - 1681x ('FCRA').

[72] *See generally* Thomas et al, *Credit Scoring*, 10 (defining credit scores); Josh Lauer, *Creditworthy: A History of Consumer Surveillance and Financial Identity in America* (New York 2017) (examining the rise of 'consumer credit surveillance systems' as inextricably linked to the 'ascent of consumer capitalism'); Crowther, *Consumer Credit*, 369ff (predicting the expansion of credit reporting and the credit information market as computing becomes cheaper); Kenneth G Younger, *Report of the Committee on Privacy (Younger Committee)* (Cmnd 5012, 1972) (hereinafter 'Younger, *Privacy*'), 73-88 (discussing the growth of credit rating agencies in England and associated concerns relating to consumer privacy); Alya Guseva and Akos Rona-Tas, 'Uncertainty, Risk, and Trust: Russian and American Credit Card Markets Compared' (2001) 66(5) American Sociological Review 623 (arguing that the development of credit information markets and risk calculation technologies enabled the

formally be traced back to the early 1940s, in the US, when techniques such as linear discriminant analysis were first applied to the task of classifying borrowers, it gathered pace in the late 1970s.[73] Credit scoring systems developed in the US were 'imported' to the UK, beginning in the 1980s, in response to the relative ineffectiveness of manual, judgmental credit analysis, which was blamed for a rise in non-performing loans, and cost-cutting pressures resulting from the growing demand for credit and increased competition for banks' traditional customer base, inter alia.[74] As noted earlier, the liberalization of consumer credit markets and growing demand for credit increased the commercial value of statistical credit scoring and credit referencing via CRAs for lenders.[75]

We can refer to the period of technological development in statistical credit scoring spanning, in the UK, from the 1980s to the mid-2000s as 'credit scoring 1.0'.[76] Credit referencing and statistical credit scoring systems improved lenders' ability to sort 'good' borrowers from 'bad', based on their credit risk, in order to decide whether to extend credit and at what price. As a result, these technologies enabled lenders to extend (unsecured) credit, including smaller loans, to a much larger and wider range of consumers, at a lower

---

expansion of credit markets in the US, whilst the lack of similar developments inhibited credit markets in Russia, which remained 'trust-based').

[73] Ronald A Fisher, 'The Use of Multiple Measurements in Taxonomic Problems' (1936) Annals of Eugenics 179; David Durand, 'Credit-Rating Formulae' in Durand (ed) *Risk Elements in Consumer Instalment Financing* (NBER 1941), 83-91 <https://www.nber.org/system/files/chapters/c9265/c9265.pdf>; Thomas, *Consumer Credit Models*, 5 (discussing the historical background of default-based credit scoring); Leyshon and Thrift, *Lists Come Alive*, 444.

[74] Leyshon and Thrift, *Lists Come Alive*, 436 (dating the expansion of credit-scoring systems in the British financial services industry to the 1980s); 443ff (further attributing the demand for statistical credit scoring systems to the contraction of the bank branch network in the late 70s, partly caused by the shift to telephone-based distribution of financial products and services).

[75] Younger, *Privacy*, 78; Jack, *Banking Services*, 33.

[76] *See* Matthew A Bruckner, 'The Promise and Perils of Algorithmic Lenders' Use of Big Data' (2018) 93(1) Chicago-Kent Law Review, 11-17 (distinguishing two phases of 'algorithmic lending' — 1.0 and 2.0); Nate Cullerton, 'Behavioral Credit Scoring' (2013) 101 Georgetown Law Journal 807 (distinguishing 'behavioral credit scoring' 1.0 and 2.0). Note that this categorization describes different periods of *innovation* in statistical credit scoring, rather than their use. Credit scoring 1.0 techniques are still very much in use today (*see further* ch 3).

cost.[77] They also offered to reduce implicit and explicit bias in lending decisions, which, as noted earlier, more adversely affected non-White and female borrowers.[78]

At a high level, credit scoring 1.0 was characterized by the use of linear statistical methods and a limited number of fixed, 'hard', historical variables to assess borrowers' creditworthiness.[79] Credit repayment history—how a borrower has managed their debts in the past—was typically the highest weighted variable.[80] This approach reflects both demonstrated statistical correlation between a borrower's credit history and their likely credit risk, as well as traditional limits on lenders' access to non-credit and non-financial data

[77] *See e.g.* Leyshon and Thrift, *Lists Come Alive*, 448 ('credit scoring is bringing about a greater level of financial inclusion, in that in Britain at least the widespread use of such systems has accompanied a continuous expansion of the customer base of the retail banking market.'); Thomas, *Consumer Credit Models*, 5 ('The expansion in the credit card market in 1966, when the BankAmericard was franchised all over the USA and the first credit card, Barclaycard, was launched in the UK, could only happen because credit scoring had proved its worth as an automated way of estimating default risk for consumer credit.'); Liberti and Petersen, n 65, 2 ('The growth in the amount of numerical data available about borrowers, and the subsequent ability to automate the credit decision, transformed banking from an exclusively local and personal market to a national, competitive, and in some cases impersonal market.'); Thomas et al, *Credit Scoring*, 4-5 ('The number of people applying for credit cards each day made it impossible both in economic and manpower terms to do anything but automate the lending decision.'); Hunt, n 67, 19 ('The advantages of access to a credit bureau information will be greater if lenders frequently encounter potential customers they don't know very much about.').

[78] Leyshon and Thrift, *Lists Come Alive*, 448 (noting the Equal Opportunities Commission's support for statistical credit scoring 'on the grounds that credit-scoring is more "objective" than the more traditional system of vetting'). In the US, *see e.g.* Thomas et al, *Credit Scoring*, 5 (noting that the passage of the Equal Credit Opportunity Act in the US, in 1975 and 1976 'ensured the complete acceptance of credit scoring' by outlawing 'discriminating in the granting of credit unless the discrimination "was empirically derived and statistically valid."').

[79] Thomas et al, *Credit Scoring*, 14-18 (discussing the 'scorecard' approach to credit scoring, and distinguishing 'application scoring', which relies on static data and is mainly used to determine whether to approve a credit application, and 'behavioural scoring', which utilizes more dynamic performance and transaction data to assess the future probability of borrower default), 25-97 (describing different statistical methods for building scorecards), 157-177 (describing different statistical methods for behavioural scoring); David J Hand and William E Henley, 'Statistical Classification Methods in Consumer Credit Scoring: A Review' (1995) 160(3) Journal of the Royal Statistical Society 523; Nick Ryman-Tubb, 'An Overview of Credit Scoring Techniques' (2000) 21(1/2) Credit Control 39. Of course, soft information would still play a role in credit decisions, especially in community and relationship lending. *See e.g.* Mitchell A Petersen and Raghuram G Rajan, 'The Benefits of Lending Relationships: Evidence From Small Business Data' (1994) 49(1) Journal of Finance 3; Allen N Berger and Gregory F Udell, 'Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure' (2002) 112(477) The Economic Journal. *See further* ch 3.

[80] Equifax, 'How are Credit Scores Calculated?' (2019) <https://bit.ly/2I7ppm6>.

beyond limited categories of demographic data.[81] The latter typically includes the borrower's age, income, marital status, and address (obtained from the borrower's credit application form or interview), and public record data, such as where the borrower is registered to vote, and any recent bankruptcies or court judgments (obtained from the borrower's credit file). Lenders in the UK would request consumers' credit files and credit scores from one or more of the three main CRAs—Equifax, Experian, and TransUnion.[82] This would be combined with the lender's proprietary data, whether obtained from the customer application form or third parties, and credit scores derived from this data.[83]

Of course, credit scores, and credit risk assessment, are not the totality of a credit *decision*.[84] Moreover, credit scores were, and still are, designed and interpreted by humans—leaving room for 'soft' information, including personal biases, to shape credit decisions. As Part Two will examine in further detail, the terms of credit, including price, are influenced by a range of individual and firm-specific factors (such as the lender's profit motive and the informedness of consumers).[85] Lenders often have firm-specific policies, such as group interest rates based on the credit scoring range (or 'bin') that the borrower falls into, as well as a 'cut-off' interest rate above which (credit score below which) they will not lend.[86] Credit

---

[81] Thomas et al, *Credit Scoring*, 157 ('[t]he characteristics that turn out to be most powerful are those that show whether the borrower has defaulted in the past and the current status of the borrower's arrears position.').

[82] In the UK, credit reports obtained from CRAs are called 'Statutory Credit Reports'. *See* ch 4, section 4.2.4.

[83] *See further* ch 3.

[84] *See e.g.* Jorge Galindo and Pablo Tamayo, 'Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modelling Applications' (2000) 15 Computational Economics 107 ('In economics and finance, classification or predictive models derived from data are not used in isolation but as part of a larger model or in conjunction with interpretative theories, often in the context of policy setting.').

[85] Thomas et al, *Credit Scoring*, 12 (discussing the evolution of credit scoring to a tool for maximising lenders' profits through more behavioural demand-based credit pricing: '[b]anks began to realize that, with consumer lending, the objective should not be to avoid any losses, but to maximize profits.'); Leyshon and Thrift, *Lists Come Alive*, 445-6 (describing the rise of a 'marketing discourse' in business, and the combination of marketing programmes and credit-scoring in the 90s to target good customers more effectively). *See further* ch 4, section 4.2.1.

[86] For example, some lenders have a specific policy not to lend to applicants who have previously been bankrupt or have a criminal record—whilst others focus specifically on lending to specific (often historically

allocation and the terms of credit are, inevitably, also shaped by a wide range of structural factors. These include the competitiveness of the market, macroeconomic conditions, and regulatory restrictions (such as interest rate limits and obligations to mitigate money laundering and fraud).[87]

***

Evidently, the rise of credit scoring is a case study in the co-evolution of markets, law, technology, social norms, and the political economy.[88] More particularly, advances in technology and the expansion of consumer credit markets are symbiotic. Advances in computing and statistical techniques enabled the expansion of consumer credit markets. At the same time, the commercial opportunity for firms to profit from lending to consumers,

---

marginalized) communities. *See e.g.* Croydon Caribbean Credit Union, https://cccreditunion.co.uk/membership/ (members need to live within the 'common bond' geographic area). Different CRAs have different credit score ranges, and lenders will price these ranges differently (or use custom scores/ranges). For example, the Experian UK credit score ranges from 0 to 999, with a 'good' score defined as between 881 and 960 (*see* Experian, 'Your Free Experian Credit Score' <https://www.experian.co.uk/consumer/experian-credit-score.html>); FCA, 'High-Cost Credit Review: Technical Annex 1' (July 2017) <https://www.fca.org.uk/publication/feedback/fs17-02-technical-annex.pdf>, 12 (distinguishing the 'prime', 'sub-prime', and 'new-to-credit' consumer segments). In the US, the FICO score spans from 300 to 850, where a score of 670 to 739 is defined as 'good' or 'prime' (*see* Jim Akin, 'What Are the Different Credit Scoring Ranges?' (*Experian Blog*, Jun 23 2020) <https://www.experian.com/blogs/ask-experian/infographic-what-are-the-different-scoring-ranges/>. 'Subprime' generally refers to a FICO score of less than 670, i.e., poor to fair (*see e.g.* Louis DeNicola, 'What Does Subprime Mean?' (*Experian Blog*, July 9 2022) <https://www.experian.com/blogs/ask-experian/what-is-subprime/>.

[87] Thomas et al, *Credit Scoring*, 15-17. *See further* ch 4, section 4.2.1. Some lenders, notably informal, unauthorised moneylenders ('loan sharks'), do not participate in the formal credit referencing system, nor use risk-based credit scores to inform credit decisions. Historically, unregulated 'pay day' lenders also did not typically rely on an assessment of the borrower's credit risk, instead automatically deducting loan and interest repayments from a borrower's next paycheck. The high interest rate on payday loans often reflects the high-risk profile of this borrower segment, rather than excessive rent-seeking by lenders (or excessive market concentration). *See e.g.* John Y Campbell et al, 'Consumer Financial Protection' (2011) 25(1) Journal of Economic Perspectives 91; Will Dobbie and Paige M Skiba, 'Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending' (2013) 5(4) American Economic Journal: Applied Economics 256. *But see* section 5.3.4 (discussing the extension of creditworthiness assessment regulations to payday lending and other high-cost short-term credit markets). In their early days, p2p, or 'marketplace', lending platforms also relied primarily on peer assessments of a borrower's creditworthiness, rather than information shared through the formal credit referencing system. *See e.g.* Adair Morse, 'Peer-to-Peer Crowdfunding: Information and the Potential for Disruption in Consumer Lending' (2015) 7 Annual Review of Financial Economics 463; Rajkamal Iyer et al, 'Screening Peers Softly: Inferring the Quality of Small Borrowers' (2016) 62(6) Management Science 1554. *But see* section 5.3.4 (discussing the extension of the regulatory perimeter).

[88] *See generally* Louis Hyman, 'Debtor Nation: How Consumer Credit Built Postwar America' (2008) 9(4) Enterprise & Society 614, 614 ('The narrative attests that this debt economy, though not accidental, did not spring forth one day *fait accompli*. Business choices, institutional contexts, and government policies converged to produce a world for which no one planned but nonetheless came to be.'). *See further* ch 3 and 4.

and competition for market share, drove further invention and innovation in credit scoring, statistical techniques, and digital technology more broadly.[89]

Importantly, credit market-driven technological development was not limited to credit or financial markets. Much of the advances in (applied) AI, and ML specifically, in the latter part of the twentieth century occurred in the context of credit scoring and credit markets.[90] In this way, consumer credit markets catalysed broader advances in technology, and the digital transformation and datafication of other parts of the economy and society—a process that I refer to as the 'technology-credit cycle'.[91] The law incentivized and legitimated these developments.[92]

[89] On the broader dialogic, bi-directional, cyclical relationship between technology, markets, and society, *see e.g.* Langdon Winner, *The Whale and the Reactor* (University of Chicago Press, 1986); Donald Mackenzie and Judy Wajcman, *The Social Shaping of Technology* (1985); Wiebe E Bijker, Thomas P Hughes, and Trevor Pinch (Eds.), *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology* (1st edition, MIT Press 1987); Schumpeter, n 5; Langdon Winner, *Autonomous Technology: Technics-out-of-Control as a Theme in Political Thought* (MIT Press 1978); Karl Marx, *Das Kapital* (1867) (particularly, chapter 15, Machinery and Large-Scale Industry); Yochai Benkler, *The Wealth of Networks: How Social Production Transforms Markets and Freedom* (Yale 2006) (noting at 17, 'Neither deterministic nor wholly malleable, technology sets some parameters of individual and social action').

[90] *See e.g.* Vijay S Desai, Jonathan N Crook, and George A Overstreet, 'A Comparison of Neural Networks and Linear Scoring Models in the Credit Union Environment' (1996) 95(1) European Journal of Operations Research 24; William E Henley and David J Hand, 'Construction of a K-Nearest Neighbour Creditscoring System' (1997) 8(4) IMA Journal of Management Mathematics 305; Hand and Henley, n 79; David West, 'Neural Network Credit Scoring Models' (2000) 27(11-12) Computers and Operations Research 1131. *See further* ch 3, section 3.3 (discussing machine learning), and Appendix 2 (background on AI and ML).

[91] *See generally* Paul M Romer, 'Endogenous Technological Change' (1990) 98(5) Journal of Political Economy S71(arguing that technological change is endogenous, arising 'in large part because of intentional actions taken by people who respond to market incentives.' and emphasising the role of private, profit-maximising behaviour in driving technological change and therefore growth). *See also* Carlota Perez, 'The Double Bubble at the Turn of the Century: Technological Roots and Structural Implications' (2009) 33 Cambridge Journal of Economics 779, 780 (distinguishing 'major technology bubbles (MTBs) as a special class of bubbles that constitute a recurring endogenous phenomenon, caused by the way the market economy absorbs successive technological revolutions.'); 781-2 ('Technological innovation is swiftly followed by financial innovation. The world of finance itself is among the pioneers in adopting the new paradigm'). *See* ch 8, section 8.2.1 (proposing future research on the technology-credit cycle).

[92] *See* ch 4 (examining the legal drivers of alternative credit scoring). The rise of credit scoring also encouraged the broader growth of risk-management, quantification, scientific 'rationality,' self-government and neoliberal governmentality as paradigms of governance. *See e.g.* Leyshon and Thrift, *Lists Come Alive*; Martha Poon, 'Scorecards as Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated' (2007) 55(2) The Sociological Review 284, (examining the constitution of credit markets through risk calculation devices such as credit scorecards); Donncha Marron, '"Lending by Numbers": Credit Scoring and the Constitution of Risk Within American Consumer Credit' (2007) 36(1) Economy and Society 103 (describing the rise of risk management devices such as credit scoring as part of a 'Keynesian rationality of economic governance',

2.2 Credit scoring 2.0

By the beginning of the 21st century, consumer credit had become central to the economy, and society, driven in no small part by advances in information technology. This generated contrasting policy concerns about access to credit. On the one hand, credit performed an increasingly useful economic and social function. As a result, more consumers wanted and needed access to credit. However, not all consumers enjoyed access to credit, at least not on *affordable* terms, i.e., credit that they were able to repay on time and in a sustainable manner, without experiencing financial or non-financial distress.[93] This generated concern about *too little* access to (affordable) credit—often discussed under the rubric of 'financial in/exclusion'— particularly for higher-risk, lower-income consumers, and ethnic minority consumers against whom lenders continued to discriminate.[94]

On the other hand, some consumers were taking on more debt than they could afford, contributing to over-indebtedness, financial (and non-financial) distress, and a rise in consumer bankruptcy (or, private alternatives to bankruptcy).[95] This generated concern

sanctioned by the state through civil rights legislation); Marion Fourcade, 'Ordinal Citizenship' (2021) 72(2) British Journal of Sociology 154.

[93] *See* definition of affordability in the FCA Handbook, Consumer Credit Sourcebook (CONC) <https://www.handbook.fca.org.uk>, s 5.2A.10ff. *See further* ch 4, section 4.2.2.2 (discussing creditworthiness assessment under UK consumer credit regulation as requiring an assessment of both credit risk and credit affordability—which are often, but not always, correlated).

[94] *See e.g.* Solomon Y Deku, Alper Kara, Philip Molyneux, 'Exclusion and Discrimination in the Market for Consumer Credit' (Working Papers in Responsible Banking and Finance WP No. 13-006, 2013) <https://www.st-andrews.ac.uk/business/rbf/workingpapers/RBF13_006.pdf> (finding evidence of discrimination in consumer credit against non-White households in the UK); Will Dobbie et al, 'Measuring Bias in Consumer Lending' (2021) 88 Review of Economic Studies 2799 (finding evidence of 'significant bias against immigrant and older applicants' in UK high-cost credit markets). On financial inclusion and access to credit as policy goals *see e.g.* HM Treasury, 'Financial Inclusion Report: 2020-2021' <https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1038537/Financial_Inclusion_Report_2020-21.pdf>, 3 ('being "financially included" remains of central importance throughout peoples' financial lives, from the basic necessity of being able to open your first bank account, to accessing credit, insurance, and the right mortgage products at an affordable price'); Financial Inclusion Commission, <https://financialinclusioncommission.org.uk>.

[95] Iain Ramsay, *Personal Insolvency in the 21st Century* (Bloomsbury 2017); UK Insolvency Service, 'Individual Voluntary Arrangement Outcomes, 1990 to 2013' (Statistical Release, 12 November 2014) <https://www.gov.uk/government/statistics/individual-voluntary-arrangement-outcome-statistics> (showing that between 1990 and 2013 'The number of new IVAs registered each year has increased substantially over the period covered, from fewer than 10,000 annually up to 2003, to a peak of over 50,000 in 2010, with a

about *too much* access to (unaffordable) credit and augmented the image of credit as a potentially harmful product, particularly for low-income, vulnerable consumers.[96] The inclusion of low-income consumers in high-cost, unaffordable (credit) markets is often referred to as 'predatory inclusion'.[97]

In both cases—too little and too much access to credit—a key concern was fairness, particularly *distributional* fairness, or *distributive justice*.[98] Put simply, distributive justice concerns the fairness of the distribution of benefits and burdens in society.[99] In the UK, and in many other countries including the US, the prevailing policy 'benchmarks' of distributive justice are 'poverty' and 'inequality', corresponding, respectively, to absolute and relative levels of household income and wealth (and to a lesser extent, consumption).[100] *Too little* access to

---

particularly rapid increase between 2004 and 2006.'); Spooner, n 53; Mia Gray, Katherine Moser, and Jodi Gardner, 'Understanding Low-Income Debt in a High-Income Country' in Gardner, Gray and Moser, *Debt and Austerity*, 17 (noting that the 'move towards privatised mechanisms of debt reduction is a problem, as it reduces the re-allocative effect of debt relief,'). For a discussion of parallel trends in the US, *see generally* Sullivan, Warren, and Westbrook, n 41 (examining the rapid rise in bankruptcy filings in the 80s); New York Fed, n 44, 17 (chart showing that the number of new bankruptcies peaked in Q1 2006, at over 900,000 consumers, and the number of new foreclosures peaked in Q1 2009, at nearly 600,000 consumers).

[96] *See* Ramsay, *Changing Policy Paradigms*, 162 (contrasting the ideas of 'consumer credit as a lubricant' and 'consumer credit as a potentially dangerous product.').

[97] Louise Seamster and Raphael Charron-Chénier, 'Predatory Inclusion and Education Debt: Rethinking the Racial Wealth Gap' (2017) 4(3) Social Currents 199 (proposing the concept of 'predatory inclusion' as a framework for understanding the racial disparity in credit outcomes in the US, and defining it as 'a process whereby members of a marginalized group are provided with access to a good, service, or opportunity from which they have historically been excluded but under conditions that jeopardize the benefits of access').

[98] Of course, this was not the only normative concern. *See* n 8 and Nikita Aggarwal, 'The Norms of Algorithmic Credit Scoring' (2021) 80(1) Cambridge Law Journal 42 (discussing normative concerns relating to the rise of credit scoring, including consumer privacy).

[99] Cohen, n 3, 3 ('principles of distributive justice, principles, that is, about the just distribution of benefits and burdens in society'). *See generally*, Julian Lamont, 'Distributive Justice' (1996) <https://plato.stanford.edu/entries/justice-distributive/>.

[100] *See* n 3 (discussing the non-ideal approach to distributive justice adopted in this thesis). On inequality and poverty-reduction as policy goals, at least rhetorically, *see e.g.* Department for Levelling Up, Housing and Communities (2022), 'Levelling up the United Kingdom' <https://www.gov.uk/government/publications/levelling-up-the-united-kingdom>; Child Poverty Act 2010; Department for Education, 'A New Approach to Child Poverty: Tackling the Causes of Disadvantage and Transforming Families' lives' (2011) <https://www.gov.uk/government/publications/a-new-approach-to-child-poverty-tackling-the-causes-of-disadvantage-and-transforming-families-lives>; and *generally* Glennerster et al, n 58. At the international level, *see e.g.* United Nations, 'UN Sustainable Development Goals'

credit, on favourable terms—particularly for low-income, credit marginalized consumers—appeared to deny them the opportunity to smooth consumption and grow their incomes and wealth through borrowing, in turn alleviating poverty and inequality.[101] Conversely, *too much* credit—on unfavourable terms—appeared to diminish their material position due to the compounding costs of debt servicing, with associated regressive distributional effects.[102]

Credit scoring (1.0) played a key role in shaping these dual distributional effects. As discussed earlier, advances in statistical credit scoring had reduced distributional unfairness, as well as inefficiency, due to manual, judgmental credit analysis.[103] At the same time, however, by narrowing and fixing the criteria for credit access, and cloaking them with a veil of scientific, risk-based objectivity, statistical credit scores created new avenues for credit market exclusion.[104] Notably, the focus on 'credit history' as a key factor in credit decisions helped to construct, and perpetuate the exclusion of, the credit invisible population—those who, often as a direct result of historic credit market exclusion, had inferior or missing credit histories.[105]

<https://sdgs.un.org/goals/goal10> (inequality reduction). *See further* ch 5, section 5.1 and Appendix 1 (discussing measures of poverty and inequality).

[101] *See e.g.* Iain Ramsay, *Consumer Protection: Text and Materials* (Weidenfeld and Nicholson 1989) (hereinafter, 'Ramsay, *Consumer Protection*'), 336 ('it might be argued that, since credit is an integral part of consumption, a person has a 'right' to credit and ought not to be arbitrarily refused access to credit facilities'); Marco Meyer, 'The Right to Credit' (2018) 26(3) The Journal of Political Philosophy 304 (arguing that 'any justifiable property regime needs to recognize a right to credit' for all citizens, conditional on their creditworthiness); Marek Hudon, 'Should Access to Credit be a Right?' (2009) 84 Journal of Business Ethics 17 (proposing that access to credit should be considered a moral right in a 'goal-right system'). *See further* ch 5 (examining the functions and distributional effects of credit access).

[102] As examined in ch 5.

[103] n 67 et seq and associated text; n 78 and associated text.

[104] Leyshon and Thrift, *Lists Come Alive*, 448 (discussing 'weaknesses in the accuracy and objectivity of the practice of credit scoring' and noting that 'credit scoring systems…have set new conventions for deciding who is a 'good' and who is a 'bad' consumer, producing new patterns of inclusion and exclusion.'); Capon, n 66 (criticizing the 'brute force empiricism' of conventional statistical credit scoring).

[105] *See further* ch 3, section 3.1 (discussing credit invisibility) and ch 4, section 4.2.4 (discussing the credit referencing system).

More broadly, by enabling the growth of consumer credit markets,[106] increasing consumers' dependence on credit, and making consumer credit a more central engine in the economy, the adoption of statistical credit scoring and digital technology by credit firms exacerbated the dual distributional concerns due to too much and too little credit market access.[107] Indeed, the technologically enabled expansion of predatory, high-cost consumer credit directly contributed to the rise in inequality and poverty during the latter part of the 20th century. In these ways, poverty and inequality not only begot credit, but credit begot inequality and poverty.[108]

Predatory lending, and in particular the growth of subprime mortgage credit in the US, would lead to a credit-housing bubble and once-in-a-lifetime global financial crisis

---

[106] *See also* Krippner, *Financialization of the American Economy*, 174 (defining financialization as 'a pattern of accumulation by which profits accrue primarily through financial channels rather than through trade and commodity production.').

[107] More generally, poor credit scores due to a lack of credit access limited consumers' access to *non-credit* goods and services—such as employment, housing, insurance, internet, and telephone services—that increasing relied on credit scores, with associated distributional effects. *See e.g.* Experian, 'Credit Reference Agency Information Notice', (Version 1.1, 26 March 2020) <https://www.experian.co.uk/legal/crain/> (describing how CRAs obtain, process, and share personal data about consumers and businesses); Shelter, 'How to Rent with a Poor Credit Score' <https://england.shelter.org.uk/housing_advice/private_renting/how_to_rent_with_a_poor_credit_history>; Dan Whitworth, 'I Was Refused a Home Testing Kit After a Credit Check' *BBC News* (7 November 2020) <https://www.bbc.com/news/business-54841185>. *See also*, in the US context, Barbara Kiviat, 'The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores' (2019) 84(6) American Sociological Review 1134 (examining the use of credit scores in car insurance pricing decisions); Foohey and Greene, n 13, 102 ('Credit scoring is no longer merely about accessing credit. It determines people's ability to access the fundamentals of economic citizenship.').

[108] *See* n 52 and associated text, et seq (discussing how poverty and inequality drive consumer credit growth); Steven Yamarik, Makram El-Shagi, Guy Yamashiro, 'Does Inequality Lead to Credit Growth? Testing the Rajan Hypothesis using state-level data' (2016) 148 Economic Letters 63 (finding evidence, in the US context, that growth of consumer (housing) credit causes an increase in income inequality, and that this causality is bi-directional dependent on a country's institutional characteristics); Iversen and Rehm, n 57 (arguing that credit is a 'significant driver of inequality', because 'access to, and the terms of, credit vary by risk of default, which is closely tied to income.'). *See also* Aveyard et al, *Politics of Consumer Credit*, 9-10 ('The Conservative government's liberalization of financial markets in the 1980s, its encouragement of working-class home ownership, and its creation of increased social inequality all facilitated the emergence of the UK's sub-prime credit market.'); 192ff (tracing the growth of the subprime market to political changes in the 80s and the banking crises in the early 90s which left many consumers with impaired credit histories as well as leading to a retraction of credit supply by mainstream bank lenders). *See further* ch 4 and 5 (unpacking the distributional effects of consumer credit and credit scoring), Appendix 1 (discussing the relationship between poverty, inequality, and consumer credit), and ch 8 (identifying the need for further empirical investigation into the distributional effects of consumer credit markets, and technological developments therein).

(GFC), culminating in 2007/2008.[109] Overconfidence in the market mechanism, a liquidity bubble, and technological and financial innovation in credit risk management were key determinants of the GFC and the Great Recession that followed.[110] In the wake of the crisis, banks tightened credit underwriting standards and reduced lending to higher-risk (lower income) borrowers.[111] Stricter prudential and consumer protection rules further restricted the scope for lending by banks and traditional credit providers, notably to high-risk borrowers.[112]

The resulting credit crunch, austerity policies, and rise in levels of poverty and inequality,[113] combined with a low-interest environment as central banks, globally, sought to stimulate demand, collectively strengthened the commercial opportunity for less regulated, non-bank fintech entrepreneurs to tap unmet demand for credit.[114] This includes, in

[109] Thomas et al, *Credit Scoring*, 312 (noting that from the late 1990s to 2005/6 the demand for subprime mortgages increased due, inter alia, to low credit teaser rates, low policy interest rates, and 'NINJA' loans). On the growth of subprime lending in the US and generally, *see* Kathleen C Engel and Patricia A McCoy, 'A Tale of Three Markets: The Law and Economics of Predatory Lending' (2002) 80 Texas Law Review 1255; Rajan, *Fault Lines*; Atif Mian and Amir Sufi, *House of Debt* (University of Chicago Press 2014); Kathleen C Engel and Patricia A McCoy, *The Subprime Virus: Reckless Credit, Regulatory Failure, and Next Steps* (OUP 2016).

[110] *See generally* Engel and McCoy, ibid; Rajan, *Fault Lines,* 2 ('deregulation and developments like securitization had increased competition, which increased the incentives for bankers (and financial managers more generally) to take on more complex forms of risk.'); Raghuram Rajan, 'Has Financial Development Made the World Risker?' (NBER Working Paper 11728, 2005) https://www.nber.org/papers/w11728; Hyman, *Politics of Consumer Debt*, 46 ('Many of the "new" financial instruments of the 1970s and 1980s had actually existed in the 1920s and before, but had been jettisoned for their contribution to the Great Depression.'); Dan Awrey, 'Complexity, Innovation, and the Regulation of Modern Financial Markets' (2012) 2 Harvard Business Law Review 235; Perez, n 91. *See also* Guseva and Rona-Tas, n 72 (discussing the transformation of uncertainty into risk through institutions of risk calculation, such as credit scores and CRAs); Katharina Pistor, 'A Legal Theory of Finance' (2013) 41 Journal of Comparative Economics 315 (arguing that, under conditions of Knightian uncertainty and liquidity volatility, risk diversification through securitization 'cannot offer full protection against future events or a reversal of liquidity abundance.'). *See also* n 92 (discussing credit scoring as scientific rationality).

[111] UK Parliament, 'Household Debt: Key Economic Indicators' (Research Briefing, 28 October 2022) <https://commonslibrary.parliament.uk/research-briefings/sn02885/> (showing a tapering in UK household debt since 2008, to 133.9% DTI in Q2 2022, and noting that 'During the 2008/09 recession, banks were much more reluctant to lend money and consumers were less inclined to take on credit, with some focusing on paying off existing loans during difficult economic conditions.').

[112] *See* ch 4, section 4.2.2.

[113] *See further* Appendix 1.

[114] Cf. the high-interest rate conditions under which subprime lending grew in the wake of the financial crises of the late 80s, and as mainstream bank lenders reduced lending to higher risk borrowers. *See* Aveyard et al,

particular, new 'peer to peer' (p2p) lending platforms.[115] Advances in computing—particularly due to advances in ML methods and their application to consumer credit scoring—along with the wider diffusion of the Internet and mobile phone telephony, enabled fintech entrepreneurs to lend to marginalized consumers.[116] They relied, in particular, on 'alternative' credit scoring, a key building block in the fintech credit business model.[117]

The rise of alternative credit scoring (i.e., credit scoring *2.0*) represents a second technology-credit cycle, and a continuation of the co-evolution of consumer credit markets, law, technology, norms, and the political economy.[118] At a high level, alternative credit scoring entails the use of a greater volume and variety of data and/or more sophisticated

Politics of Consumer Credit, 9-10; 192ff; Perez, n 91, 790-1 (noting that the failure to tighten regulation following the bursting of the tech bubble in the early 2000s contributed to the liquidity bubble in the early 2000s).

[115] Also known as 'crowdfunding' platforms or 'marketplace' lenders. Prior to 2014, p2p lending in the UK was largely unregulated. *See further* ch 4.

[116] *See generally* William Jack and Tavneet Suri, 'Mobile Money: The Economics of M-Pesa' (2011) National Bureau of Economic Research Working Paper 16721 <https://www.nber.org/system/files/working_papers/w16721/w16721.pdf>; Doug W Arner, Jan N Barberis and Ross P Buckley, 'The Evolution of Fintech: A New Post-Crisis Paradigm?' (2015) <https://doi.org/10.2139/ssrn.2676553>; Greg Buchak, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 'Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks' (2018) 130(3) Journal of Financial Economics 453; Committee on the Global Financial System (CGFS) and Financial Stability Board (FSB), 'FinTech Credit: Market Structure, Business Models and Financial Stability Implications' (2017) <https://bit.ly/2W6yGF5>.

[117] *See* Aitken, n 9. Alternative credit scoring is also referred to as: *'algorithmic credit scoring'* (see Rachel O'Dwyer, 'Are You Creditworthy? The Algorithm Will Decide' (2018) *Undark* (5 July 2018) <https://undark.org/2018/05/07/algorithmic-credit-scoring-machine-learning/>; Nikita Aggarwal, 'Machine Learning, Big Data and the Regulation of Consumer Credit Markets: The Case of Algorithmic Credit Scoring', in Nikita Aggarwal et al (eds) *Autonomous Systems and the Law* (Beck 2019); Aggarwal, n 98; 'algorithmic lending' (*see* Bruckner, n 76; *'AI credit scoring'* (*see* Katja Langenbucher, 'Responsible AI Credit Scoring: A Legal Framework' (2020) 25 European Law Review 1); *'Behavioural credit scoring'* (*see* Thomas, *Consumer Credit Models* and Cullerton, n 76); *'Big Data Scoring'* (Hurley and Adebayo, n 9); and '*social credit*' (*see* Nizan Geslevich Packin and Yafit Lev-Aretz, 'On Social Credit and the Right to Be Unnetworked' (2016) Columbia Business Law Review 339). *See also* Danielle K Citron and Frank Pasquale, 'The Scored Society: Due Process for Automated Predictions' (2014) 89 Washington Law Review 1.

[118] It is worth noting that alternative credit scoring has a longer history in emerging market economies. *See e.g.* LenddoEFL <https://lenddoefl.com>; Daithí Mac Sithigh and Mathias Siems, 'The Chinese Social Credit System: A Model for Other Countries?' (2019) 82(6) Modern Law Review.

statistical techniques relative to conventional statistical credit scoring (credit scoring 1.0).[119] The new types of data used for alternative credit scoring are commonly referred to as 'alternative data', as a counterpoint to conventional credit data, such as credit history.[120] The alternative statistical techniques used in alternative credit scoring fall into the category of ML, a sub-category of applied AI.[121]

Crucially, for the purposes of this story, alternative credit scoring has been presented by entrepreneurs, embraced by policymakers, and proselytized by the popular media as a solution to the problem of too little credit market access, and financial exclusion more generally. By using alternative data and alternative statistical techniques, fintech lenders and CRAs promise to improve access to credit for consumers, particularly lower income, marginalized, 'credit invisible' consumers. Implicit in this rhetoric is the promise of smoother consumption, and greater income and wealth for these consumers through borrowing, in turn alleviating the poverty of low-income consumers, as well as reducing inequality between lower and higher income consumers.[122] This, as noted earlier, is the distributional promise of alternative credit scoring.

---

119 *See further* ch 3 (examining the technologies of alternative credit scoring).

120 *See* ch 3, section 3.2. The boundary between conventional and alternative data is porous and dynamic. Moreover, many lenders continue to use credit scoring 1.0 data and techniques. As such, credit scoring 1.0 and 2.0 are overlapping, rather than distinct, paradigms.

121 As with alternative data, the boundary between conventional and alternative statistical techniques (ML techniques used under credit scoring 1.0 and those used under credit scoring 2.0) is porous. ML is typically used to estimate creditworthiness directly, rather than 'score' or rank borrowers. For simplicity, I will continue to refer to credit 'scoring'. *See* Shafi Rahman, 'Combining Machine Learning with Credit Risk Scorecards' (*FICO Blog*, March 24 2022) <https://bit.ly/2JDKObw>. *See further* ch 3, section 3.3.

122 *See* text to n 7 and 8, and *e.g.* Experian, <https://www.experian.co.uk/assets/rental-exchange/rental-exchange-main-brochure.pdf> ('Helping your tenants build better futures, innovating for social benefit to increase fairness'); Zopa and Clearscore, 'Clearscore and Zopa Launch First-in-Market Open Banking Partnership to Provide Credit to Those That Need it Most' (2021) <https://www.innovatefinance.com/news/clearscore-and-zopa-launch-first-in-market-open-banking-partnership-to-provide-credit-to-those-that-need-it-most/> ('This represents a first-in-market Open Banking integration between a credit marketplace and credit partner, designed to give access to credit products for people who need them most but who would likely be declined based purely on what is displayed on their credit report'). In the US, *see* Foohey and Greene, n 13, 102 ('Businesses, banks, lenders, and some advocates herald

In the UK, the potent combination of austerity, a low-growth macroeconomic environment, and populism in the wake of the GFC, reinforced the political imperative to lean on credit markets as a supplement for social welfare and to boost aggregate demand, couched in the rhetoric of 'democratizing' access to credit.[123] Recent governments have more explicitly centred the reduction of poverty and inequality in their political agendas, at least rhetorically.[124] Policymakers thus embraced and sought to enable alternative credit scoring—and fintech innovation more broadly—for their promise to boost 'effective competition in the interests of consumers' and increase financial inclusion.[125] In the US, alternative credit scoring and fintech have additionally been presented as solutions to the pathologies of racial injustice, particularly the 'racial wealth gap'.[126]

---

these alternate scores as a major breakthrough in increasing access to credit for all, particularly those individuals traditionally left out of credit markets.').

123 Gray, Moser and Gardner, n 95, 8 ('[j]ust as the economic downturn after the financial crisis heightened the need for social welfare provision, the state shrunk its redistributive focus').

124 *See* n 100.

125 *See* n 6 and 10, and *e.g.* Irina Mnohoghitnei et al, 'Embracing the Promise of Fintech' (Bank of England Quarterly Bulletin, 2019) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3419994> (identifying the promise and perils of fintech, and asserting that 'The Bank of England is committed to embracing fintech to deliver its mission.'); FCA, 'Project Innovate: Call for Input' (11 Jul 2014) <https://www.fca.org.uk/publication/call-for-input/project-innovate-call-for-input.pdf> ('The objective of Project Innovate is to foster innovation that can genuinely improve the lives of consumers.'); Christopher Woolard, 'Testimony of Christopher Woolard at the Hearing before the Task Force on Financial Technology of the Committee on Financial Services' (Jun 25 2019) <https://www.govinfo.gov/content/pkg/CHRG-116hhrg39497/html/CHRG-116hhrg39497.htm> ('as well as seeking to prevent risks to the system, which all financial regulators do, we also consider the dangers of potentially beneficial innovations not happening or coming to market.'); UK Office for Artificial Intelligence, 'National AI Strategy' (2021) <https://www.gov.uk/government/publications/national-ai-strategy>. In the US, *see e.g.* Richard Cordray, former Director of the Bureau of Consumer Financial Protection (CFPB), 'Prepared Remarks of CFPB Director Richard Cordray at the Alternative Data Field Hearing' (Feb 16, 2017) <https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-alternative-data-field-hearing/> ('Adding this kind of alternative data into the mix thus holds out the promise of opening up credit for millions of additional consumers.'), cited in Marco Di Maggio, Dimuthu Ratnadiwakara, and Don Carmichael, 'Invisible Primes: Fintech Lending with Alternative Data' (2021) <https://ssrn.com/abstract=3937438>, 1; CFPB, 'Consumer Financial Protection Bureau Issues No Action Letter to Facilitate the Use of Artificial Intelligence For Pricing and Underwriting Loans' (Nov 30, 2020) <https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-issues-no-action-letter-facilitate-use-artificial-intelligence-pricing-and-underwriting-loans/>; Odinet, n 13 ('This exuberance [from scholars, public and private sector actors] for all things tech in finance has led to a quiet yet aggressive deregulatory agenda,').

126 *See* Kenneth P Brevoort, Philipp Grimm, Michelle Kambara, 'CFPB Data Point: Credit Invisibles' (2015) <https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf> (finding that, in 2015,

In these ways, alternative credit scoring has been presented as a win-win solution that can achieve both 'economic' market efficiency goals, as well as 'social' distributional fairness and consumer empowerment goals. In a self-fulfilling manner, the credit industry has leveraged the financial inclusion policy agenda to promote the distributional promise of alternative credit scoring. This rhetoric has been amplified by the news media, which has promoted the distributional promise of alternative credit scoring (whilst also cautioning against its perils).[127]

Of course, despite the warm and fuzzy rhetoric, lenders and CRAs are not, for the most part, charities. They are for-profit corporations[128] that view the financially excluded

approximately 15% of Blacks and Hispanics were credit invisible compared to 9% of Whites and Asians, and a further 13% of Blacks and 12% of Hispanics were unscored compared to 7% of Whites); Sarah Chenven and Carolyn Shulte, 'The Power of Rent Reporting Pilot—A Credit Building Strategy' (Credit Builder's Alliance, 2015) <https://www.creditbuildersalliance.org/wp-content/uploads/2019/06/CBA-Power-of-Rent-Reporting-Pilot-White-Paper.pdf> ('Given that a good credit history is an increasingly important financial asset, denying renters the opportunity to build their credit through on-time rent payments may exacerbate already high levels of wealth inequality.'); Jung Hyun Choi et al, 'Reducing the Black-White Homeownership Gap Through Underwriting Innovations—The Potential Impact of Alternative Data in Mortgage Underwriting' (Urban Institute, October 2022) <https://www.urban.org/sites/default/files/2022-10/Reducing%20the%20Black-White%20Homeownership%20Gap%20through%20Underwriting%20Innovations.pdf#page=38> ('Black households are disproportionately likely to have no FICO scores and to have FICO scores below 620, which is the typical cut-off for mortgage approval. Therefore, including alternative data into mortgage underwriting could help many Black households obtain mortgages and get a lower price for the loan.'); New York Times Editorial Board, 'The Race-Based Mortgage Penalty' *New York Times* (Mar 7 2018) <https://www.nytimes.com/2018/03/07/opinion/mortage-minority-income.html> ('A bill pending in the Senate would open the door for the mortgage industry to use an alternative credit-scoring system, which would be one step in the right direction.'); Patti Waldmeir, 'Tackle the 'Credit Invisibles' to Help Close the Racial Wealth Gap' *Financial Times* (November 28, 2022) <https://www.ft.com/content/ee7e19bd-631e-4575-b0b7-8b747f74185a>. On the racial wealth gap, *see generally* Mehrsa Baradaran, *How the Other Half Banks: Exclusion, Exploitation, and the Threat to Democracy* (HUP 2018); Seamster and Charon-Chenier, n 97.

[127] *See* Olson, n 12 and *e.g.* Ben McLannahan, 'Being 'Wasted' on Facebook May Damage Your Credit Score' *Financial Times* (Oct 14 2015) <https://www.ft.com/content/d6daedee-706a-11e5-9b9e-690fdae72044>; Laura Whateley, 'Facebook Can Hit Your Mortgage Chances' *The Times of London* (Jan 09 2016) <https://www.thetimes.co.uk/article/facebook-can-hit-your-mortgage-chances-z2cd9s65p08>. On the role of the news media in amplifying hype in financial markets, *see generally* Robert Shiller, *Irrational Exuberance* (Princeton 2016, 3rd edition).

[128] This is intended to be a descriptive, not normative, statement. *See generally* William J Magnuson, *For Profit* (Basic Books 2021) (arguing that the profit motive was not historically, and should not be, the sole purpose of corporations). Of course, there are firms, including lenders, that explicitly operate on a not-for-profit basis, such as credit unions. *See e.g.* Croydon Caribbean Credit Union, n 86 (describing itself as 'not for profit ethical financial institution', with the interest rate on loans capped at 12.68% APR). *See generally* UK Cabinet Office, 'Scaling Community Lenders: The Role of Social Investment' (2015) <https://www.gov.uk/government/publications/scaling-community-lenders-the-role-of-social-investment>; Aveyard et al, *Politics of Consumer Credit*, 185ff (discussing the rise of minority credit unions in Britain); Karen Rowlingson, 'High-Cost Credit in the UK: What's the Problem and How Should Policy Respond?' in Gardner,

primarily as an untapped source of profit.[129] In adopting and promoting solutions such as alternative credit scoring, lenders and CRAs are seeking to increase their profits from lending. Likewise, as discussed earlier, governments have strong political incentives to promote credit access and consumption, and therefore solutions such as alternative credit scoring that could increase access to credit—even if they are not aligned with the best interests of all consumers, or the economy, at least over the medium to long-run. Indeed, the rise and fall of Wonga—the exuberant online payday lender that we met in Chapter 1[130]—is a salutary lesson in the perils of alternative credit scoring, and the boundaries of its distributional promise.

Gray, and Moser, *Debt and Austerity*, 194-218 (discussing the role of credit unions as alternatives to high-cost credit).

129 *See e.g.* Equifax, 'Expand Access to Credit with Alternative Data from Equifax' <https://www.equifax.com/resource/-/asset/video/expand-access-to-credit-with-alternative-data-from-equifax/> ('Your visibility into credit applicants determines whether you'll offer more loans or miss profitable opportunities. But when millions of people aren't scorable by traditional methods, how do you expand your pool of creditworthy consumers?'); Experian, 'Alternative Data Credit Trends and Beyond' <https://www.experian.com/consumer-information/alternative-financial-services> ('Alternative credit data can help you grow your portfolio and gain access to the growing $140 billion alternative financial services industry'); McLannahan, n 127 ('Both FICO and TransUnion say they are responding to demand from their ultimate customers, the banks, which worry that by declining people without traditional credit scores they are turning away potential sources of profit.'). For commentary*, see e.g.* Hyman, *Politics of Consumer Debt*, 40 ('Every debt is an investment…for those who extend credit, the decision is always considered in light of other uses of money.').

130 *See* text to n 12 et seq; 'Wonga Collapses into Administration' *BBC News* (30 August 2018) <https://www.bbc.co.uk/news/business-45359395>. The company was dissolved in 2020. *See* Debt Camel, 'Wonga—Administration Ended, Company Dissolved' <https://debtcamel.co.uk/wonga-has-stopped-issuing-loans/>.

3 THE SOCIO-TECHNICAL DRIVERS OF ALTERNATIVE CREDIT SCORING

This chapter examines in further detail two of the key socio-technical drivers of alternative credit scoring, and its distributional promise: (i) the credit invisible population (and credit market exclusion more generally); and (ii) advances in data-driven, predictive technology. It is important to note at the outset, however, that credit invisibility and advances in digital technology are part of a much more complex mix of different mechanisms that explain the development of alternative credit scoring, and the construction of its distributional promise. As such, the presentation in this chapter (as well as the next) is necessarily stylized.

The chapter proceeds as follows. Section 3.1 examines credit invisibility and credit market exclusion in the UK. Section 3.2 examines the different types and sources of data—conventional and alternative—used in alternative credit scoring, and recent developments in the UK. Section 3.3 examines the use of ML for alternative credit scoring. **Appendices 2** and **3**, which are associated with this chapter, provide further context on AI, ML, and the fintech credit ecosystem in the UK.

3.1 Credit invisibility

In 2018, Experian estimated that nearly 5.8 million adults—roughly 9 percent of the UK population—were 'credit invisible'.[131] Credit invisibles are defined as consumers with thin or non-existent credit files with the three main CRAs.[132] In addition to consumers who are credit invisible, certain consumers have blemished credit files. Experian estimates that, in 2018, approximately 4 percent of the UK population (2.5 million people) were 'thick files' who were narrowly rejected for common consumer credit products due to blemished or out-of-date credit histories.[133]

As conventional approaches to credit scoring (credit scoring 1.0) rely heavily on data from a person's credit report, particularly their credit history, they are unable to generate a score for credit invisibles.[134] Lenders and CRAs may therefore use the average probability of delinquency to score credit invisibles, adjusted for any available information such as age or postcode (zip code).[135] Or, they may treat credit invisibles as de facto high risk, i.e., the lack

---

[131] Experian, 'Making the Invisible Visible' (2018) <https://www.experian.co.uk/assets/consumer-credit-risk/making-the-invisible-visible.pdf> (hereinafter, 'Experian, *Making the Invisible Visible*'); Experian, 'Britain's Unseen Problem: 5.8 Million People 'Invisible' to the Financial System' (9 November 2018) <https://www.experianplc.com/media/latest-news/2018/britain-s-unseen-problem-58-million-people-invisible-to-the-financial-system/>. More recent data from 2022 indicate that the number of credit invisibles in the UK has fallen to approximately 5 million (7% of the population)—a reduction that is attributed to the inclusion of alternative data in credit scoring. *See* Experian, 'Meet the 5 Million 'Credit Invisible' Brits Still at Risk of Exclusion From the Financial System' (21 March 2022) <https://www.experianplc.com/media/latest-news/2022/meet-the-5-million-credit-invisible-brits-still-at-risk-of-exclusion-from-the-financial-system/>.

[132] Also referred as 'thin files' and 'no files'. *See* Experian, *Making the Invisible Visible*, 3. On credit invisibility in the US, *see* Brevoort et al, n 126 (estimating that, in 2015, approximately 11% of the adult population was credit invisible, defined as those *without* a credit file with one of the three main credit reporting agencies, and a further 8.3% were 'unscorable' or thin-files—at the time, a total of 45 million Americans). Recent estimates from Experian and Oliver Wyman indicate that these proportions have not changed over the last 7 years. *See* Experian and Oliver Wyman, n 7 ('Nineteen percent of American adults do not have a conventional credit score. This includes 28 million adult Americans who are credit invisible and 21 million who are unscoreable. An additional 57 million have subprime or below credit scores.').

[133] Experian, *Making the Invisible Visible*, 4.

[134] Brevoort et al, n 126, 4.

[135] Teresa Bono, Karen Croxson, Adam Giles, 'Algorithmic Fairness in Credit Scoring' (2021) 37(3) Oxford Review of Economic Policy 585, 595.

of conventional credit data is treated as a negative signal of creditworthiness. As a result, credit invisibles (as well as those with blemished files) are often offered more expensive credit, or denied credit altogether by mainstream lenders who are unwilling to lend to consumers with a high perceived credit risk i.e. higher probability of default (PD) and loss given default (LGD).[136] In turn, these consumers may be forced to rely on payday lenders, or other high-cost and/or unregulated sources of credit, often at punitive interest rates and exposing them to abusive lending practices and greater financial and non-financial distress.[137]

There are various determinants of credit invisibility. Credit invisibility may solely be a function of a consumer's past *choice* not to use credit, or more particularly, credit products that report to CRAs.[138] This includes savers (those with a greater propensity to save than consume) and renters (those who make rental rather than mortgage payments).[139] Low-income, younger borrowers are more likely to rent than buy, and more likely to spend than

---

[136] Experian, *Making the Invisible Visible*, 1 ('With little or no information available to make an informed decision, lenders consider the 'Invisibles' to be high risk and so can only offer them financial products at higher rates, if at all.'); Brevoort et al, n 126, 4 ('If a consumer does not have a credit record with one of the NCRAs or if the record contains insufficient information to assess her creditworthiness, lenders are much less likely to extend credit. As a result, consumers with limited credit histories can face substantially reduced access to credit.'). *See further* ch 4, section 4.2.2.1 (discussing the regulation of credit risk).

[137] *See e.g.* FCA, 'Technical Annexes Supplement to CP14/10 Proposals for a Price Cap on High-Cost Short-Term Credit' (July 2014) <https://www.fca.org.uk/publication/consultation/cp-14-10-technical-annexes.pdf> (finding causal evidence that high-cost-short-term credit, such as payday lending, reduces borrower welfare); John Gathergood and Benedict Guttman-Kenney, 'Can We Predict Which Consumer Credit Users Will Suffer Financial Distress?' (FCA Occasional Paper 20, August 2016) <https://www.fca.org.uk/publication/occasional-papers/occasional-paper-20.pdf> (finding non-causal evidence that consumers of high-cost credit products 'are substantially more likely to experience financial distress than holders of other forms of credit, such as personal loans'); John Gathergood, Benedict Guttman-Kenney, Stefan Hunt, 'How Do Payday Loans Affect Borrowers? Evidence from the U.K. Market' (2019) 32(2) The Review of Financial Studies 496 (finding that payday borrowing in the UK caused persistent increase in default rates and breach of overdraft limits by borrowers). As noted earlier (*see* n 87), moneylenders typically do not use formal credit scores or risk-based pricing, nor report credit data to the main CRAs. Of course, these markets also cater to credit 'visible' borrowers.

[138] In addition to e.g. failing to get on the electoral roll (a form of traditional credit data), whether out of choice or due to ineligibility based on age. *See* section 3.2 (summarizing different types of traditional and alternative data in credit reports and credit scores).

[139] Mortgage payments, as credit repayments, are included in traditional credit files. Historically, rental payments were not directly included (although could be reflected in credit card and other financial account transaction data, for example). However, this is changing. *See* section 3.2.

save.[140] Younger borrowers also increasingly favour the use of debit and pre-paid cards, as well as alternative credit products such as 'buy-now-pay-later' (BNPL) that have not traditionally reported credit data to the main CRAs.[141]

Credit invisibility may alternatively, or additionally, be a function of a consumer's past *lack of opportunity or inability* to use credit, or at least traditional CRA-reporting credit products. This includes younger, first-time ('new-to-credit') borrowers, who have necessarily had less time to build a credit history.[142] It also includes recent immigrants and consumers who have been excluded from credit markets due to discrimination.[143] A consumer's lack of opportunity or inability to use traditional CRA-reporting products could also be due to a lack of income necessary to repay the debt. These consumers are likely to have sought but been denied access to traditional credit markets, and thus failed to build a credit history. Of course, their lack of income is likely to be the result of a various individual and structural factors, including historic discrimination.

---

140 Renters are also significantly more likely to come from low-income backgrounds. *See* UK Parliament House of Commons Library, 'Poverty in the UK: statistics' (13 April 2022) <https://commonslibrary.parliament.uk/research-briefings/sn07096/>, 6 (citing research from the Joseph Rowntree Foundation finding that 'Social renters have the highest rate of poverty at 46% reflecting their comparatively lower incomes, while a third of private renters are in poverty.').

141 BNPL lenders have, however, recently started to report to CRAs. *See e.g.* Experian, 'Does Short-Term Buy Now Pay Later Credit Impact Your Credit Score?' <https://www.experian.co.uk/consumer/help-discover/discover/guides/short-term-buy-now-pay-later.html>. Similarly, the main CRAs in the US have recently launched BNPL bureaus/tradelines, although BNPL companies are yet to commence reporting. *See e.g.* Greg Wright, 'Introducing the Buy Now Pay Later Bureau from Experian' (*Experian Blog*, Jan 26 2022) <https://www.experian.com/blogs/news/2022/01/26/buy-now-pay-later-bureau/>. For a discussion of BNPL and risks to consumers, *see* Nikita Aggarwal, D Bondy Valdovinos Kaye, and Christopher K Odinet, '#Fintok and Financial Regulation' (2023) Arizona State Law Journal (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4216952>.

142 Experian, *Making the Invisible Visible*, 3; FCA, n 86 (technical annex to high-cost-short-term credit review; distinguishing prime, sub-prime, and new-to-credit consumer segments).

143 *See* text at n 68 et seq, n 78 and n 94 (discussing lending discrimination in the UK); Foohey and Greene, n 13, 102-103 ('Credit scores rely on a handful of inputs that are largely based on prior credit decisions. These inputs reflect a legacy of discrimination, like redlining and aggressive marketing of subprime credit to people of color.').

The determinants of credit invisibility influence how meaningful it is as a signal of consumer creditworthiness. Credit invisibility that results solely from a consumer's *choice* not to use CRA-reporting credit products is less likely to be an accurate proxy for either credit risk to the lender, or the affordability of credit for the borrower. These consumers may be able to repay credit, without distress—i.e. they are a low credit and affordability risk, and thus 'creditworthy'—but simply lack the conventional forms of data required to demonstrate their creditworthiness. Where credit invisibility reflects a consumer's *lack of opportunity or inability* to access credit markets, its accuracy as a proxy for creditworthiness depends on the reasons for the lack of opportunity or inability, and particularly whether it is a function of insufficient income.

Similarly, blemishes on a consumer's credit file could be a purely informational problem, and thus an imperfect signal of a consumer's true creditworthiness. Credit files are notorious for containing erroneous and obsolete information, such as mistaken identities, discharged debts, and obsolete joint accounts.[144] Alternatively, blemishes on a consumer's credit file could reflect a consumer's adverse past (credit) behaviour, such as past credit defaults, a criminal record, bankruptcy, or other adverse legal judgments. Depending on the CRA, information on past bankruptcies can remain on a consumer's credit file for up to 10 years, and credit (default) history for up to 11 years.[145] Of course, even if factually correct,

[144] *See e.g.* Anna Tims, 'A Tiny Error in Your Address Could Wreck Your Credit Rating' *Guardian* (10 October 2022) <https://www.theguardian.com/money/2022/oct/10/a-tiny-error-in-your-address-could-wreck-your-credit-rating>; Gretchen Morgenson, 'Held Captive by Flawed Credit Reports' *New York Times* (Jun 21 2014) <https://nyti.ms/2QaYxrG>. In the US, the inclusion of unpaid medical debt/debt collection on credit files has long been seen as a source of inaccuracy and unfairness due to weak correlation with credit risk. *See* Kenneth P Brevoort and Michelle Kambara, 'CFPB Data Point: Medical Debt and Credit Scores' (2014) <https://files.consumerfinance.gov/f/201405_cfpb_report_data-point_medical-debt-credit-scores.pdf>; CFPB, 'CFPB Publishes Analysis of Potential Impacts of Medical Debt Credit Reporting Changes' (July 27 2022) <https://www.consumerfinance.gov/about-us/newsroom/cfpb-publishes-analysis-of-potential-impacts-of-medical-debt-credit-reporting-changes/>.

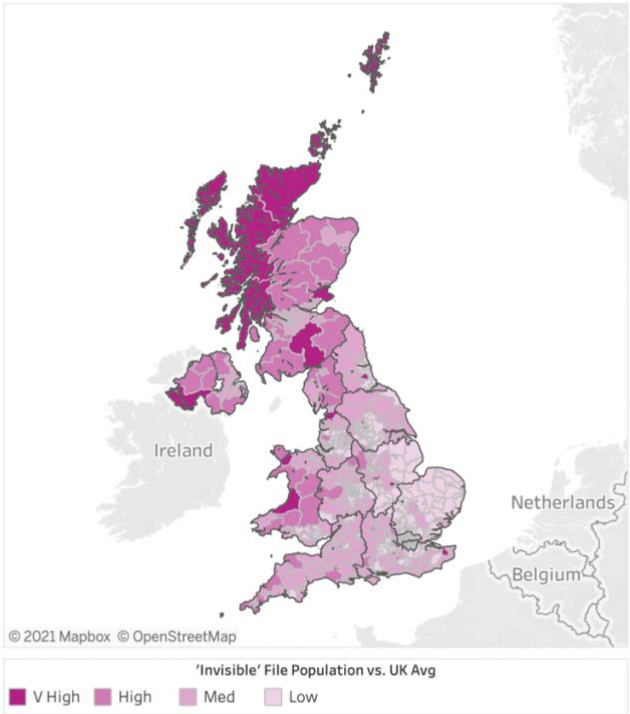
[145] *See* ch 4, section 4.2.4.

this historic data may be obsolete and unreliable as proxy for a person's current and future creditworthiness.

Available data on credit invisibles in the UK supports the hypothesis that the causes of credit invisibility, and the socio-economic status of credit invisibles, are heterogeneous. For example, data from Experian shows that the UK constituencies with the highest rates of credit invisibility are in northern Scotland, Northern Ireland, northern England, and Wales (**Figures 5** and **6**). More specifically, the constituencies of Lancaster and Fleetwood, Sheffield Central, Edinburgh East and Edinburgh North and Leith have some of the highest credit invisibility rates. Although these constituencies also have relatively high poverty levels (**Figure 7**), Experian observes that the principal reason for the high rate of credit invisibility in these constituencies is their large student populations.[146]

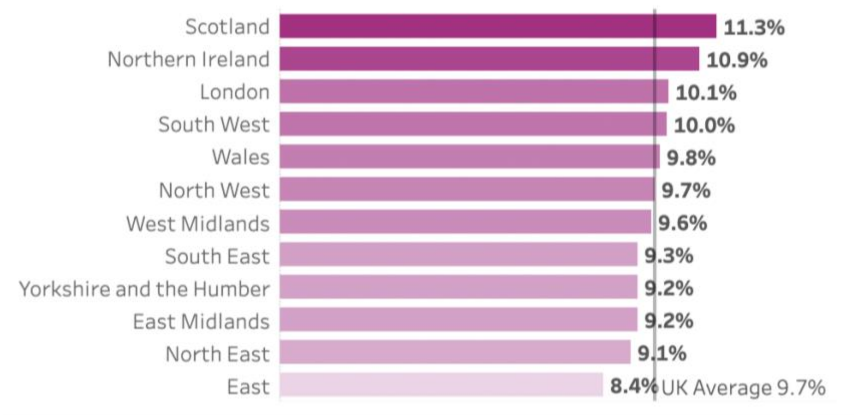
[146] Experian, *Making the Invisible Visible*.

Figure 5. Distribution of Credit Invisibles in the UK (2021)



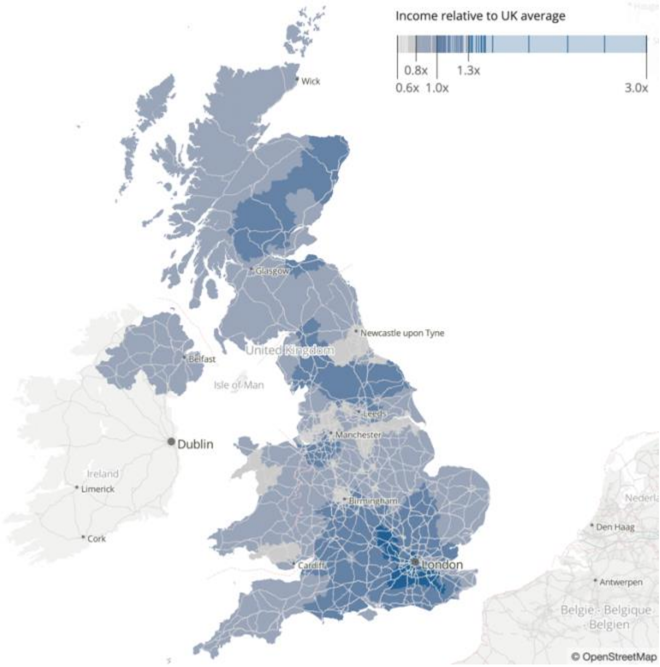
Source: Experian, 2021, <https://public.tableau.com/app/profile/experian.ltd/viz/ExperianUK-Credit-2021InvisibleFilePopulation/Experian-InvisibleFileUK>.

Figure 6. Credit Invisibility by Region Relative to UK Average (2021)



Source: Experian, 2021, <https://public.tableau.com/app/profile/experian.ltd/viz/ExperianUK-Credit-2021InvisibleFilePopulation/Experian-InvisibleFileUK>.

Figure 7. Regional Household Income Relative to UK Average (2021)



Source: ONS, 2021, <https://www.ons.gov.uk/visualisations/dvc1370/>[147]

Although this data is insufficiently granular to draw any definitive conclusions, at the very least it suggests that credit invisibles come from a range of demographic and socio-economic backgrounds, not solely low-income populations. As Part Two will examine further, the distributional implications of alternative credit scoring in the credit invisible segment depend in large part on the underlying causes of credit invisibility, and thus whether credit invisibility is a cloak for positive or negative information relevant to a borrower's creditworthiness.

[147] For data on household income levels by region and constituency, *see* Office of National Statistics, 'Regional Gross Disposable Household Income, UK: 1997 to 2018' <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/bulletins/regionalgrossdisposablehouseholdincomegdhi/1997to2018>; ONS, 'Regional Gross Disposable Household Income: Local Authorities by ITL1 Region' <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/datasets/regionalgrossdisposablehouseholdincomelocalauthoritiesbyitl1region>.

3.2 Alternative credit scoring data

In recent years, the volume of available (personal) data has increased exponentially as society has become increasingly networked, digitised, and 'datafied', as well due to improvements in computing power and the tools and infrastructure needed to capture and process this data.[148] Today, most of our daily activities generate digital data—from the movies we watch to the books we read, the places we visit, the things we buy, and the people we communicate with.[149] This datafication of society has driven the development of more powerful statistical models and computing systems—discussed under the rubric of applied AI, and its key sub-category, ML—and the rapid growth of the data analytics industry.[150]

Alternative credit scoring is both driven by, and drives, advances in ML, computing, and data analytics. To recap, alternative credit scoring (credit scoring 2.0) describes the use of a greater volume and variety of data and/or more sophisticated statistical techniques relative to conventional statistical credit scoring (credit scoring 1.0). These two features of alternative credit scoring are inherently interconnected. ML is more useful—i.e., offers greater improvement in predictive accuracy—when used to analyse large, alternative datasets.[151] In practice, there is considerable heterogeneity and dynamism in the scope of alternative credit scoring, due to the use of different types of (alternative) data and different

---

[148] Petroc Taylor, 'Volume of Data/Information Created, Captured, Copied, and Consumed Worldwide From 2010 to 2025' (*Statista*, 8 Sept 2022) <https://www.statista.com/statistics/871513/worldwide-data-created/>; Viktor Mayer-Schönberger and Kenneth Cukier, *Big Data: A Revolution That Will Transform How We Live, Work and Think* (John Murray 2013) (coining the term 'datafication').

[149] *See generally* Mayer-Schönberger and Cukier, ibid.

[150] The phenomenon of collecting, processing, and analysing large and complex datasets is also commonly called 'big data' (*see* Mayer-Schönberger and Cukier, ibid). However, this term has become less popular in recent years. On AI and ML *see* section 3.3 and Appendix 2.

[151] *See further* section 3.3.

statistical techniques. Indeed, many lenders and alternative credit score providers use alternative data without recourse to (newer, more sophisticated) ML techniques.[152]

Alternative data is a key enabler of alternative credit scoring, and its distributional promise, particularly in the credit invisible segment. Despite their lack of conventional credit data, or blemished data, many credit invisible consumers have alternative data that can demonstrate to lenders that they are more creditworthy, i.e., more viable credit and affordability risks than their credit invisibility might imply.[153] For example, they may pay their rental or other bills consistently and on time. Recent empirical studies demonstrate that the use of certain types of alternative data, and ML methods, for alternative credit scoring can improve the accuracy of creditworthiness prediction relative to conventional statistical credit scoring.[154] It is worth noting, however, that there are also socio-economic disparities in the production of alternative data. For example, due to greater mobile phone and internet access and usage, younger and/or more affluent consumers are more likely to generate alternative data through mobile phones and internet-connected devices.[155]

Alternative data encompasses a wide range of types and sources of data, as summarized in **Table 1**, below. It includes new types of 'hard' data—such as cash-flow and online subscription payment data—as well as 'soft' data that has been 'encoded' as hard data,

---

[152] Ibid.

[153] *See* text to n 138 et seq and ch 4, section 4.2.2 (discussing the regulation of credit risk and affordability).

[154] *See further* ch 6.

[155] Ofcom, 'Adults' Media Use and Attitudes Report' (2022) <https://www.ofcom.org.uk/__data/assets/pdf_file/0020/234362/adults-media-use-and-attitudes-report-2022.pdf> (disaggregating media usage by age, gender, and socio-economic group); Jonas Lerman, 'Big Data and its Exclusions' (2013) 66 Stanford Law Review Online 55 ('billions of people remain on its margins [of the big data revolution] because they do not routinely engage in activities that big data and advanced analytics are designed to capture.'). *See also* Mary Madden, Michele Gilman, Karen Levy, and Alice Marwick, 'Privacy, Poverty, and Big Data: Matrix of Vulnerabilities for Poor Americans' (2017) 95(1) Washington University Law Review 53 (showing that poor communities in the US are more reliant on mobile phone connectivity and arguing that this reliance combined with lesser use of privacy-preserving technologies exposes them to greater risk of 'networked privacy harms'.).

such as a person's sociability as proxied by the size of their mobile phone or social media network.[156] It includes financial as well as non-financial, social and behavioural data. At its broadest, alternative data encompasses more data formats than conventional credit data: not only text, but also videos, images, and sounds.[157] Many types of alternative data, particularly social and behavioural data, are less structured and more feature-rich ('high-dimensional') than conventional credit or other financial data.[158]

---

[156] Liberti and Petersen, n 65 (distinguishing hard and soft data). *See also* J Christina Wang, 'Technology, the Nature of Information, and FinTech Marketplace Lending' (Federal Reserve Bank of Boston Current Policy Perspectives No. 18-3, 2018) <https://www.bostonfed.org/publications/current-policy-perspectives/2018/technology-nature-of-information-fintech-marketplace-lending.aspx>. On the distinction between soft and hard *alternative* data, *see* Iyer et al, n 87, 1555. Of course, the suggestion that soft information can be quantified and measured accurately via proxy variables is controversial and raises important epistemic and normative questions. *See generally* Andreas Tsamados et al, 'The Ethics of Algorithms: Key Problems and Solutions' (2022) 37 AI & Society 2015.

[157] Hurley and Adebayo, n 9; CFPB, 'Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process' (2017) 82 FR 11183 <https://bit.ly/2IMH7NK>.

[158] High-dimensional data is data that can provide typically thousands of measured parameters/variables/features, e.g., emails, text documents (Word docs, PDFs, etc.), social media posts, videos, audio files, and images.

Table 1. Types of Data Used for Credit Scoring in the UK

		Financial	Non-Financial
Conventional		- Current account turnover (CATO) data - Credit account performance data (including data from utilities, telecom, and insurance agreements)[159] - Financial connections/associates.	- Public record data – electoral roll, court judgments, bankruptcy, fraud - Personal identification data—name, age, date of birth, salary/income, marital status, employment, address/postcode (current and past) - Search footprints - Aliases, address links - Consumer complaints, notices of correction - Aggregated demographic data (e.g. financial status in particular postcodes)
Alternative	Mainstream alternative	- Rental data (payments and related) - Digital subscriptions e.g. Netflix, Spotify, Amazon Prime - Council tax payments - Savings and investment account transactions	
	"Fringe" alternative[160]		- Social network data and analysis - Geolocation data - Mobile phone usage data - Browser data - Consumer interaction with lender's website

[159] *E.g.* Experian's 'Credit Account Information Sharing' database (CAIS).

[160] David Robinson and Harlan Yu, 'Knowing the Score: New Data, Underwriting, and Marketing in the Consumer Credit Marketplace' (*Upturn*, October 2014), <https://www.upturn.org/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf>, 2 (coining the term 'fringe alternative data').

Sources: Experian/Equifax/TransUnion Credit Reference Agency Information Notice (CRAIN);[161] SCOR Principles of Reciprocity;[162] Experian Boost;[163] Aire;[164] Klarna;[165] Zopa.[166]

Although presented as distinct, the four quadrants in **Table 1** are overlapping, and thus the boundaries between alternative and conventional, financial and non-financial data porous and dynamic. For example, analysis of a consumer's financial data—such as their bank account transactions—can also yield non-financial data, such as information about their employment history. Moreover, the dynamic nature of the exercise means that what is considered alternative data today could likely be considered conventional data in a few years' time (likewise for the boundary between 'mainstream' and 'fringe' alternative data). To illustrate, whilst today mobile phone payment data is considered conventional credit data, five years ago it was considered alternative data. Similarly, the growing inclusion of alternative rental and council tax payment data in the mainstream credit referencing system suggests that, in a few years' time, they too will be considered conventional credit data.

3.2.1 Recent trends

In recent years, the main trends in alternative data for credit scoring in the UK have been: (i) increasing use of *(positive) financial* data, such as rental and online subscription payments, and

161 *See e.g.* Experian, n 107.

162 Steering Committee on Reciprocity ('SCOR'), 'Principles of Reciprocity Version 41', <https://www.scoronline.co.uk/key-documents/>. *See* ch 4, section 4.2.4.

163 Experian, 'Instantly Improve Your Score with Experian Boost', <https://www.experian.co.uk/consumer/experian-boost.html>.

164 <www.aire.io>.

165 Cassel et al (Klarna AB), 'Method for Using Supervised Model to Identify User' (2018), US patent application no. US 2018/0158037 A1 <https://patentimages.storage.googleapis.com/25/e0/a0/cfd88514addf2c/US20180158037A1.pdf>.

166 Tamsin Fanning, 'The Tech Behind Borrowing Power' (*Zopa Blog*, 15 October 2019) <https://perma.cc/XL6F-E7TF?type=image>.

a relative decline in the use of non-financial alternative data;[167] (ii) increasing adoption of alternative credit scoring by mainstream CRAs and (bank) credit providers, rather than only non-bank fintech lenders;[168] and (iii) an increase in direct sharing of alternative (financial data) by consumers with lenders and CRAs, particularly using tools built on the Open Banking platform. As will be examined in Part Two, these trends are relevant to the distributional effects of alternative credit scoring, and thus the strength of its distributional promise.

The greater emphasis on alternative financial data in recent years reflects, in part, concerns about the accuracy of non-financial alternative data for estimating consumer creditworthiness, particularly social and behavioural data. Among other things, financial/credit variables are more likely to be causally related to, rather than merely correlated with, a borrower's creditworthiness. For example, a borrower's income and monthly expenditure directly determine the amount of disposable income that they have available to service debt, and thus the affordability of debt.[169]

The greater popularity of alternative financial data in recent years also reflects growing unease about the legality and ethics of using social and behavioural data for credit scoring, particularly where this data is collected without the consumer's explicit consent. In

---

[167] As above, this should be distinguished from the use of non-financial *inferences* from financial data, for example, relating to a borrower's employment history.

[168] Bank of England and Financial Conduct Authority, 'Machine Learning in UK Financial Services' (2019) <https://www.fca.org.uk/publications/research/research-note-machine-learning-uk-financial-services>; David Bholat, Mohammed Gharbawi and Oliver Thew, 'The Impact of Covid on Machine Learning and Data Science in UK banking' (2020) <https://www.bankofengland.co.uk/quarterly-bulletin/2020/2020-q4/the-impact-of-covid-on-machine-learning-and-data-science-in-uk-banking>; Lukas Ryll et al, 'Transforming Paradigms. A Global AI in Financial Services Survey' (2020) <https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/transforming-paradigms/>.

[169] *See generally* FCA, 'Preventing Financial Distress by Predicting Unaffordable Consumer Credit Agreements: An Applied Framework' (Occasional Paper 28, July 2017) <https://www.fca.org.uk/publication/occasional-papers/op17-28.pdf>; Iversen and Rehm, n 57, 3. For older discussions of this point, *see* Capon, n 66 (advocating for explanatory credit scoring models rather than brute force empiricism); Leyshon and Thrift, *Lists Come Alive*.

particular, the Facebook/Cambridge Analytica scandal increased the salience of legal and ethical concerns relating to behavioural profiling with personal data.[170] Indeed, some credit scoring vendors—such as Aire, a UK-based 'challenger' CRA—actively promote the fact that they do *not* rely on social media data in light of accuracy and ethical concerns, preferring instead to gather alternative data directly from the consumer (so-called 'first-party data').[171] In the wake of the Cambridge Analytica scandal, Facebook and other social media platforms have also made it more difficult for third parties to collect user data, for example through the use of scraping and web tracking tools.[172] Although data brokers, such as Experian and Axciom, sell alternative datasets, the lawfulness of this practice is highly questionable and increasingly under scrutiny from data protection regulators.[173]

---

[170] Cambridge Analytica scraped the personal data of Facebook users without their knowledge and consent and used this data to target voters with polarizing ads in advance of the Brexit referendum, in the UK, and the 2016 presidential election, in the US. *See generally* Information Commissioner's Office (ICO), 'Investigation Into Data Analytics for Political Purposes', <https://ico.org.uk/action-weve-taken/investigation-into-data-analytics-for-political-purposes/>. For analysis, *see* Moritz Laurer and Timo Seidl, 'Regulating the European Data-Driven Economy: A Case Study on the General Data Protection Regulation' (2020) 13(2) Policy and Internet 257 (describing the Snowden revelations and Cambridge Analytica scandal as a 'salience shock' that strengthened the rationale for data protection regulation. *See further* ch 4, section 4.2.3 (discussing developments in data protection regulation) and ch 7 (examining the distributional effects of data protection regulation in consumer credit markets).

[171] Aire, 'An Introduction to First Party Data' (2020) <https://aire.io/wp-content/uploads/2020/10/Introducing-first-paty-data-from-Aire-US.pdf >; Aneesh Verma, 'Pulse from Aire: The Opportunity the Ecosystem is Waiting For' *Medium* (29 July 2020) <https://medium.com/aire-life/pulse-the-opportunity-the-ecosystem-is-waiting-for-f68c534d7f1a>. *See also* Graham Ruddick, 'Facebook Forces Admiral to Pull Plan to Price Car Insurance Based on Posts' *Guardian* (Nov 2 2016) <https://www.theguardian.com/money/2016/nov/02/facebook-admiral-car-insurance-privacy-data> (discussing a similar shift in the alternative insurance pricing context). Other challenger CRAs include Crediva Reveal (owned by LexisNexis), Credscope, and Credit Kudos (recently acquired by Apple). *See* Ryan Browne, 'Apple Buys UK Fintech Start-up Credit Kudos' *CNBC* (March 23 2022) <https://www.cnbc.com/2022/03/23/apple-buys-uk-fintech-start-up-credit-kudos.html>.

[172] Facebook, 'An Update on our Plans to Restrict Data Access on Facebook' (2018) <https://about.fb.com/news/2018/04/restricting-data-access/>; Brian X Chen, 'To Be Tracked or Not? Apple is Now Giving us the Choice' *New York Times* (26 April 2021) <https://www.nytimes.com/2021/04/26/technology/personaltech/apple-app-tracking-transparency.html>.

[173] ICO, 'Enforcement Notice', (2020) <https://ico.org.uk/media/action-weve-taken/enforcement-notices/2618467/experian-limited-enforcement-report.pdf> (enforcement action against Experian after data broking investigation); ICO, 'Investigation Into Data Protection Compliance in the Direct Marketing Data Broking Sector' (2020) <https://ico.org.uk/media/action-weve-taken/2618470/investigation-into-data-protection-compliance-in-the-direct-marketing-data-broking-sector.pdf> (finding 'significant data protection failures' at the three CRAs, Experian, Equifax, and TransUnion).

Another key driver of the trend for alternative *financial* data is Open Banking. Open Banking has enabled greater sharing of alternative (and conventional) financial data with non-bank lenders and CRAs using 'Application Programming Interfaces' (APIs).[174] More particularly, Open Banking allows consumers to share their bank account data directly with lenders and alternative credit score providers, without going through the main CRAs. Among other things, this enables a prospective borrower's income to be verified directly, rather than indirectly from their bank account statements (typically, an uploaded pdf file), potentially improving the accuracy of creditworthiness assessment. The scope and frequency of data-sharing through Open Banking is also significantly greater than through the formal credit referencing system. Whereas credit providers typically share data with CRAs on a monthly, lagging basis,[175] via Open Banking, banks can be required to provide this data much more frequently, even daily.

To illustrate how Open Banking is being used in alternative credit scoring, in 2018 Experian launched a service to allow consumers to share positive rental payments data with CRAs, and to incorporate this data into their Statutory Credit Reports (i.e., the credit reports that consumers are entitled by law to receive from CRAs).[176] More recently, Experian launched 'Experian Boost', which allows consumers to share additional types of positive

---

[174] <https://www.openbanking.org.uk/>; FCA, 'Open Finance' (2021) Feedback Statement FS21/7 <https://www.fca.org.uk/publications/feedback-statements/fs21-7-open-finance-feedback-statement>. Open Banking was created pursuant to the Second EU Payment Services Directive (Directive 2015/2366 on Payment Services in the Internal Market [2015] OJ L337/35). For scholarly analysis of the opportunities and risks of open banking, *see* Cesare Fracassi and William J Magnuson, 'Data Autonomy' (2021) 71 Vanderbilt Law Review 327; Dan Awrey and Joshua Macey, 'The Promise and Perils of Open Finance' (ECGI Working Paper, March 2022) <https://ecgi.global/sites/default/files/working_papers/documents/maceyawreyfinal.pdf>.

[175] *See* ch 4, section 4.2.4.

[176] *See* n 82 (definition of statutory credit reports); Experian, 'The Rental Exchange' <https://www.experian.co.uk/assets/rental-exchange/rental-exchange-main-brochure.pdf >, <https://www.experian.co.uk/business/customer-insights/risk-analysis/rental-exchange/tenant-information> ('The Rental Exchange gives you the credit you deserve for paying your rent on time, whether you're a social housing tenant or are renting privately. With the Rental Exchange, you can enhance your credit report without taking on new credit agreements.'). Equifax introduced an equivalent product in 2020. *See* Equifax, n 6.

payment data with Experian to boost their credit scores. This includes rental payments, Council tax payments and digital services payments (e.g., from Netflix or Spotify).[177] For rental payments data, both Experian and Equifax use CreditLadder, a UK-based start-up that relies on Open Banking APIs to discern rental data from consumers' bank account transaction data.[178] Similarly, the UK-based fintech lender Zopa recently partnered with the Open Banking start-up Clearscore to gather more current and accurate information about consumers for the purpose of assessing their creditworthiness.[179] Of course, Open Banking APIs necessarily only serve consumers that have bank accounts, and moreover, accounts with banks that participate in Open Banking.[180] In all cases, consumers are required to actively opt-in to the sharing of their data.

Although the use of non-financial, social and behavioural data for consumer credit underwriting has declined in recent years, it remains more prevalent in other parts of the credit lifecycle—such as marketing, identity verification and fraud/AML monitoring—as well as in business credit underwriting.[181] Alternative *social* data includes a person's activity on

---

177 *See* n 163; Experian, 'Open Banking and Experian Boost' <https://www.experian.co.uk/consumer/experian-boost-open-banking.html>. In the US, *see* Experian, 'Only Experian Can Raise Your FICO Score Instantly—For Free' <https://www.experian.com/consumer-products/score-boost.html>.

178 <https://www.creditladder.co.uk/tenants>. *See also* Friendly Score (<https://friendlyscore.com/case-studies/affordability>), Credit Kudos (<https://friendlyscore.com/case-studies/affordability>) and Bud (<https://www.thisisbud.com/credit-risk>). More broadly, the Open Banking ecosystem includes several 'data aggregators', such as TrueLayer and Envestnet/Yodlee, that enable consumers to share information with lenders. *See e.g.* <https://www.yodlee.com>.

179 <https://www.zopa.com/blog/article/open-banking-what-it-is-why-it-matters-and-how-zopa-uses-it >. *See further* Appendix 3 (discussing Zopa and the fintech credit ecosystem)

180 Currently, only the 9 largest banks and building societies in the UK are required to make customer account data available through Open Banking, although several more have chosen to do so. *See* <https://www.openbanking.org.uk/faqs/>. Note also that although Open Banking formally only requires banks to share financial account data, it is also being used to share non-account, non-financial data.

181 *See e.g.* Experian's alternative credit scoring product for businesses, 'Social Media Insight' <https://www.experian.com/business-information/social-media-insight>; Natwest, 'Natwest Privacy Notice' (June 2022) <https://www.natwest.com/privacy-policy.html>, 3 (including in the description of information that they process 'online profile and social media information and activity, based on your interaction with us and our websites and applications, including for example your banking profile and login information, Internet Protocol (IP) address, smart device information, location coordinates, online and mobile banking security authentication, mobile phone network information, searches, site visits and spending patterns;'), 4 (including in

social media websites/apps, such as their 'likes' and friendship network, what groups they belong to, information from their profiles such as education and employment history, photos and locations they have been tagged in, and status updates.[182] It also includes borrowers' mobile phone data, including usage (e.g., average time spent on the phone), size of social network,[183] email usage[184] and the number and types of apps installed.[185] Alternative *behavioural* data includes borrowers' online browsing behaviour and data on how they interact with the lender's website, such as time spent reading the website and how they complete a loan application form.[186] It also includes psychometric data.[187] **Figure 8** illustrates the wide range of socio-demographic and psychometric variables used for alternative credit scoring.

---

the list of how they obtain information 'Information that you make public on social media e.g. Facebook and Twitter'.). The use of non-financial data is also more prevalent in emerging market economies. *See* n 118.

182 *See e.g.* Yanhao Wei et al, 'Credit Scoring with Social Network Data' (2015) 35(2) Marketing Science 234; Sofie De Cnudde et al, 'What Does Your Facebook Profile Reveal About Your Creditworthiness? Using Alternative Data for Microfinance' (2019) 70(3) Journal of the Operational Research Society 353; Christer Holloman, 'Your Facebook Updates Now Determine Your Credit Score' *Guardian* (August 28 2014) <https://www.theguardian.com/media-network/media-network-blog/2014/aug/28/social-media-facebook-credit-score-banks>.

183 Daniel Björkegren and Darren Grissen, 'Behaviour Revealed in Mobile Phone Usage Predicts Credit Repayment' (2020) 34(3) The World Bank Economic Review 618; María Óskarsdóttir et al, 'The Value of Big Data for Credit Scoring: Enhancing Financial Inclusion Using Mobile Phone Data and Social Network Analytics' (2019) 74 Applied Soft Computing 26.

184 Viani B Djeundje et al, 'Enhancing Credit Scoring with Alternative Data' (2021) 163 Expert Systems with Applications 1.

185 Sumit Agarwal et al, 'Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech' (2019) <http://dx.doi.org/10.2139/ssrn.3507827>.

186 Tobias Berg et al, 'On the Rise of FinTechs—Credit Scoring using Digital Footprints' (2020) 33(7) The Review of Financial Studies 2845.

187 Djeundje et al, n 184.

Figure 8. Social and Behavioural Data Used for Alternative Credit Scoring by LenddoEFL (Non-UK)

Table A.1. Descriptive statistics of the three datasets in Ensemble A.

Variable name	Mean	# valid cases
Socio-demographic		
How long phone	11.28	1826
Number of dependents	1.058	1826
Weekly workhours slide	44.98	1812
Workexperience slide	9.98	1823
Age (years)	33.74	1826
Gender (male = 1)	0.499	1826
Income_cns_dol	987.25	1802
Psychometric		
Has accounts at other financial institutions	1.337	1751
Money now or in three months	1.5991	1826
Money now or in six months	1.6358	1826
Number of contacts	2.529	1826
Time taken to answer simple questions	111.57	1826
Financial products desired but not yet have	17.97	1826
Team player or individualist	0.8471	1818
Measure of moderation	3.0253	1826
Median time to express agreement	7.0175	1826
Similarity of answer to repeated question	0.0069	1785

Source: Djeundje et al (2021)

Similar trends have emerged in the US. Early exuberance for the use of social and behavioural data among fintech lenders has attenuated in recent years, a result of changing perceptions about the accuracy and relative utility of this data,[188] as well as ethical (privacy) and legal ('fair lending') concerns.[189] As in the UK, the US has also seen greater integration

[188] Telis Demos and Deepa Seetharam, 'Facebook Isn't So Good at Judging Your Credit After All' *Wall Street Journal* (February 24 2016) <https://www.wsj.com/articles/lenders-drop-plans-to-judge-you-by-your-facebook-friends-1456309801>; ZestAI, 'A Lender's Roadmap to AI Adoption' (2020) <https://assets.website-files.com/5fd0851c241bd8619aefc08f/602868b79f875613cf85b260_Lender%27s%20Roadmap%20to%20AI%20adoption%20ZestAI.pdf>, 12.

[189] *See e.g.* CFPB, n 157; CFPB, 'Request for Information: Equal Credit Opportunity Act and Regulation B' (2020) <https://www.consumerfinance.gov/rules-policy/notice-opportunities-comment/archive-closed/request-information-equal-credit-opportunity-act-and-regulation-b-extension/>; Zest AI, 'More Data is Useful But Not All Data is Equally Important' <https://www.zest.ai/insights/alternative-data-is-dead-long-

of alternative credit scoring into the mainstream credit reporting system and credit scores, particularly the use of alternative (positive) financial data. It is worth noting, however, that the use of alternative credit scoring by mainstream lenders and CRAs has a longer history in the US relative to the UK. For example, FICO and Vantage Score began incorporating certain types of alternative financial data into credit scores as early as the mid 2000s.[190]

More recent developments include the take up of alternative data for credit scoring by 'government sponsored enterprises', as well as legislation mandating and/or endorsing the use of alternative financial data. For example, Fannie Mae now incorporates positive (only) rental payment data into mortgage underwriting for qualified renters with limited credit histories.[191] The state of Maryland requires lenders to take account of (positive and negative) alternative data, including utility payments, rental payments, school, and work attendance when assessing a credit applicant's creditworthiness.[192] Other states, such as California, have introduced optional rental data reporting schemes.[193]

live-inclusive-data>; Board of Governors of the Federal Reserve System, CFPB, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency, 'Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning' (2021) <https://www.federalregister.gov/documents/2021/03/31/2021-06607/request-for-information-and-comment-on-financial-institutions-use-of-artificial-intelligence>; CFPB, 'CFPB Issues Order to Terminate Upstart No Action Letter' (Jun 08 2022) <https://www.consumerfinance.gov/about-us/newsroom/cfpb-issues-order-to-terminate-upstart-no-action-letter/> (recent withdrawal of the no-action letter to allow Upstart to use additional variables in underwriting *cf.* CFPB, n 125).

190 *See generally* Katy Jacob and Rachel Schneider, 'Market Interest in Alternative Data Sources and Credit Scoring' (The Center for Financial Services Innovation, December 2006) <https://s3.amazonaws.com/cfsi-innovation-files/wp-content/uploads/2017/02/05053225/The-Predictive-Value-of-Alternative-Credit-Scores.pdf>.

191 Fannie Mae, 'Fannie Mae Introduces New Underwriting Innovation to Help More Renters Become Homeowners' (August 11, 2021) <https://www.fanniemae.com/newsroom/fannie-mae-news/fannie-mae-introduces-new-underwriting-innovation-help-more-renters-become-homeowners>; Fannie Mae, 'FAQ: Positive Rent Payment History in Desktop Underwriter', <https://singlefamily.fanniemae.com/originating-underwriting/faqs-positive-rent-payment-history-desktop-underwriter>.

192 Maryland Department of Labor, 'Evaluation Rules and Alternative Methods of Determining Creditworthiness' (September 2 2021) <https://content.govdelivery.com/accounts/MDDLLR/bulletins/2ef8d8c>.

193 Cal. Civ. Code § 1954.06 (2023) ('beginning July 1, 2021, any landlord of an assisted housing development shall offer the tenant or tenants obligated on the lease of each unit in that housing development the option of having the tenant's rental payment information reported to at least one nationwide consumer reporting agency.'). Other states, such as Colorado and Washington DC, have recently proposed similar schemes. *See*

3.3 Machine learning for alternative credit scoring

The second key technological enabler of alternative credit scoring is ML, a sub-category of a broader category of computational methods referred to as applied AI. **Appendix 2** provides a high-level primer on AI, and more detailed discussion of the key features and challenges of ML. Due to the rapid digitisation and datafication of society in recent years, ML—and its sub-category, 'deep learning' (DL)—have emerged as the most promising approaches for building AI systems that can operate in complex real-world environments.[194] More particularly, the greater volume of available data, significant increases in computational power and processing speeds, and advances in distributed and cloud-based computing in recent years have enabled larger and more powerful ML models to be built.[195] Indeed, many of the ML/DL techniques that are now showing promise—including but not only for credit scoring—were developed several decades ago, in part spurred by the introduction of stricter credit risk modelling rules for banks under the Basel prudential regulatory framework.[196] Until recently, however, they were missing the data and hardware needed to power them. As such, past attempts to use ML for credit scoring did not yield sufficient improvements in predictive accuracy to justify their increased cost and complexity.[197]

---

further National Consumer Law Center, 'Even the Catch-22s Come With Catch-22s: Potential Harms and Drawbacks of Rent Reporting' <https://www.nclc.org/wp-content/uploads/2022/10/IB_Catch_22_Rent.pdf> (highlighting the false promise of rental payment data reporting for low-income, minority consumers).

194 Ian Goodfellow, Yoshua Bengio, Aaron Courville, *Deep Learning* (MIT 2015), 8 (hereinafter, 'Goodfellow et al, *Deep Learning*').

195 n 148 and associated text; Gary Marcus and Ernest Davies, *Rebooting AI: Building Artificial Intelligence We Can Trust* (Paragon 2019), 43 (discussing the repurposing of 'graphic processing units' for ML/DL systems, and the development of more powerful and efficient ML-optimized chips, such as Google's 'tensor processing unit': *see* Google, 'Cloud TPU' <https://cloud.google.com/tpu>).

196 *See* ch 4, section 4.2.2.1.

197 Goodfellow et al, *Deep Learning*, 12-22; Galindo and Tamayo, n 84 (observing that if more data were available, a lower classification error rate could be achieved); Desai et al, n 90 (observing that ML methods are unlikely to yield significant gains in predictive accuracy when applied to conventional data that lacks non-linear variables).

In recent years, ML algorithms have been shown to parse large, raw, unstructured (or semi-structured),[198] high-dimensional,[199] and/or anonymized datasets to capture features and patterns that are relevant to predicting borrower creditworthiness.[200] Importantly, ML can accurately capture complex, non-linear relationships in data, as well as reflect changes in the population and environment.[201] This allows for a more multi-dimensional, real-time and up-to-date view of a consumer's creditworthiness.[202]

3.3.1 *Building an ML credit scoring model*

The main challenge of ML is to train a model (a function mapping input to output) that predicts well for new, previously unseen data. This requires, first, that the model fits the training data ('optimization'); and second that it performs well on new data ('generalization').[203] There are three main approaches to training an ML model, categorized according to the type of feedback available for the computer agent to learn from:[204]

---

198 Unstructured data is normally written in natural language, not formulated for neat databases and 'not already coded in terms of the researcher's analytical categories': *see* David Boulton and Martyn Hammersley, 'Analysis of Unstructured Data' in Roger Sapsford and Victor Jupp (Eds) *Data Collection and Analysis* (2nd Edition, Sage Publications 2006).

199 *See* n 158.

200 *See e.g.* Amir E Khandani, Adlar J Kim and Andrew W Lo, 'Consumer Credit Risk Models via Machine Learning Algorithms' (2010) 34(11) Journal of Banking and Finance 2767.

201 *See e.g.* Apaar Sadhwani, Kay Giesecke and Justin A Sirignano, 'Deep Learning for Mortgage Risk' (2021) 19(2) Journal of Financial Econometrics 331; Huseyin Ince and Boran Aktan, 'A Comparison of Data Mining Techniques For Credit Scoring in Banking: A Managerial Perspective' (2010) 10(3) Journal of Business Economics and Management 233. A non-linear relationship is one in which the output does not change in direct proportion to changes in any of the input variables.

202 *See further* ch 6.

203 Goodfellow et al, *Deep Learning*, 108-114.

204 Stuart Russell and Peter Norvig, *AI: A Modern Approach* (Third Edition, Prentice Hall 2010), 693ff.

- *Supervised learning* – the agent observes some example input-output pairs (a dataset with selected labelled features, or independent variables, and labelled target variable, or dependent variable); the agent learns a function that maps input to output;

- *Unsupervised learning* – the agent learns patterns in the input data even though no explicit feedback is supplied i.e. the training data is not labelled; and

- *Reinforcement learning* – the agent learns to optimize for a reward based on feedback (similar to the way humans, especially children, learn from the reactions that their behaviour elicits).

In practice, a combination of these approaches is used. For example, in *semi-supervised learning* the agent is given some labelled examples to help it learn patterns in a larger unlabelled dataset.

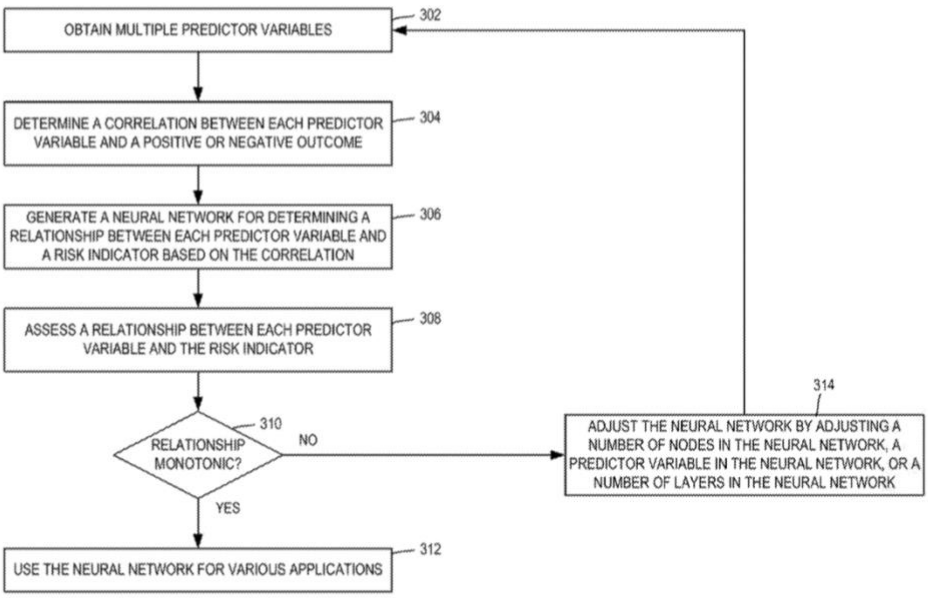
Credit scoring is a 'classification' task that typically uses supervised learning.[205] Popular ML/DL algorithms used for credit scoring include individual classifiers, such as support vector machines (SVMs) and (to a lesser extent) artificial neural nets (**Figure 9**), as well as ensemble methods, particularly tree-based classifiers such as random and gradient boosted forests. ML (and non-ML) techniques are commonly combined, in so-called 'two stage' or 'ensemble' models.[206]

---

[205] On different ML tasks, *see* Goodfellow et al, *Deep Learning*, 97-101, and Appendix 2 (Primer on AI and ML).

[206] *See e.g.* Galindo and Tamayo, n 84, 110 ('for complex, real-world data, where noise, non-linearity and idiosyncrasies are the rule, a good strategy is to take an interdisciplinary approach that combines statistics and machine learning algorithms'); West, n 90; Wang et al, 'A Comparative Assessment of Ensemble Learning for Credit Scoring' (2011) 38 Expert Systems with Applications 223; Djeundje et al, n 184 (summarizing at section 4.2 and Appendix A2 the algorithms used for credit scoring); Majid Bazarbash, 'FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk' (IMF Working Paper, 2019) <https://bit.ly/2U2zckG>, 13-20 (describing key machine learning techniques).

Figure 9. Equifax Method for Optimizing Neural Networks for Risk Assessment[207]



At a high level, there are three key stages in the development of a supervised ML credit scoring model, as summarized below.[208] **Figure 10** provides a simplified illustration of these three stages.[209]

i. Defining the problem to be solved (outcome to be predicted), e.g., whether a borrower will default or become delinquent on a loan; specifying a target variable representing the outcome to be predicted, e.g., the probability of default or delinquency;[210]

[207] Turner et al, 'Optimizing Neural Networks for Risk Assessment' Patent number US10133980B2, November 2018 <https://patentimages.storage.googleapis.com/33/7d/5c/8e298e321906a8/US10133980.pdf>.

[208] Hurley and Adebayo n 9, 168-183.

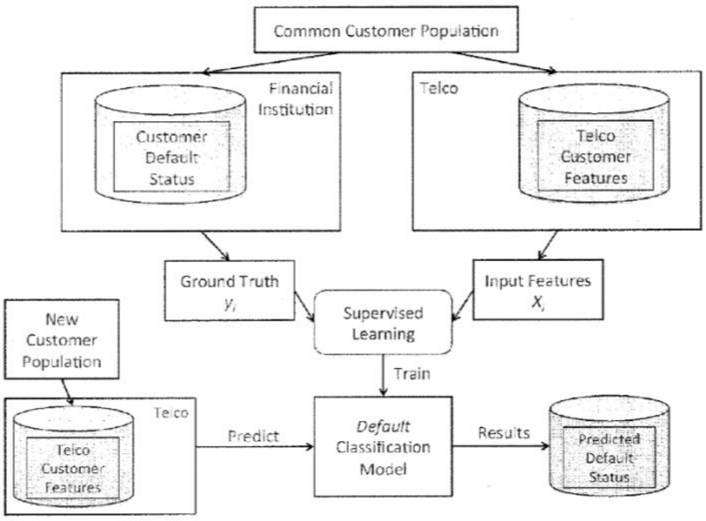
[209] Telefonica Digital España SLU, 'Computer-Implemented Method, a System and Computer Program Products For Assessing the Credit Worthiness of a User' (US20170039637A1) <https://patents.google.com/patent/US20170039637A1/en?oq=US20170039637A1>. Telefonica trades in the UK as o2 (https://www.o2.co.uk/) and is one of the world's largest mobile phone network providers.

[210] *See e.g.* Bono et al, n 135, 593ff (defining the target variable as the probability of future delinquency).

ii. Gathering data, transforming the data into a useable form by extracting and selecting a relevant set of features (e.g., the borrower's age, education, employment, income, number of mobile phone apps etc.), augmenting the data, if necessary,[211] and labelling the target variable (e.g., whether they have defaulted on a loan);[212]

iii. Developing and refining the ML model through exposure to training and test data,[213] and adjusting the model's hyperparameters to improve predictive accuracy.

Figure 10. Telefonica Patent for a Method for Assessing Consumer Creditworthiness Using Supervised Machine Learning, Loan Outcome Data, and Telecom Data



[211] For example, by 'balancing' the training sample to increase representation of the 'defaulting' sub-population. Defaulters are likely to be the minority in a loan outcome dataset—generally most borrowers do not default—which could result in a model trained on this dataset over-predicting non-default. *See e.g.* Agarwal, n 185, 24-25.

[212] Where the state of default is typically assigned a value of 1, and non-default is assigned a value of 0.

[213] In practice, the data will be divided into multiple sub-sets e.g. training, test/hold-out, and validation sets, or more, as in *k*-fold cross-validation (*see* Goodfellow et al, *Deep Learning*, 119-120).

A model's predictive accuracy (or, 'performance') is measured by the classification error rate. That is, the model's predicted default rate compared to the 'true' default rate in the training dataset.[214] There are various ways of measuring classification error, and thus model performance. This includes overall 'balanced accuracy', measured as the total number of correct predictions (i.e. true positives and true negatives) as a share of all predictions;[215] 'recall', measured as the number of true positives as a share of the total number of positive examples (i.e. true positives and false negatives); 'precision', measured as the total number of true positives as a share of total true positives and false positives; and error curves, notably 'area under the curve' (AUC).[216]

3.3.2 Predictive inaccuracy

There are various sources of predictive inaccuracy in ML credit scoring models, as well as conventional, statistical credit scoring models. To begin with, it is important to note that the reported predictive accuracy of an ML model, on each of the measures described above, depends on the chosen cut-off, or threshold, probability for classification, i.e., the probability above which a predicted outcome is classified as 'default', and below which it is classified as 'non-default'. As such, even a model with a reported 0 percent classification error rate (or, 100 percent accuracy) is expected to generate inaccurate predictions in practice.[217] More

---

[214] Rather than predicting credit outcomes (default, delinquency etc), an ML credit scoring model can also be trained to predict credit *approval*—using a training dataset of credit approval and rejection decisions rather than, or in addition to, actual borrower outcomes. Ostensibly, past credit decisions are a less accurate proxy for creditworthiness than past credit outcomes, particularly where those decisions have been influenced by lenders' personal prejudices against certain groups. *See e.g.* Agarwal, n 185 (analysing both approved and rejected applicant data, as well as loan approval data); Bono et al n 135.

[215] Where a true positive (true negative) is a *correct* prediction of non-default (default), and a false positive (false negative) is an *incorrect* prediction of non-default (default).

[216] One could also calculate true negative (false positive) rates i.e. the number of true negatives (false positives) as a proportion of the total number of true negatives and false positives. *See e.g.* Agarwal, n 185, 21-23; Iyer et al, n 87.

[217] An error rate that may, however, be deemed acceptable to lenders, and regulators. *See further* ch 4.

generally, ML credit scoring models, and ML models generally, are statistical tools that enable lenders to infer how an individual *might* behave with credit based on their characteristics and past behaviour, as well as those of others like them. In developing an ML (credit scoring) model, the labels in the training dataset, including historical borrower default, are treated as the 'ground truth', and consumers' creditworthiness inferred from it. These labels are, however, only proxies for a consumer's 'true' creditworthiness, and may not be accurate proxies.[218] Moreover, there is inherent uncertainty in credit and life outcomes and this uncertainty can only ever be imperfectly quantified using risk calculation techniques such as credit scores.[219]

Predictive inaccuracy could also result from statistical bias, notably due to poor model optimization and/or generalization.[220] Poor *optimization* describes the situation where a model does not obtain a sufficiently low classification error rate on the training data (also referred to as 'underfitting').[221] Poor *generalization* describes a situation where the gap between the model's training and test classification error rates is too large (also referred to as

---

218 Solon Barocas and Andrew Selbst, 'Big Data's Disparate Impact' (2016) 104 California Law Review 671, 682 ('[t]he labels applied to the training data must serve as ground truth.').

219 *See generally* Frank H Knight, *Risk, Uncertainty, and Profit* (Houghton Mifflin 1921); Friedrich Hayek, 'The Pretence of Knowledge' (1989) 79(6) American Economic Review 3; Matthew Salganik et al., 'Measuring the Predictability of Life Outcomes with a Scientific Mass Collaboration' (2020) 117 (15) Proceedings of the National Academy of Sciences 8398 <https://doi.org/10.1073/pnas.1915006117>; n 110 (discussing the conversion of uncertainty to risk through credit scoring); danah boyd and Kate Crawford, 'Critical Questions for Big Data' (2012) 15(5) Information, Communication, and Society 662 (discussing the social construction of (big) data, and risks of quantification and context loss); Aitken, n 9 (arguing that 'experiments in alternative credit data both constitute the unbanked as a category of knowledge and offer a particular kind of financialization.'); n 92 (discussing credit scoring as a form of scientific rationality); David J Hand, 'Classifier Technology and the Illusion of Progress' (2006) 21(1) Statistical Science 1 (cited in Barocas and Selbst, ibid, 678).

220 *See generally* Jacob Metcalf, 'Translation Tutorial. Engineering for Fairness: How a Firm Conceptual Distinction Between Unfairness and Bias Makes it Easier to Address Un/Fairness' (ACM FAT*, Feb 2019) <https://par.nsf.gov/biblio/10112010> (defining statistical bias as the 'gap between model and world', and distinguishing it from 'social bias', discussed further *infra*).

221 *See* Goodfellow et al, *Deep Learning*, 109-110.

'overfitting').[222] Overfitting might occur where a model is trained on data from, and optimized for, a population with a particular set of features and distribution thereof, however it fails to generalise well to (i.e., yields low classification accuracy for) a target population that has different features or distribution thereof. Statistical inaccuracy could also arise from variations in the distribution of features at the sub-group level. As a result, a model that is optimized for overall predictive accuracy (minimizing overall error) could yield less accurate predictions for minority groups—in both the training dataset, as well as in the target population.[223]

A related source of statistical inaccuracy is the lack of outcome data on rejected applicants, or negative feedback, i.e., data corroborating whether consumers were rightly or wrongly denied credit (true and false negatives). A lender generally has no observed credit outcomes for the applicants that they deny.[224] As a result, loan outcome datasets used to train credit scoring models will be biased towards the outcomes of the accepted applicant population.[225] This could perpetuate inaccuracy and/or unfairness in credit decisions with respect to consumers that have historically been denied access to credit markets—particularly ethnic minority populations—and that are, as a result, under-represented in the

---

222 *See* Goodfellow et al, ibid; Jon Kleinberg et al, 'Human Decisions and Machine Predictions' (2018) 133(1) The Quarterly Journal of Economics 237.

223 Alexandra Chouldechova and Aaron Roth 'The Frontiers of Fairness in Machine Learning' (2019) <https://arxiv.org/abs/1810.08810>, 2 ('[i]f we train a group-blind classifier to minimize overall error, if it cannot simultaneously fit both populations optimally, it will fit the majority population.').

224 David J Hand and William E Henley, 'Can Reject Inference Ever Work?' (1993) 5(1) IMA Journal of Management Mathematics 45 ('The true good/bad status of applicants accepted for credit is ultimately known. However, the status of rejected applicants will never be known.'). However, *see* Agarwal et al, n 185 (analysing both approved and rejected applicant data, as well as loan approval data). Relatedly, missing data on protected characteristics undermines assessment of discriminatory impacts. *See e.g.* Robert B Avery, Kenneth P Brevoort, Glenn B Canner, 'Does Credit Scoring Produce a Disparate Impact?' (2012) 40(1) Real Estate Economics S65, 2; Talia B Gillis, 'The Input Fallacy' (2022) 106 Minnesota Law Review 1175.

225 Capon, n 66, 87 ('The correct way to develop a credit scoring system is to sample randomly an historic applicant population…Since a considerable proportion of applicants was historically denied credit, systems based only on a population of accepted applicants where there is a corresponding population of denied applicants must be biased.').

training and test datasets.[226] Statistical bias and predictive inaccuracy could also result from changes in the relationship between the feature and target variables, a phenomenon referred to as 'model drift' or 'concept drift'.[227]

Various techniques can be used to help mitigate predictive inaccuracy due to statistical bias. For example, techniques such as 'reject inference' and 'counterfactual analysis' may be used where data on rejected applicants is not readily available.[228] The training and test data used to build an ML model can also be drawn from different time periods to mitigate the risk of model drift.[229] More generally, frequent testing and training of ML models can help to mitigate model drift.

A related concern is that certain 'black-box' ML methods, particularly DL methods, are more opaque (less 'interpretable') than conventional statistical credit scoring methods, which could make it more difficult to identify and mitigate ex ante the sources of inaccuracy in the model.[230] There is anecdotal evidence that bank lenders are avoiding the use of these methods in order to ensure compliance with regulatory model validation and risk management obligations.[231] Responding to these concerns, an important focus of current ML

---

[226] *See generally* Barocas and Selbst, n 218, 677-693 (discussing sources of statistical and social bias in data mining); Hurley and Adebayo, n 9. *See further* ch 6.

[227] Goodfellow et al, *Deep Learning*, 494; Jon Danielsson, Robert Macrae and Andreas Uthemann, 'Artificial Intelligence and Systemic Risk' (2022) 140 Journal of Banking and Finance.

[228] Hand and Henley, n 224.

[229] Bono et al, n 135, 594.

[230] *See e.g.* Bryce Goodman and Seth Flaxman, 'EU Regulations on Algorithmic Decision-Making and a "Right to Explanation"' (2017) <https://doi.org/10.1609/aimag.v38i3.2741>; Cynthia Rudin, 'Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead' (2019) 1(5) Nature Machine Intelligence 206; Zachary C Lipton, 'The Mythos of Model Interpretability' <https://dl.acm.org/doi/pdf/10.1145/3236386.3241340>.

[231] *See e.g.* Samantha Regan et al, 'Model Behaviour. Nothing Artificial—Emerging Trends in the Validation of Machine Learning and Artificial Intelligence Models' (2017) <https://accntu.re/2HQcFzi>.

research is the development of more interpretable, or 'explainable', ML models,[232] as part of the growing field of 'fair ML' research.[233]

Statistical bias, and predictive inaccuracy due to statistical bias, must be distinguished from *social* bias and inaccuracy.[234] The latter describes differences between different social groups in the underlying population—for example, where certain social groups have a higher 'true' credit or affordability risk. A model that is well-calibrated to the underlying population may be statistically unbiased but socially biased. That is, the predictions are statistically accurate but socially undesirable. This distinction is often discussed in terms of 'actuarial fairness' versus 'moral fairness', where the former treats an allocation or decision as fair if it is based on an accurate assessment of risk (such as credit risk), even though this may not be considered fair in a moral (including distributional) sense.[235] Notably, social bias could be the result of historic and structural discrimination, whether in lending—where certain groups have historically been excluded from credit markets, or granted more onerous terms that increased their chance of defaulting—or broader social disadvantage, such as in accessing

---

232 Another important area of focus in ML research is increasing ML efficiency using techniques such as 'transfer learning', 'self-supervised learning', synthetic data, and smaller datasets. *See e.g.* Ashish Shrivastava et al, 'Learning from Simulated and Unsupervised Images through Adversarial Training' (2016) <arXiv:1612.07828>; Henri Ots, Innar Liiv, Diana Tur, 'Mobile Phone Usage Data for Credit Scoring' in Tarmo Robal, Hele-Mai Haav, Jaan Penjam, Raimundas Matulevičius (eds) *Databases and Information Systems* (Springer 2020) (developing an ML credit scoring model using a small dataset); H Brendan McMahan et al, 'Communication-Efficient Learning of Deep Networks from Decentralized Data' (2016) <arXiv:1602.05629>; Reuben Binns and Valerie Gallo, 'Data Minimization and Privacy Preserving Techniques in AI Systems' <https://ico.org.uk/about-the-ico/media-centre/ai-blog-data-minimisation-and-privacy-preserving-techniques-in-ai-systems/>.

233 *See e.g.* <https://www.fatml.org>; Solon Barocas, Moritz Hardt, and Arvind Narayanan, *Fairness and Machine Learning: Limitations and Opportunities* <https://fairmlbook.org>.

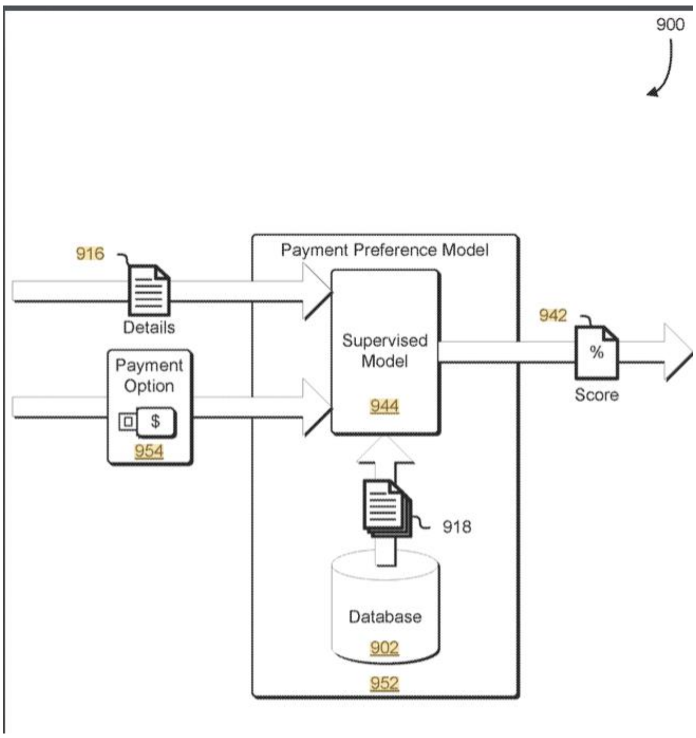
234 Metcalf, n 220; Reuben Binns, 'Fairness in Machine Learning: Lessons from Political Philosophy' (2018) 81 Proceedings of Machine Learning Research 1 <https://arxiv.org/pdf/1712.03586.pdf>.

235 *See* Kenneth Arrow, 'Uncertainty and the Welfare Economics of Medical Care' (1963) 53 The American Economic Review 941, 960 (coining the term 'actuarial fairness' and defining insurance premiums as actuarially fair where they reflect the expected loss of the insured risk); Kiviat, n 107.

education and healthcare, that have worsened the perceived creditworthiness of certain groups (i.e., increased their credit and affordability risk).[236]

Finally, it is important to reiterate that (ML) credit scoring models are only one part of a broader credit decision-making system.[237] Lenders typically take account of factors beyond credit scores in deciding whether to extend credit and on what terms. Furthermore, the statistical methods used in credit scoring, including ML methods, are commonly used by lenders to predict consumers' preferences and behaviour in other parts of the credit cycle—such as marketing, identity verification, and fraud/AML monitoring, as **Figure 11** illustrates.

Figure 11. Klarna Patent 2018—Embodiment of Supervised Scoring Model to Predict Consumers' Preferred Payment Options[238]



[236] Barocas and Selbst, n 218, 683-4 (describing statistical and social bias in data mining: 'Because data mining relies on training data as ground truth, when those inputs are themselves skewed by bias or inattention, the resulting system will produce results that are at best unreliable or at worst discriminatory.'), 691 ('[i]f features held at a lower rate by members of protected groups nevertheless possess relevance in rendering legitimate decisions, such decisions will necessarily result in systematically less favorable determinations for these individuals.'); Lerman, n 155 (discussing digital exclusion).

[237] *See* n 84 et seq and associated text.

[238] Cassel et al (Klarna AB), n 165.

4 THE LEGAL DRIVERS OF ALTERNATIVE CREDIT SCORING

This chapter zooms in on the role of law and regulation in constructing alternative credit scoring, and its distributional promise.[239] It focuses on how changes in three bodies of law—banking and consumer credit regulation, information (data protection and privacy) regulation, and credit referencing regulation—from the early 1970s onwards, helped to constitute the environment in which (alternative) credit scoring emerged. As with the previous chapter, the analysis in this chapter is stylized. Changes in financial and information law are especially salient to the emergence of alternative credit scoring, as well as the development of consumer credit markets more broadly. They are, however, necessarily part

[239] On the role of law and regulation in constituting credit/financial markets more generally *see e.g.* Pistor, n 110 (arguing that 'the legal structure of finance is of first order importance for explaining and predicting the behaviour of market participants as well as market-wide outcomes.'); Iain Ramsay, 'Consumer Credit Law, Distributive Justice and the Welfare State' (1995) 15(2) Oxford Journal of Legal Studies 177, 179 (discussing the 'distributional role of the law in constituting the credit market'); Trumbull, *Regulating for Legitimacy* (arguing that regulation constitutes credit markets, and differences in regulation explain the differences in the development of credit markets in the US and France); Hyman, *Politics of Consumer Debt*, 43 (noting in the US context that 'New Deal policies not only legitimated borrowing but constructed the infrastructure necessary for credit networks to function.'), at 48 ('State power existed at every step of the credit society's development by making markets, founding institutions, and fostering innovation in financial instruments such as the mortgage-backed security.'); Omarova, n 7, 739 ('technology enables and drives financial transactions, but so does public policy embodied in financial laws and regulations.'). On the broader role of law and regulation in constituting markets *see generally* Karl Polayni, *The Great Transformation: The Political and Economic Origins of Our Time* (Beacon 1957 / Farrar 1944) (arguing that markets are embedded in society and constituted by law); Clifford Shearing, 'A Constitutive Conception of Regulation' in Peter N Grabosky and John Braithwaite (eds) *Business Regulation and Australia's Future* (Canberra 1994) (noting that 'law and regulation are prior, not secondary, to the market'), cited in Robert Baldwin, Martin Cave and Martin Lodge, *Understanding Regulation: Theory, Strategy, and Practice* (OUP 2012), 22; Kathleen Thelen, *How Institutions Evolve: The Political Economy of Skills in Germany, Britain, the United States, and Japan* (CUP 2012) (examining modes of institutional change and the political processes through which they occur).

of a much more complex mix of mechanisms that explain the development of alternative credit scoring, and the construction of its distributional promise. This includes other legal institutions (including but not limited to bankruptcy law, anti-discrimination law, and intellectual property law),[240] as well as broader socio-technical and socio-political mechanisms, as examined in the previous two chapters.

The chapter is organized chronologically. Section 4.1 examines key inflection points in the development of financial and information law between c. 1970 and c. 1988. As discussed in Chapter 2, the liberalization and globalization of consumer credit markets beginning in the early 1970s drove the growth of statistical credit scoring as a market practice, as lenders sought to grow their loan portfolios and manage credit risk more effectively. Credit scoring and credit referencing—and thus the growth of consumer credit markets—were also enabled by advances in computing technology. Section 4.1 will demonstrate that these developments were facilitated by relatively permissive financial and information laws in the 1970s and early 1980s.

Section 4.2 examines key inflection points in the development of financial and information law between c. 1988 and c. 2018. It demonstrates that the introduction of prudential rules requiring banks to model default risk in their loan portfolios—first in the wake of the financial crises of the late 1980s, and latterly in the wake of the 2008 GFC—strengthened the incentives for firms to invest in more sophisticated, 'alternative' statistical credit scoring techniques. This includes both traditional lenders (banks and building societies) needing to model and better manage credit risk in their loan portfolios, as well as, latterly, non-bank fintech lenders seeking to tap higher-risk, credit invisible borrowers excluded from mainstream credit markets. In parallel, industry self-regulation of the credit

[240] *See e.g.* Joseph Farrell and Carl Shapiro, 'Intellectual Property, Competition, and Information Technology' in Varian, Farrell, and Shapiro, n 61, 49ff (discussing the 'important role of intellectual property law in influencing the economics of information technology.'). A fuller analysis of these frameworks is reserved for future work (*see* ch 8, section 8.2.2).

information market, which began to develop in the early 1990s, and the information gaps that this framework created, helped to constitute the credit invisible population. As discussed in Chapter 3, credit invisibility is an important driver of alternative credit scoring.

More recently, the tightening of consumer protection regulation in credit markets—particularly the introduction of mandatory creditworthiness assessment rules and restrictions on 'high-cost short-term credit' (HCSTC) in the early 2010s—may have helped to construct alternative credit scoring, and its distributional promise, in two related ways. First, the requirement for mandatory creditworthiness assessment, and particularly the requirement to assess credit *affordability*, increased the regulatory demand for, and thus incentivized further investment in, statistical credit scoring by authorized credit providers, especially non-banks not already subject to credit risk management requirements under prudential regulation. Second, and relatedly, stricter credit affordability rules limited the ability of authorized credit firms to extend credit on high-cost, unaffordable terms. This in turn created an opportunity for unauthorized firms outside the regulatory perimeter—such as Wonga, the exuberant payday lender we met in Chapter 1, and p2p platform lenders—to extend high-cost, often unaffordable credit to marginalized borrowers, leveraging data-driven practices such as alternative credit scoring.[241]

4.1 Legal developments c. 1970 to 1988

The early evolution of information and consumer credit regulation in the UK corroborates both public and private interest theories of regulation. The state intervened to correct perceived market failures (inefficiency) in consumer credit markets—notably, due to 'imperfect information'—but largely avoided more intrusive regulation, in part due to the

[241] As discussed in section 4.2.2.2 below, these lenders would not be brought within the perimeter of consumer credit regulation until 2014.

outsized influence of private financial industry interests.[242] It also corroborates the strong influence of rational choice theory and neoclassical economics on market regulation during this period.[243] More broadly, the historical trajectory of information and consumer credit regulation speaks to the co-evolution of law, social norms, markets, technology, and the political economy, including the role of law in both constituting as well as responding to changes in market practices.[244]

4.1.1 *The evolution of consumer credit regulation*

Consumer credit regulation in the UK—and, arguably, consumer credit as a legal concept—originated in the Consumer Credit Act 1974 (CCA).[245] The CCA, in turn, was based on the

---

[242] On market failures as grounds for regulatory intervention in financial markets, *see generally* Ramsay, *Consumer Protection*, 15-24 (discussing rationales for intervention in the consumer marketplace); Anthony Ogus, *Regulation: Legal Form and Economic Theory* (Oxford: Clarendon Press 1994), 29-46 (discussing public interest grounds for regulation, including market failure); John Armour et al, *Principles of Financial Regulation* (OUP 2016), (hereinafter, 'Armour et al, *Principles*'), 55ff. On the role of private interests in shaping (financial) regulation, *see generally* George J Stigler, 'The Theory of Economic Regulation' (1971) 2(1) Bell Journal of Economics and Management Science 3; Efraim Benmelech and Tobias J Moskowitz, 'The Political Economy of Financial Regulation: Evidence from U.S. State Usury Laws in the 19th Century' (2010) LXV(3) Journal of Finance 1029 (finding that financial regulation is driven by private interests capturing rents from others rather than public interests protecting the underserved); Omri Ben-Shahar and Carl E Schneider, 'The Failure of Mandated Disclosure' (2011) 159 University of Pennsylvania Law Review 647 (explaining the predominance of disclosure-based regulation of credit agreements based on lobbying by the financial sector); John C Coffee, 'The Political Economy of Dodd-Frank: Why Financial Reform Tends to be Frustrated and Systemic Risk Perpetuated' (2012) 97 Cornell Law Review 1019; Armour et al, *Principles*, 91-95.

[243] *See generally* Hal R Varian, *Intermediate Microeconomics: A Modern Approach* (7th Edition, W.W. Norton and Company 2006); Richard A Posner, *Economic Analysis of Law* (Wolters Kluwer 2014, 9th Edition) (applying rational choice theory to legal analysis); Armour et al, *Principles*, 51ff; Daniel Hausman, Michael McPherson and Debra Satz, *Economic Analysis, Moral Philosophy and Public Policy* (3rd Edition, CUP 2017), 21-26 (discussing the key principles of orthodox welfare economics).

[244] Trumbull, *Regulating for Legitimacy*, 35 ('Market regulation has conventionally been justified in terms either of the public interest in correcting market failures or of the social welfare interest in restricting market functions. Each kind of account relies on features of markets to justify regulation. The case of consumer credit suggests that the historical context in which markets have been constructed as legitimate matters for the way in which they are regulated.').

[245] Karen Fairweather, 'Redressing Inequality in Personal Credit Transactions: 1700-1974' in Kit Barker et al (eds) *Private Law and Power* (Hart Publishing 2016), 60. In December 2022, the UK government began consulting on reforms to the CCA. *See* HM Treasury, 'Reform of the Consumer Credit Act: Consultation' (9 December 2022) <https://www.gov.uk/government/consultations/reform-of-the-consumer-credit-act-consultation> (stating that 'It is the government's intention that this reform will facilitate innovation in the credit sector and increase accessibility of credit products, contributing to growth in the sector and the economy more broadly. This is also an opportunity for the government to bolster existing consumer protections to ensure customers remain adequately protected in a modern and increasingly digital economy.').

recommendations of the Crowther Committee on consumer credit, published in 1971.[246] Prior to that, consumer credit markets were primarily regulated through common law and equity, supplemented to a very limited extent by statute. Examples of the latter include the statutes on Building Societies, Money Lending, Usury and Hire Purchase, which were adopted in a piecemeal fashion during the latter part of the 19th and early 20th centuries.[247] In addition, the government directly controlled the terms of consumer credit contracts through a nominal interest rate ceiling, set at 48 percent p.a., and direct bank lending ceilings, imposed by the Bank of England, which were intended to control the money supply.[248]

Various socio-political and technological changes coalescing in the post-war period fuelled the dismantling of the system of direct governmental credit control and the liberalization of consumer credit markets, as well as the development of consumer credit regulation. Although there was a shift, in the immediate post-war period, from private ordering and 'free' markets to greater public ordering and state intervention—influenced largely by Keynesian economic thinking[249]— the perceived failure of Keynesianism in preventing macroeconomic crises contributed to the resurgence of neoliberal political thought and a return to the free market paradigm in the 1970s.[250]

Paradoxically, the resurgence of laissez faire, free market capitalism, and the retrenchment of the welfare state, was accompanied by the rise of a national and

---

[246] Crowther, *Consumer Credit*. *See* Ramsay, *Consumer Protection*, 316 (describing the Crowther Report as the 'source of the principles in the Consumer Credit Act').

[247] Crowther, *Consumer Credit*, 9-10, para 1.1.18 ('Previous committees in this field'); Fairweather, n 245, 59-60.

[248] *See generally* Crowther, *Consumer Credit*, Part 8 ('Statutory control of credit terms'); Donald R Hodgman, 'Credit Controls in Western Europe: An Evaluative Review' (Credit Allocation Techniques and Monetary Policy, Federal Reserve Bank of Boston Conference Series No. 11, 1973), 142-147.

[249] Ogus, n 242, 8-9 (noting that the influence of Keynesianism increased support for state intervention in markets).

[250] *See also* n 47 and associated text.

supranational regulatory state.[251] It was in this context that the UK government in 1968 established the Crowther Committee, with a mandate to review the legal framework governing consumer credit markets in the UK. This led to the publication of the Crowther Report, in 1971, and the adoption of the CCA, in 1974.

Consistent with the economic orthodoxy of the day, the Crowther Committee was guided by the goal of increasing allocative efficiency in consumer credit markets. The Committee's main aim was to make consumer credit markets more 'efficient' by liberating them from 'the antiquated provisions, and from the official restrictions, that hobble it'[252]—i.e., credit and terms control—and maximizing competition.[253] Although the Crowther Committee was attuned to the potential regressive distributional effects of too much credit market access for vulnerable, low-income consumers, it took the view that a more competitive and efficient market would benefit consumers overall, by mitigating unfair lending practices and improving the terms of credit access for poorer consumers.[254] The Committee emphasised the social and economic benefits of consumer credit over the social dangers of indebtedness, warning against imposing overly restrictive measures simply to

---

[251] This was partly due to the expansion of the European Union. *See generally* Giandomenico Majone, 'The Rise of the Regulatory State in Western Europe' (1994) 17 Western Europe Politics 77 (noting at 79 that 'privatisations tend to strengthen, rather than weaken, the regulatory capacity of the state'); Cento Veljanovski, 'The Regulation Game' in Cento Veljanovski (ed) *Regulators and the Market: An Assessment of the Growth of Regulation in the UK* (London: Inst. of Economic Affairs 1991), 3-28; Cass Sunstein, *After the Rights Revolution: Reconceiving the Regulatory State* (HUP 1993), 11-47 (discussing similar developments in the US).

[252] Crowther, *Consumer Credit*, p. iv. The expansion of the consumer credit market, the rise of new forms of consumer credit, and the entry of foreign firms into increasingly open consumer credit markets, also made the Bank of England's system of credit control (which only applied to certain forms of credit) increasingly difficult to operate. *See* Crowther, *Consumer Credit*, part 8; Aveyard et al, *Politics of Consumer Credit*, 196-221.

[253] Crowther, *Consumer Credit*, chapter 9.4.

[254] *See further* Ramsay, n 239 (observing that Crowther and the CCA also sought to protect the poor and vulnerable from harm due to too much credit access and unfair credit products and practices). The CCA did little to directly address concerns about discrimination in consumer credit markets—particularly against women and ethnic minorities. However, these concerns were taken up by cross-sectoral legislation, notably, the Race Relations Acts (1965 et seq), later repealed and replaced by the Equality Act 2010.

protect 'the minority of borrowers who get into trouble'.[255] In the Committee's view, to the extent that certain consumers found themselves struggling with excessive indebtedness, social policy—including consumer education and social work—offered a more appropriate remedy than ex ante restrictions on lending.[256]

As such, the Crowther Report and the CCA embodied a largely laissez faire, light-touch, market-based approach to regulation.[257] They largely avoided more intrusive 'product' regulation, relying instead on informational mechanisms—such as licensing of, and pre-contractual disclosure by, credit providers—to improve the functioning of consumer credit markets and protect consumers.[258] In the model of neoclassical welfare economics, they assumed that consumers are rational actors capable of understanding the information provided to them and taking measures to avoid personal over-indebtedness.[259] Contrary to the Crowther Committee's recommendation, however, the CCA did not extend the nominal interest rate ceiling to all credit agreements,[260] instead preferring to expand the powers of the courts to reopen extortionate credit bargains ex post.[261]

The CCA also strengthened the contractual rights of consumers.[262] Inter alia, it gave consumers new post-contractual rights of cancellation, as well as rights to access and correct

---

[255] Crowther, *Consumer Credit*, chapters 3.6 and 9.1.

[256] Crowther, *Consumer Credit*, chapters 3.9, 9.2, 9.3.

[257] Fairweather, n 245, 60.

[258] *See* Armour et al, *Principles*, 222-223 (discussing conduct regulation); 245-272 (discussing product regulation).

[259] Posner, n 243. The assumptions of rational choice theory, including that revealed preferences are a reliable proxy for value, have been strongly challenged by insights from behavioural law and economics, as discussed further in section 4.2.1.2, below.

[260] Crowther, *Consumer Credit*, chapter 6.6.

[261] CCA ss 137-140 (as enacted), as discussed in Ramsay, *Consumer Protection*, 344ff.

[262] Roy M Goode, 'The Consumer Credit Act 1974' (1975) 34(1) Cambridge Law Journal 79; Ramsay, *Consumer Protection*, 52-53.

information held by CRAs.[263] From a normative perspective, these rights were largely grounded in an orthodox welfarist goal of increasing allocative efficiency in consumer credit markets. That is, giving consumers rights to access and correct information on their credit files could prevent them from being denied access to credit due to inaccurate information, which is likely to be inefficient (as well as unfair, in both an interpersonal as well as distributional sense).[264] To a lesser extent, these rights were also motivated by the autonomy and dignity interests of consumers, including their right to control the use of their personal information.[265] Indeed, the Crowther Committee explicitly highlighted concerns about the loss of consumer privacy due to the growth of credit registers.[266] Arguably, then, the CCA was the first instance of data protection regulation in the UK.[267]

Since the mid-1980s, consumer credit regulation has been influenced significantly by EU law. As with the CCA, however, early EU consumer credit law was also 'light-touch' and focused primarily on correcting information failure in consumer credit markets through enhanced disclosure to consumers.[268] This is partly a function of the EU's limited

---

263 Examined further in section 4.2.4, below.

264 *See further* ch 5.

265 Ramsay, *Consumer Protection*, 52 (discussing individual rights as an ethical rational for consumer protection regulation). *See also* the literature conceptualizing consumer protection rights as fundamental rights, e.g., Iris Benöhr and Hans Micklitz, 'Consumer Protection and Human Rights' in Geraint Howells, Iain Ramsay and Thomas Wilhelmsson (Eds) *Handbook of Research on International Consumer Law* (2nd Edition, Edward Elgar 2018).

266 Crowther, *Consumer Credit*, para 9.1.26.

267 Ramsay, *Consumer Protection*, 337. *See also* Simon Chalton, 'The Transposition into UK Law of EU Directive 95/46/EC (the Data Protection Directive)' (1997) 11(1) International Review of Law, Computers and Technology 25, 26.

268 *See* Directive 87/102/EEC of 22 December 1986 for the Approximation of the Laws, Regulations and Administrative Provisions of the Member States Concerning Consumer Credit [1986] OJ L42/48. This directive was amended in 1990. *See* Directive 90/88/EEC of 22 February 1990 amending Directive 87/102/EEC OJ L61/14. For commentary *see* Ramsay, *Changing Policy Paradigms*, 164; Sefa M Franken, 'The Political Economy of the EC Consumer Credit Directive' in Johanna Niemi, Iain Ramsay, and William C Whitford (Eds) *Consumer Credit, Debt and Bankruptcy: Comparative and International Perspectives* (Hart Publishing 2009), 130. *See also* developments in general consumer (protection) law *e.g.* Council Directive 93/13/EEC on Unfair Terms in Consumer Contracts [1993] OJ L95/29, implemented in the UK by the Unfair Terms in Consumer Contracts Regulations 1999, SI 1999/2083 (latterly superseded by the Consumer Rights Act 2015);

competences and the principle of subsidiarity, and partly a function of the prevailing laissez faire economic orthodoxy and economic paradigm of imperfect information.[269] Concerns about protecting consumers from excessive borrowing—which might have advocated for tighter regulation of consumer credit markets and curbed the growth of consumer credit—were outside the explicit competence of the EU, and thus largely left to Member States (including, at the time, the UK). Any efforts to harmonize and strengthen consumer protection in individual Member States at the EU level were characterized as a conduit for supporting market integration.[270]

4.1.2 *The evolution of data protection regulation*

Permissive consumer credit laws played a critical role in enabling the growth of consumer credit markets and (alternative) statistical credit scoring. However, these developments could not have occurred but for the relaxation of *information* law—notably, the near death of the banker's duty of confidentiality, and the development of relatively permissive data protection regulation—which enabled the greater processing of consumer data and thus advances in digital technology. Indeed, these changes in information law were themselves triggered, in large part, by the liberalization of consumer credit markets. As such, the growth of consumer credit markets and the ascent of statistical credit scoring both enabled, and were enabled by,

---

FCA Handbook, 'Unfair Contract Terms Regulatory Guide' <https://www.handbook.fca.org.uk/handbook/UNFCOG/1/?view=chapter>.

[269] *See* n 64 (citing Stiglitz and Weiss, Akerlof, and others on the economics of imperfect information).

[270] *See* Olha O Cherednychenko, 'Two Sides of the Same Coin: EU Financial Regulation and Private Law' (2021) 22 European Business Organization Law Review 147, 154 (calling attention to an 'interpersonal justice deficit' in EU retail financial market regulation, which 'regards the contracting parties not as ends in themselves with their own justified interests, but rather as market functionaries… protective measures are primarily justified by the considerations of ensuring access to the internal market'.). The 1986 Consumer Credit Directive gave Member States discretion to adopt more stringent standards in minimum harmonisation areas, and MSs were free to legislate in areas not governed by the Directive. *See* Vanessa Mak, 'Financial Services and Consumer Protection' in Christian Twigg Flesner (ed) *Research Handbook on EU Consumer and Contract Law* (Edward Elgar 2016).

changes in information law. Sub-section 4.1.2.1 examines the erosion of the duty of bank confidentiality; sub-section 4.1.2.2 examines the development of data protection regulation, beginning in the early 1970s.[271]

4.1.2.1 The banker's duty of confidentiality

Until the early 1970s, information privacy was primarily a 'private not public concern'.[272] As it was too costly for third parties to acquire and process (personal) data from private market transactions,[273] the use of personal data, and thus individual information privacy, was regulated by private contract law, the common law of confidence, and in consumer financial transactions specifically, the common law duty of bank confidentiality. The banker's duty of confidentiality creates an implied contractual duty for banks to keep confidential and not misuse the personal information of their customers.[274] As a special instance of the general law of confidence, the duty extends to any information generated within the bank–customer relationship that relates to the customer. This includes both financial as well as non-financial

[271] *See also* Trumbull, *Regulating for Legitimacy*, 2, 21-24 (observing that strict data privacy laws in France restricted the growth of credit databases and thus consumer credit markets, especially lending to riskier borrowers—whereas the US took a vastly different trajectory). On the relationship between information law and technological development more broadly *see further* Joel Reidenberg, 'Lex Informatica: The Formulation of Information Policy Rules Through Technology' (1998) 76(3) Texas Law Review 553; Larry Lessig, *Code and Other Laws of Cyberspace: Version 2.0* (Basic Books 2006); Bryan Pfaffenberger, 'Technological Dramas' (1992) 17 Science, Technology, & Human Values 282, as cited in Helen Nissenbaum, 'From Preemption to Circumvention: If Technology Regulates, Why Do We Need Regulation (and Vice Versa)' (2011) 26 Berkeley Technology Law Journal 1367; Andrew Murray, 'Nodes and Gravity in Virtual Space' (2011) 5 Legisprudence 195; Simon Deakin and Christopher Markou, 'The Law-Technology Cycle and the Future of Work' (2018) 158 (2) Giornale di Diritto del Lavoro e di Relazioni Industriali 445.

[272] Fred Norman, 'History of Information Policy' (1999) <http://www.laits.utexas.edu/~anorman/long.extra/information/history.html>.

[273] Orla Lynskey, *The Foundations of EU Data Protection Law* (OUP 2015), 1-3.

[274] *Tournier v National Union and Provincial Bank of England* [1924] 1 KB 461. Although various Private Members' Bills on privacy were introduced during the 1960s, none of these were adopted. *See* Younger, *Privacy*, para. 634-650.

information relating to the customer,[275] provided that the information is non-trivial, has a confidential quality of which the bank has notice, and is not public or common knowledge.[276] Among other things, the recognition of a duty of bank confidentiality—as a legal and not simply moral duty[277]—was deemed to be necessary to protect the reputation of a bank's customers and in turn their ability to access credit,[278] to protect the relationship of trust between banks and their customers,[279] and to maintain public trust in banks.[280]

The banker's duty of confidentiality was, however, subject from the beginning to clear qualifications permitting banks to disclose customers' information on public interest and business efficacy grounds.[281] Pertinently for the present analysis, these qualifications permitted banks to share customer information amongst themselves for the purposes of credit referencing.[282] These qualifications gradually expanded over the course of the 20th century, narrowing the scope of the duty of bank confidentiality.[283] In particular, the

---

[275] *Tournier*, ibid, as discussed in Tanya Aplin et al, *Gurry on Breach of Confidence: The Protection of Confidential Information* (2nd edn, OUP 2012), 383.

[276] *Attorney-General* v. *Guardian Newspapers Ltd. (No. 2)* [1990] 1 AC 109 (HL), 281–282 (Goff LJ). The duty of bank confidentiality also applies to credit unions and building societies (*see Bodnar v Townsend* [2003] TASSC 148, 6), and could conceivably extend to other non-bank financial institutions. *See* Ross S Cranston et al, *Principles of Banking Law* (OUP 2018), 258.

[277] Robert Stokes, 'The Genesis of Banking Confidentiality' (2011) 32(2) The Journal of Legal History 279.

[278] *Tournier*, 474 (Bankes LJ).

[279] Aplin et al, n 275, 200, 381ff.

[280] Cranston et al, n 276, 255. More broadly, it was justified as necessary to preserve 'the kind of society in which we want to live' (*see* Jack, *Banking Services*, 34), and the desire to protect the privacy and autonomy of bank customers (*see* Aplin et al, n 275, 200).

[281] *Tournier*, 473 (Bankes LJ). Banks may also agree *express* confidentiality clauses with their customers, which is common in financial contracts. *See* Cranston et al, n 276, 257.

[282] The court in *Tournier* established four qualifications to the duty of bank confidentiality: '(a) where disclosure is under compulsion of law; (b) where there is a duty to the public to disclose; (c) where the interests of the bank require disclosure; (d) where the disclosure is made by the express or implied consent of the customer.' *See Tournier*, 473 (Bankes LJ).

[283] Gwendoline Godfrey et al, 'Banker's Confidentiality—A Dying Duty but Not Dead Yet' (2016) 17 Business Law International 173.

liberalization and expansion of consumer credit markets, beginning in the 1970s, strengthened the business rationale for bankers to share customer information for credit referencing, relative to the categorical interest in protecting the confidentiality of customer data.[284]

The technologically-enabled expansion of consumer credit markets, which instigated the erosion of the common law duty of bank confidentiality, also spurred the development of information privacy law—under the rubric of 'data protection regulation', and latterly, human rights law protecting the individual right to privacy.[285] As articulated next, this shift in the paradigm of information law—from a more restrictive, trust-based paradigm of confidentiality to a more permissive, individual control-based paradigm of data protection—supported the growth of digital technology, data-driven practices such as (alternative) credit scoring and credit referencing, and consumer credit markets.[286]

---

[284] This shift was also triggered by changes in the structure of banking, particularly: the growth of universal banking and the interest in sharing customer information within banking groups (*see* Roy M Goode, 'The Banker's Duty of Confidentiality' (1989) Journal of Business Law 269, 270; Jack, *Banking Services*, para 5.12); the growth of non-bank finance (*see* Armour et al, *Principles*, 433-448; Jack, *Banking Services*, para 2.18); as well as, more recently, national security concerns in the wake of 9/11 and the ensuing War on Terror (*see* Godfrey, ibid, 174). Today, financial institutions are required by domestic and international law to share customer information with government agencies, inter alia, to combat crimes, such as tax evasion and money laundering and counter terrorism financing (AML/CFT), and to facilitate financial supervision. *See e.g.* 2001 Protocol to the EU Convention on Mutual Assistance in Criminal Matters [2001] OJ C326/1, art 7 (prohibiting EU Member States from invoking bank secrecy as a reason for refusing a request for mutual assistance from another Member State), implemented in the UK by section 33 of the Crime (International Cooperation) Act 2003; Basel Committee on Banking Supervision, 'Banking Secrecy and International Cooperation in Banking Supervision' (1981) <https://www.bis.org/publ/bcbs00f.htm>; Basel Committee on Banking Supervision, 'Information Flows Between Banking Supervisory Authorities' (1990) <https://www.bis.org/publ/bcbsc313.htm>; Financial Services and Markets Act 2000 (FSMA), s 175(5) (setting out exceptions to the duty of (bank) confidentiality for disclosure of information to regulators or investigating authorities). Note, however, that information shared in these contexts—whether for credit referencing, enforcement, or other purposes—is generally still subject to a duty of confidentiality on the part of the recipient, and conditions limiting the use of that information. *See* Cranston et al, n 276, 262–263; FSMA, ss 348–349 (restrictions on disclosure of confidential information by FCA, PRA, etc.).

[285] Human Rights Act 2000, art 8 (the right to private life). *See generally* Aplin et al, n 275, 200ff. For related comparative analyses of the evolution of confidentiality and privacy under English, European, and American law *see* James Q Whitman, 'The Two Western Cultures of Privacy: Dignity Versus Liberty' (2004) 113 Yale Law Journal 1150; Neil M Richards and Daniel J Solove, 'Privacy's Other Path: Recovering the Law of Confidentiality' (2007) 96 Georgetown Law Journal 123.

[286] Younger, *Privacy*, para 38; Sir Norman Lindop, *Report of the Committee on Data Protection. Chairman: Sir Norman Lindop. Presented to Parliament by the Secretary of State for the Home Department by Command of Her Majesty* (Cmnd 7341, 1978) (hereinafter, 'Lindop, *Data Protection*'), paras 2.02–2.04.

4.1.2.2 Data protection regulation

Although the UK had long been a signatory to various international treaties recognizing the right to privacy—notably, the Universal Declaration of Human Rights[287] and the European Convention on Human Rights[288]—it wasn't until the early 1970s that the government began to think seriously about the need for domestic public regulation of privacy, and specifically 'information privacy'.[289] Rapid advances in computing and information processing beginning in the late 1960s, including but not only in consumer credit markets (as discussed earlier), increased concern about the potential misuse of personal data and harm to individuals.[290] It was against this backdrop that the government established a series of parliamentary committees to examine privacy under English law. The most prominent of these were the Younger Committee on Privacy, which issued its recommendations in 1972 (the 'Younger Report'), and the Lindop Committee on Data Protection, which issued its recommendations in 1978 (the 'Lindop Report').[291]

The Younger and Lindop inquiries marked a shift in focus from private contractual and common law rights and duties for the processing of non-public personal information, to a much broader set of statutory rights, duties and safeguards for the processing of personal

---

[287] Universal Declaration of Human Rights (adopted 10 December 1948 UNGA Res 217 A(III)).

[288] Convention for the Protection of Human Rights and Fundamental Freedoms (as amended, Council of Europe Treaty Series 005).

[289] Colin J Bennett, *The Privacy Advocates: Resisting the Spread of Surveillance* (MIT Press 2008), 4; 6–9; Nicola Jentzsch, 'The Regulation of Financial Privacy: The United States vs Europe' (ECRI Research Report No. 5, 2003) <https://www.ceps.eu/ceps-publications/regulation-financial-privacy-united-states-vs-europe/>, 8.

[290] A similar reckoning was taking place in the EU. *See* European Commission, 'Communication to the Council on a Community Data-Processing Policy' SEC (73) 4300 final (1973), 13; European Parliament, 'Resolution on the Protection of the Rights of the Individual in the Face of Developing Technical Progress in the Field of Automatic Data Processing' [1975] OJ C60/48. On the development of EU data protection law, *see generally* Gloria G Fuster, *The Emergence of Personal Data Protection as a Fundamental Right of the EU* (Springer 2014) and Lynskey, n 273.

[291] Younger, *Privacy*; Lindop, *Data Protection*. *See also* U.K. Home Office, *Computers and Privacy* (Cmnd 6353, 1975).

information—public as well as non-public, financial as well as non-financial.[292] With the Lindop Report, the framing of information law began to shift even further away from the concepts of 'confidentiality' and 'privacy', towards the concept of 'data protection' that was more familiar to Continental Europe.[293]

Significantly for the present analysis, the Younger and Lindop Committees were keen to avoid the costs of restrictive information privacy regulation which, in their view, would cut off the economic and social gains due to information processing, and stymie promising innovation and economic growth. They specifically highlighted access to credit as a potential casualty of more restrictive information privacy regulation.[294] As such, neither Committee, nor the Government at the time, favoured the introduction of a broad-based statutory right to privacy under English law, nor detailed regulation of computer systems.[295] Instead, their main recommendations were the establishment of a 'Data Protection Authority' and a set of 'principles for handling personal information' by computers.[296] This included the principles of 'data minimisation', 'purpose limitation', and 'data accuracy', as well as limited rights for data subjects to be told about the information held about them. The Younger and Lindop committees also made several specific recommendations for safeguarding privacy in banking and consumer credit markets. This included a new right for individuals to access on request, and object to, the information held about them by CRAs.[297]

---

[292] Younger, *Privacy*, para 38; Lindop, *Data Protection*, paras 2.02–2.04.

[293] UK Home Office, n 291, para 36; Lindop, *Data Protection*, para 2.02; Jentzsch, n 289, 8.

[294] Younger, *Privacy*, paras 27 and 583; Lindop, *Data Protection*, para 2.08.

[295] UK Home Office, n 291, para 28.

[296] Younger, *Privacy*, paras 591–600; Lindop, *Data Protection*, para 21.09.

[297] Younger, *Privacy*, paras 301–310. This right was also recommended by the Crowther Committee and enshrined in the CCA, ss. 157–159. *See further* section 4.2.4 (discussing credit referencing). At the same time, the Committees emphasized the unmet potential of the law on confidence for addressing privacy concerns. *See* Younger, *Privacy*, para 630. *See also* Jack, *Banking Services*.

It was not until the mid-80s that the principles of information management and the licensing regime, articulated in the Younger Report, would be enforced by statute, pursuant to the first UK Data Protection Act 1984 (DPA 1984).[298] Ultimately, the UK government was compelled to enact data protection legislation more out of its commercial and economic interests, rather than concern to protect individual privacy per se, or to mitigate harms to consumers due to the misuse of personal data.[299] More particularly, the government sought to avoid obstacles to the cross-border flow of data under the Council of Europe's (CoE) Convention on Data Protection.[300] As a result, the DPA 1984 closely tracks the CoE Convention.[301] Certainly, the fundamental, deontological right to control the use of one's personal information—the right to 'informational self-determination', in the German idiom—was not a foundational goal of the DPA 1984 regime, although it was foundational to many European data protection laws such as Germany's.[302]

Crucially, the DPA 1984—and the Younger and Lindop Reports that preceded it—sought to enable the processing of personal data (specifically, 'automatic processing', i.e., computer processing), whilst putting in place limited guardrails to prevent harm arising from the misuse of personal data. As such, they favoured a light-touch, market-based regime for

---

298 This also marked the beginning of a cross-sectoral approach to data protection in the UK. In contrast, countries such as the United States took a primarily sectoral approach to information regulation, including statutes that specifically regulated consumer privacy in the financial sector. This has begun to change in recent years, inter alia with state privacy laws such as the California Consumer Privacy Act of 2018 (California Civil Code §§ 1798.100 - 1798.199.100). *See generally* Godfrey, n 283; Paul M Schwartz and Karl-Nikolaus Peifer, 'Transatlantic Data Privacy Law' (2017) 106 Georgetown Law Journal 115.

299 Bennett, n 289, 141–142.

300 Convention for the Protection of Individuals with Regard to Automatic Processing of Personal Data (CETS No. 108). *See also* UK Home Office, *Data Protection, The Government's Proposals for Legislation* (Cmnd 8539, 1982), para 25. Several other countries and international organizations also adopted data protection laws and principles during this period.

301 Adam Warren and James Dearnley, 'Data Protection Legislation in the United Kingdom: From Development to Statute 1969–84' (2005) 8(2) Information, Communication and Society 238.

302 Judgment of the German Constitutional Court of December 15, 1983, 1 BvR 209/83, BVerfG 65, 1; Chalton, n 267, 32 (observing that the DPA 1984 does not include 'any express references to privacy nor any broader control over the use of personal information'); Lynskey, n 273, 94–95.

information regulation, one that would facilitate the processing of personal data whilst protecting against potential data misuse through both high-level data protection principles, applicable to data processors and controllers, and individual rights for data subjects. Consumers' strengthened rights over their data—and the obligations imposed on data processors—were, however, constrained by the overriding goal of capturing efficiencies from the processing of personal data. Moreover, the emphasis on individual rights to control the use of personal data ignored the many behavioural considerations that would make them less effective in practice.[303]

4.2 Legal developments c. 1988 to 2018

The analysis thus far has observed that relatively light-touch, permissive financial and information laws during the 1970s and 80s helped to create the environment in which consumer credit markets and statistical credit scoring developed. This section examines how developments in financial regulation—specifically, the growth of prudential rules relating to credit risk management, and rules for mandatory creditworthiness assessment under consumer credit regulation—as well as developments in data protection regulation, between the late 1980s and the mid-to-late-2010s, helped to shape the growth of consumer credit markets and the emergence of alternative credit scoring.

To understand developments in financial regulation during this period, and their role in shaping the trajectory of statistical credit scoring, it is necessary to first set out the dynamics of consumer credit markets and, more specifically, the drivers of consumer credit allocation and credit terms. Thus, sub-section 4.2.1 begins by examining how lenders' credit risk management and profit maximisation motives, combined with consumer myopia, shape credit allocation decisions and credit terms. Building on this exposition, sub-section 4.2.2

[303] *See further* section 4.2.1.2, section 6.2, section 7.2.

examines (i) the market failure in consumer credit markets due to the misalignment of incentives between lenders, borrowers, and the broader economy in allocating credit and setting credit terms;[304] (ii) how this market failure motivated the development of (bank) prudential regulation, specifically capital adequacy regulation, beginning in the late 1980s under the auspices of the Basel framework, and consumer protection regulation; and (iii) how these regimes have shaped the evolution of (alternative) statistical credit scoring. Sub-section 4.2.3 examines changes in data protection regulation, and sub-section 4.2.4 examines changes in the regulation of the system of credit referencing via CRAs.

4.2.1 Consumer credit allocation and pricing

In allocating credit, and setting the terms of credit contracts, commercial lenders are generally looking to both (i) cover the costs of lending (notably, the cost of funds, operational costs, and credit risk), and (ii) (maximise) profit from lending.[305] The ability of lenders to freely allocate credit and set credit terms is shaped by various individual and structural factors, including the informedness (myopia) of borrowers, the competitiveness of credit markets, policy interest rates, and of course law and regulation, as examined next.[306]

---

304 FCA, 'Preventing Financial Distress by Predicting Unaffordable Consumer Credit Agreements: An Applied Framework' (Occasional Paper 28, July 2017) <https://www.fca.org.uk/publication/occasional-papers/op17-28.pdf> (hereinafter, 'FCA, *Preventing Financial Distress*') 6 (referring to the misalignment of incentives between lenders and credit applicants).

305 FCA, *Preventing Financial Distress*, 5 ('Lenders typically seek to maximise profits and therefore, without regulatory intervention, make lending decisions based on expected profitability.'). *But see* n 128 (discussing not-for-profit lenders). Lenders may also be looking to satisfy non-profit, non-pecuniary preferences such as a racist or sexist preference not to lend to borrowers of a certain race or gender (so-called 'taste based' discrimination, in contrast to 'statistical discrimination'). However, the scope for lenders to engage in taste-based discrimination, as well as statistical discrimination that produces a more adverse impact on groups sharing 'protected characteristics', such as race or sex, is limited by anti-discrimination law. *See* generally Hugh Collins and Tarunabh Khaitan, 'Indirect Discrimination Law: Controversies and Critical Questions', in Hugh Collins and Tarunabh Khaitan (eds) *Foundations of Indirect Discrimination Law* (Hart 2018), 1-30. As noted previously, a detailed examination of discrimination law is beyond the scope of this thesis.

306 Lawrence M Ausubel, 'The Failure of Competition in the Credit Card Market' (1981) 81 The American Economic Review 50 (finding that credit card interest rates remained sticky relative to changes in the cost of funds and attributing this competition failure to consumer myopia and high search/switching costs); FCA, *Preventing Financial Distress*.

4.2.1.1 Credit risk management and price differentiation[307]

Lenders have a private commercial incentive to manage credit risk: to mitigate their own losses due to non-performing loans, and to maximise profitability. It follows that lenders will generally look to charge more, or lend less, to consumers with higher credit risk—i.e., those with a higher PD and LGD—in order to compensate themselves ex ante for the higher cost of lending to these consumers.[308] Lenders can also mitigate credit risk by diversifying their exposure to high-risk borrowers across many similarly situated borrowers, as well as by passing on the risk to third parties (for example, through securitization), thereby lowering their overall portfolio risk.[309] Furthermore, a lender may be willing to take on more credit risk than is profitable in the short run—i.e. operate a loss-leading business by funding unprofitable loans to high-risk borrowers—in order to subsidize market share growth.[310]

It follows that lenders will generally be unwilling to lend if they cannot compensate themselves for the cost of lending, on a portfolio basis.[311] Notably, this includes situations in which lenders are unable to adequately observe the characteristics of prospective borrowers that influence their credit risk—for example, whether they have previously defaulted or

---

[307] Mary Starks et al, 'Price Discrimination in Financial Services. How Should We Deal with Questions of Fairness?' (Financial Conduct Authority, July 2018) <https://bit.ly/2W783jl> (distinguishing 'price differentiation'—where a 'consumer pays more for a product because they cost more for a firm to serve or the quality of the product is different'—and 'price discrimination'—'practice of charging different prices to different consumers that have the same costs to serve, but different willingness to pay'); Oren Bar-Gill, 'Algorithmic Price Discrimination: When Demand Is a Function of Both Preferences and (Mis)Perceptions' (2019) 86(3) The University of Chicago Law Review 217 (distinguishing 'price differentiation' based on risk, and 'price discrimination' based on demand). Price differentiation is also referred to as 'cost-based pricing' (see FCA, *Preventing Financial Distress*) and 'actuarial pricing' (*see* Arrow, n 235).

[308] FCA, *Preventing Financial Distress*, 13-14. In *secured* credit markets, lenders also compensate themselves ex ante by taking collateral.

[309] *See* n 110 (discussing the effect of securitization on risk-taking by lenders). *See also* n 87 (discussing payday lending and 'loan sharks').

[310] *See e.g.* Ben-David et al, n 14.

[311] Including where they are prevented by law from compensating themselves ex ante through higher credit costs (e.g., due to interest rate caps) or due to regulatory capital costs (discussed *infra*).

fallen into arrears, and thus their willingness to service the debt.[312] Due to this informational asymmetry (hereinafter, 'creditor ignorance'),[313] lenders will be uncertain about the quality of prospective borrowers who know more than lenders about characteristics that influence their credit risk. More particularly, in market segments characterized by creditor ignorance lenders will be uncertain about the *relative* quality of borrowers: prospective 'good' (low risk) borrowers cannot easily be distinguished from prospective 'bad' (high risk) borrowers.[314]

The classical model of consumer credit markets due to Stiglitz and Weiss (the 'Stiglitz-Weiss model') predicts that where lenders are unable to distinguish and price differentiate between borrowers based on credit risk, they are compelled to offer uniform credit terms based on the average risk of default.[315] This gives rise to an 'adverse selection' effect: offering an interest rate based on the average risk of borrowers will be more likely to deter lower-than-average risk borrowers, and attract high-risk borrowers, i.e., the lender faces an adverse selection of customers.[316] According to the Stiglitz-Weiss model, as increasing the interest rate beyond a given point decreases returns to the lender due to adverse selection,

---

312 It also includes situations in which lenders are unable to adequately monitor and control a prospective borrower's actions after lending, which influence their credit risk, as articulated further below.

313 Eric Posner and Richard M Hynes, 'The Law and Economics of Consumer Finance' (2001) 4 American Law and Economics Review 168 (coining and contrasting 'creditor ignorance' and 'consumer ignorance' informational asymmetry).

314 Akerlof, n 64; Dwight M Jaffee and Thomas Russell, 'Imperfect Information, Uncertainty and Credit Rationing' (1976) 90 Quarterly Journal of Economics 651.

315 Stiglitz and Weiss, n 64 (showing that under conditions of informational asymmetry, where lenders cannot 'screen' and distinguish good quality/low risk and bad quality/high risk borrowers, they will ration credit to all borrowers rather than increasing the interest rate to meet demand); Karla Hoff and Joseph Stiglitz (1990) 'Imperfect Information and Rural Credit Markets: Puzzles and Policy Perspectives' (1990) 4(3) World Bank Economic Review 235, 239 (citing Adam Smith, *Wealth of Nations* 'If the legal rate…was fixed so high... the greater part of the money which was to be lent would be lent to prodigals and profectors [sic], who alone would be willing to give this higher interest'). *See also* ch 3, section 3.1 (discussing credit pricing in the credit invisible segment, which is characterized by creditor ignorance).

316 William Adams, Liran Einav and Jonathan Levin, 'Liquidity Constraints and Imperfect Information in Subprime Lending' (2009) 99(1) American Economic Review 49 (finding evidence of allocative inefficiency in subprime US auto-lending markets due to moral hazard and adverse selection effects resulting from informational asymmetry).

lenders respond by 'rationing' the supply of credit (to both high and low risk borrowers), rather than further tightening credit terms to meet excess demand. In subsequent work, Stiglitz and Weiss showed that creditor ignorance *after* credit is extended also leads lenders to ration credit in order to mitigate 'moral hazard' effects. This arises, inter alia, where lenders are unable to perfectly and costlessly monitor and control the actions of borrowers that could affect their likelihood of default. As the borrower does not, as a result, internalize the full costs of default, they have a reduced incentive to take actions to avoid default.[317]

Of course, advances in statistical credit scoring and credit referencing since the early 1980s—that is, after the Stiglitz-Weiss model was published—have significantly reduced (ex ante) creditor ignorance in many consumer credit market segments, and credit rationing due to creditor ignorance.[318]

4.2.1.2 Consumer myopia, lenders' profit motive, and price discrimination

The Stiglitz-Weiss model assumes that borrowers and lenders are both rational agents, such that the borrower strategically selects and defaults on higher risk loans (the adverse selection and moral hazard problems). There is now an extensive body of research dispelling this assumption and demonstrating that, rather than being perfectly rational actors, borrowers,

---

[317] Joseph Stiglitz and Andrew Weiss, 'Asymmetric Information in Credit Markets and its Implications for Macro-Economics' (1992) 44(4) Oxford Economic Papers 694.

[318] As discussed further in ch 6. *See* Liran Einav, Mark Jenkins and Jonathan Levin, 'The Impact of Credit Scoring on Consumer Lending' (2013) 44(2) RAND Journal of Economics 249 (finding that better information following the adoption of credit scoring and risk-based pricing mitigated inefficiency due to adverse selection problems in US subprime auto-loan markets, by enabling more efficient screening of marginal borrowers (and screening out of high-risk borrowers), and better customization of contract terms for infra-marginal borrowers (and offer of larger loans to the lowest risk borrowers), thereby increasing profitability); Calomiris et al, n 64, 9 (noting additionally that although credit rationing is a less important phenomenon today than it once was, 'an important potential role remains for credit rationing, particularly as it pertains to financial allocations in emerging markets, *the pricing of particularly opaque segments of the lending markets of developed economies*…'. Emphasis added); Liberti and Petersen, n 65 (noting that advances in information technology enabled the expansion of consumer lending); Susan Block-Lieb and Edward Janger, 'The Myth of the Rational Borrower' (2006) 84(6) Texas Law Review 1481, 1509. Other factors that influence credit allocation/rationing include the availability of liquid secondary markets, the money supply, collateral, and other credit risk management tools such as securitization (as discussed *supra* n 110).

particularly in retail financial markets, experience 'bounded rationality', their decision-making impaired by various behavioural biases and cognitive limitations.[319] Less well-off, less financially sophisticated consumers are more likely to experience impaired decision-making due to behavioural biases and cognitive limitations.

Particularly relevant to consumer credit markets is 'instant gratification' bias (or 'present' bias), due to which consumers make choices that diminish their future welfare in ways that they later regret but do not presently.[320] More generally, consumers often struggle to estimate—and internalise—the aggregate costs of individual (financial) decisions over the long term.[321] This includes both the economic and psychological costs of high cost, potentially unaffordable borrowing. Many financial transactions are carried out infrequently by consumers, thereby reducing the scope for learning by trial and error (more so for high value credit products, such as mortgages), as well as the fact that products are often differentiated by lenders and thus harder to compare.[322] In contrast, lenders are typically better informed and understand more than borrowers about the (often complex) terms of credit products, and their use patterns and performance over time.

---

[319] *See generally* Herbert Simon, *Models of Man: Social and Rational; Mathematical Essays on Rational Human Behavior in a Social Setting* (Wiley 1957). For an overview of the behavioural biases and heuristics that shape decision-making, *see* Daniel Kahneman, *Thinking Fast and Slow* (Farrar, Straus and Giroux 2011). On behavioural law and economics*, see generally* Cass R Sunstein, Christine Jolls and Richard H Thaler, 'A Behavioural Approach to Law and Economics' (1998) 50 Stanford Law Review 1471; Russell B Korobkin and Thomas S Ullen, 'Law and Behavioral Science: Removing the Rationality Assumption from Law and Economics' (2000) 88 California Law Review 1051; Cass Sunstein, 'Boundedly Rational Borrowing' (2006) 73(1) University of Chicago Law Review 249; Omri Ben-Shahar and Carl E Schneider, n 242; Omri Ben-Shahar and Carl E Schneider, *More Than You Wanted to Know: The Failure of Mandated Disclosure* (Princeton 2014).

[320] David Laibson, 'Golden Eggs and Hyperbolic Discounting' (1997) 112(2) Quarterly Journal of Economics 443. This body of research also shows that, rather than having complete, transitive, and stable preferences, consumers' preferences are in fact dynamic and inconsistent due to income, wealth, and endowment effects, among other things. *See* Korobkin and Ullen, ibid, (summarizing).

[321] Alfred Kahn, 'The Tyranny of Small Decisions: Market Failures, Imperfections, and the Limits of Economics' (1966) 19(1) Kyklos International Review for Social Sciences 23 (arguing that individuals struggle to estimate the aggregate impact of cumulative 'small' decisions).

[322] *See generally* Armour et al, *Principles*, 215ff.

Under a rational borrower model, such as the Stiglitz-Weiss model, this directionally opposite 'consumer ignorance' informational asymmetry would be expected to give rise to allocative inefficiency (market failure) due to the problem of adverse selection.[323] In practice, however, borrower irrationality staves off market failure: despite their ignorance, consumers continue to purchase credit products the terms of which they do not fully understand, and which they may not be able to repay in a sustainable manner, i.e., debt that is unaffordable.[324]

As examined further infra, credit affordability encapsulates the borrower's willingness and ability to not only repay credit on time (credit risk), but also to do so in a sustainable manner, i.e., without experiencing financial or non-financial distress.[325] This implies that the borrower is not only 'solvent' but also 'liquid', i.e., they have sufficient liquid assets to make up for interruptions to income and repay the debt. It also implies that the borrower has adequate income and assets to service their debt while continuing to meet their basic needs.[326] Given their lower levels of income and wealth, and thus thinner safety nets, low-income consumers are more susceptible to debt becoming unaffordable ex post, inter

---

[323] Akerlof, n 64; Posner and Hynes, n 313. Consumer ignorance in financial markets is often discussed under the rubric of 'financial (il)literacy'.

[324] This has been referred to as 'behavioural market failure': *see* Oren Bar-Gill, 'The Behavioural Economics of Consumer Contracts' (2008) 92 Minnesota Law Review 749. *See also* Ausubel, n 306; FCA, *Preventing Financial Distress*, 6 ('Consumers may take out credit agreements with a high risk of unaffordability because they find it difficult to evaluate the uncertain costs and benefits of borrowing. It may result from consumers exhibiting 'behavioural biases''); Jonathan Zinman, 'Restricting Consumer Credit Access: Household Survey Evidence on Effects Around the Oregon Rate Cap' (2010) 34(3) Journal of Banking and Finance 546, 546 ('[a] growing body of work on psychological biases in household finance suggests that many consumers overborrow relative to an unbiased benchmark.'); Paige Skiba and Jeremy Tobacman, 'Payday Loans, Uncertainty, and Discounting: Explaining Patterns of Borrowing, Repayment, and Default' (Vanderbilt Law and Economics Research Paper No. 08-33, 2008) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1319751> (finding that the behaviour of payday borrowers, such as costly delay of default, is consistent with naïve quasi-hyperbolic discounting).

[325] *See further* section 4.2.2.2 below.

[326] *See* FCA, *Preventing Financial Distress*.

alia due to unexpected income shocks—a situation that has been exacerbated by, and in the wake of, the 2008 GFC, and more recently the COVID-19 pandemic.[327]

A consumer's willingness to pay more for credit—their revealed preferences—could accurately reflect their actual, normative preferences, and thus the value that they place on gaining access to credit.[328] For example, a low-income consumer may desperately need to borrow money to finance emergency consumption, such as a life-saving medical procedure, and thus be willing to pay a higher price for it.[329] The consumer understands the true cost of servicing the debt. In that sense, their willingness to pay more for credit is 'rational' and accurately reflects the value they place on access to credit, in the short term, relative to the high, and potentially unaffordable, costs of servicing the debt in the longer term.[330]

The consumer's apparent willingness to pay more could, however, also or alternatively be a function of their *misperceptions* as to the terms and true cost of credit (and thus their inability to repay the debt, affordably), high search and switch costs, and/or

[327] Yvette Hartfree and Sharon Collard, 'Poverty, Debt and Credit: An Expert-Led Review—Final Report to the Joseph Rowntree Foundation' (March 2014) <https://www.bristol.ac.uk/media-library/sites/geography/migrated/documents/pfrc1404.pdf> (hereinafter, 'Hartfree and Collard, *Poverty, Debt and Credit*'), 12 ('Whilst for some households…problem debt started as a result of a single specific event, such as losing a job or starting a family, for others it resulted from a sequence of events or accumulation of adverse circumstances over a period of time, with no single trigger or cause.'); Jubair Ahmed and Kathleen Henehan, 'An Outstanding Balance? Inequalities in the Use—and Burden–of Consumer Credit in the UK' (2020) <https://www.resolutionfoundation.org/publications/an-outstanding-balance/>, 5 (citing research from the Resolution Foundation finding that '[f]ewer than half of low-to-middle income families reported having any savings in 2016-17, representing a rise of 15 percentage points since the financial crisis.'); Joseph Rowntree Foundation, 'Dragged Down by Debt: Millions of Low-Income Households Pulled Under by Arrears While Living Costs Rise' (October 2021) <https://www.jrf.org.uk/report/dragged-down-debt-millions-low-income-households-pulled-under-arrears-while-living-costs-rise> (discussing the increase in borrowing and arrears of low-income households caused by income loss and higher expenses due to the Covid-19 pandemic). *See further* Appendix 1, Figures 10 and 11 and associated text (examining the higher incidence of 'problem debt' among low-income households).

[328] Bar-Gill, n 307; FCA, 'Fair Pricing in Financial Services' (Discussion Paper DP18/9, October 2018) <https://www.fca.org.uk/publication/discussion/dp18-09.pdf>, para 3.6 (describing 'intrinsic preferences', or lower 'price sensitivity', as one of several reason for a consumer's greater willingness to pay).

[329] By the same token, a *high-income* consumer may have a higher willingness to pay because they have more disposable income and fewer budget constraints. *See* FCA, ibid.

[330] Orthodox welfare economics, premised on rational choice theory, treats revealed preferences as a (reliable) proxy for value (welfare). *See* n 243 and ch 5 (examining the welfare and distributional effects of consumer credit).

limited choice (lack of competition), which enable profit maximising lenders to capture more consumer surplus.[331] Profit maximizing lenders often seek to exploit consumer ignorance by charging more to consumers where they can—i.e., consumers who are 'willing' to pay more (have a higher 'reservation price'). The practice of charging different consumers (or groups of consumers) different prices based on their willingness to pay is referred to as 'price discrimination'.[332]

A notorious example of lenders exploiting consumers' misperceptions as to the true cost of credit is the design of credit card contracts with lower short-term prices—such as 'teaser' or introductory interest rates—which are more salient to the consumer, and higher long-term prices—such as back-end contingent fees—which are typically less salient.[333] Lenders also try to profit from 'sweating' borrowers: allowing them to repeatedly rollover and refinance their debts, and profiting from compounding interest and late payment fees.[334]

Less financially sophisticated, lower-income consumers are more susceptible to manipulation of their misperceptions regarding the true cost of credit, as compared to more sophisticated, higher-income consumers. They are also less likely to shop around for, and negotiate, a better price. As a result, they often pay more for credit due to this type of

---

[331] Bar-Gill, n 307; FCA, n 328; Ausubel, n 306.

[332] *See* n 307 (distinguishing price differentiation and price discrimination); Varian, n 61, 13 ('The theory of monopoly first-degree price discrimination is fairly simple: firms will charge the highest price they can to each consumer, thereby capturing all the consumer surplus.').

[333] Xavier Gabaix and David Laibson, 'Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets' (2006) 121(2) Quarterly Journal of Economics 505; Oren Bar-Gill, *Seduction by Contract* (OUP 2012), 51ff; Armour et al, *Principles*, 213-4. Because these impediments to rational decision-making go beyond a mere lack of information, they cannot simply be remedied by greater information disclosure (*see further* ch 6 and 7).

[334] Ronald J Mann, 'Bankruptcy Reform and the Sweat Box of Credit Card Debt' (2007) University of Illinois Law Review 375; FCA, 'Credit Card Market Study—Persistent Debt and Earlier Intervention—Feedback to CP 17/43 and Final Rules' (Policy Statement PS18/4, February 2018) <https://www.fca.org.uk/publication/policy/ps18-04.pdf> para 1.8, ('consumers can accumulate and sustain [credit card] debt over a long period without making significant contributions to repaying the outstanding balance. Such customers are profitable for lenders, meaning firms have an incentive to allow this to continue.').

'demand-based' price discrimination by lenders.[335] Importantly, manipulation of unsophisticated borrowers (often referred to as 'predatory lending')—and, more broadly, the ability of lenders to price discriminate based on perceived consumer demand—can occur even in technically competitive credit markets with many lenders (sellers).[336]

4.2.2 Market failure and regulation

It follows from the foregoing that: (i) lenders are inclined to assume more credit risk on a portfolio basis, and charge more for lending, than is optimal for individual borrowers and the wider economy;[337] and (ii) consumers—particularly more myopic, lower income, 'vulnerable' consumers—are inclined to take on more debt, and at a higher cost, than is individually and socially optimal. That is, unregulated consumer credit markets tend to overproduce debt. This market failure motivated the development of prudential and consumer protection regulation beginning in the late 1980s, as examined next.

---

335 In contrast to risk-based price differentiation, as discussed above. *See* Crowther, *Consumer Credit*, 137 (observing, in 1972, that '[T]he less-educated and poorer members of the community, through their ignorance both of the credit market and the protection provided by existing legislation, combined with their unwillingness to shop around, are frequently in the position of paying higher rates than is justified by their relative credit-worthiness.'); Armour et al, *Principles*, 222-223.

336 George A Akerlof and Robert J Shiller, *Phishing for Phools: The Economics of Manipulation and Deception* (Princeton 2013); Ausubel n 306; Posner and Hynes, n 313. The observation that the 'poor pay more', including through higher costs of credit, is often referred to as the 'poverty premium'. *See* David Caplovitz, *The Poor Pay More: Consumer Practices of Low-Income Families* (Collier-MacMillan 1967) (coining the term 'poverty premium') and for a discussion of the poverty premium in the UK, *see* Sara Davies and Lorna Trend, 'The Poverty Premium: A Customer Perspective' (2020) <https://fairbydesign.com/poverty-premium-research-turn2us/>; Sara Davies and Andrea Finney, 'The Poverty Premium and Debt' in Gardner, Gray, Moser, *Debt and Austerity*, 175-190. *See further* ch 6, section 6.2 (examining price discrimination due to alternative credit scoring).

337 FCA, *Preventing Financial Distress*, 5 ('[l]ending decisions only focus on narrow aspects of financial distress suffered by individuals that affect the firm—primarily the 'credit risk' of the lender arising from non-repayment, default or late payment of the credit agreement the lender is directly exposed to.'); Rajan, *Fault Lines*, 17 ('Unfortunately, the nature of the reward structure in the financial system, whether implicit or explicit, emphasizes short-term advantages and may predispose bankers to take these risks.').

4.2.2.1 Bank prudential regulation

The increasing interconnectedness of the global financial system, due to globalization and the liberalization of financial markets during the 70s and 80s, increased the risk that excessive lending and risk-taking by lenders in one country, and their subsequent failure, could adversely impact financial systems in other countries and thereby threaten global financial stability—inter alia due to systemic non-performing loans, household and bank bankruptcies.[338] The failure of Herstatt Bank, in 1974, crystallized this concern and led to the creation of the Basel Committee on Bank Supervision.[339]

Since its inception, a key focus of the Committee has been the development and coordination of international rules on bank capital adequacy, under the auspices of the Basel Accords. The first Basel Accord (Basel I) was adopted in 1988, and required banks to hold a minimum level of capital to cover credit risk in their loan portfolios.[340] The introduction of capital adequacy rules pursuant to the Basel framework increased the regulatory demand for lenders to model and stress test credit risk (i.e., PD and LGD).[341] This not only increased demand for, and investment in, statistical credit scoring, it also shifted the objective of statistical credit scoring 'from ranking the borrowers or potential borrowers in terms of their default risk to estimating the default risk more accurately.'[342]

---

[338] Thomas et al, *Credit Scoring*, 266; Armour et al, *Principles*, 53-54.

[339] *See* Bank for International Settlements, 'History of the Basel Committee' <https://www.bis.org/bcbs/history.htm>.

[340] Regulatory capital is measured as a percentage of 'risk weighted assets' (RWA). *See* Bank for International Settlements, 'International Convergence of Capital Measurement and Capital Standards' (1988) <https://www.bis.org/publ/bcbs04a.htm> (original text of the Basel Capital Accord); Thomas et al, *Credit Scoring*, 276 (discussing the calculation of RWA and capital requirements, the limitations of Basel I, and the expansion of the Basel rules in subsequent years).

[341] Thomas et al, *Credit Scoring*, 3-6; 12-13; Galindo and Tamayo, n 84 (noting that 'risk assessment of financial intermediaries is an area of renewed interest due to the financial crises of the 1980's and 90's').

[342] Thomas et al, *Credit Scoring*, 6.

The regulatory requirements for banks to manage and mitigate credit risk (on an individual, and latterly, system-wide basis, as discussed further below) have grown steadily since 1988, in each case incentivizing further investment in, and development of, statistical credit scoring.[343] As Lyn Thomas and co-authors observe, 'the greatest impact on credit scoring since 2000 is the advent of the Basel Accords.'[344] At the same time, by *limiting* risk-taking by banks, the tightening of capital adequacy rules under the auspices of the Basel framework incentivized a new wave of 'innovation' in credit risk management—notably, debt securitization, or the 'originate to distribute' model of lending.[345] Securitization was a key driver of the growth in subprime lending during the late 1990s and early 2000s, eventually culminating in a credit and housing bubble, and the GFC in 2008.[346]

The GFC, and its determinants, triggered a new wave of financial regulation, in the UK as well as internationally.[347] In a major overhaul of the regulatory architecture, the Financial Services Authority (FSA), the UK's unified regulator, was replaced in 2013 by the Financial Conduct Authority (FCA), the Prudential Regulation Authority (PRA), and the

---

343 Bank for International Settlements, 'The Basel Framework' (2023) <https://www.bis.org/basel_framework/index.htm> (latest consolidated version of prudential standards under the Basel framework); Thomas et al, *Credit Scoring*, 6 ('The Basel Accords raised the visibility and importance of scorecards and their builders in financial institutions. Senior bank managers and financial regulators needed to understand how credit scoring worked and how to measure how well a scorecard is performing.').

344 In the UK, these rules are implemented under the PRA prudential regime (applicable to banks as well as building societies, as 'CRR firms'). *See* <https://www.prarulebook.co.uk/rulebook/Content/Part/211370/01-12-2021>; Somnath Chatterjee, 'Modelling Credit Risk' (Bank of England Centre for Central Banking Studies, 2015) <https://www.bankofengland.co.uk/ccbs/modelling-credit-risk>; Bank of England, 'Model Risk Management Principles for Stress Testing' (Supervisory Statement 3/18, April 2018) <https://www.bankofengland.co.uk/prudential-regulation/publication/2018/model-risk-management-principles-for-stress-testing-ss>.

345 *See generally* Thomas et al, *Credit Scoring*, 307-321 (discussing the role of securitization in the subprime mortgage crisis). Of course, as discussed earlier, debt securitization per se was not new (*see* n 110 and associated text).

346 *See generally* Thomas et al, *Credit Scoring*, 315-320.

347 *See* HM Treasury, 'A New Approach to Financial Regulation—Consultation on Reforming the Consumer Credit Regime' (2010) <https://www.gov.uk/government/consultations/a-new-approach-to-financial-regulation-reforming-the-consumer-credit-regime>.

Financial Policy Committee (FPC).[348] Financial regulation of consumer credit markets became centred in the 'conduct' regime supervised by the FCA, and, for banks and building societies, the 'prudential' regime supervised by the PRA.[349]

Authorized consumer credit firms must comply with rules set out in the FCA's Handbook.[350] This includes the specialist Consumer Credit 'Sourcebook' (CONC), as well as rules applicable to all authorized firms, such as the high-level principles of business to, inter alia, 'treat customers fairly' and act with 'due care, skill and diligence'.[351] Firms must also comply with the retained provisions of the CCA, as amended, to the extent that it has not been repealed or replaced by FCA rules and guidance.[352] Consumer credit firms that are banks or building societies must additionally comply with the prudential rules set out under the PRA regime.[353] As ex ante specialized regulatory regimes, the PRA and FCA regimes are the most immediate sources of regulation of consumer credit markets in the UK.[354]

---

348 Financial Services Act 2012, s 6; FSMA, ss 1-18. Note, the OFT continued to oversee the regulation of *unsecured* consumer credit pursuant to the CCA until oversight was transferred to the FCA in 2014. *See* Timothy Edmonds, 'Consumer Credit Regulation' (Briefing Paper No. 06842, March 2014) <https://commonslibrary.parliament.uk/research-briefings/sn06842/>, 6-8.

349 Armour et al, *Principles*, 542. At the time of writing, Parliament is debating reforms to UK financial regulation pursuant to the Financial Services and Markets Bill. *See* <https://commonslibrary.parliament.uk/research-briefings/cbp-9594/>.

350 Note, short-term credit (repayable in less than 3 months), small value credit, and credit products that are nominally interest-free are currently excluded from the scope of this regime. However, *see* HM Treasury, 'Regulation of Buy-Now Pay-Later: Consultation Response' (2022) <https://www.gov.uk/government/consultations/regulation-of-buy-now-pay-later-consultation> (proposing an expansion of the regulatory perimeter to include short-term, interest-free credit).

351 CONC and PRIN 2, FCA Handbook <https://www.handbook.fca.org.uk>.

352 On the relationship between the CCA and the FCA Handbook, *see* FCA, 'Review of Retained Provisions of the Consumer Credit Act: Final Report' (2019) <https://www.fca.org.uk/publication/corporate/review-of-retained-provisions-of-the-consumer-credit-act-final-report.pdf>.

353 <https://www.prarulebook.co.uk>.

354 Note, these regimes incorporate various other areas of law. For example, the FCA has powers pursuant to general consumer protection law, as articulated further *infra*. *See further* Iain MacNeil, 'Rethinking Conduct Regulation' (2015) 30(7) Butterworths Journal of International Banking and Financial Law 413, 422 (observing that the FCA regime overlaps significantly with, and in some areas supersedes or gold-plates other areas of law, such as general consumer law and the common law of contract); Eilis Ferran, 'The New Mandate for Supervision of Financial Services Conduct' (2012) 65 Current Legal Problems 411, 448 (discussing the Unfair Commercial Practices Directive, art 3(9) of which allows EU Member States to impose stricter requirements for

Changes to consumer credit regulation instigated by the GFC are examined in section 4.2.2.2, below. With respect to prudential regulation, the crisis increased the salience of 'systemic' risk, inter alia due to the complexity and interconnectedness of financial institutions and products. This propelled an international effort to develop 'macroprudential regulation', focused on managing and mitigating systemic financial risk and the consequent threats to financial and economic stability—as a complement to 'micro-prudential' regulation, which, as discussed above, focuses on the safety and soundness of individual financial institutions.[355]

The tightening of prudential regulation post-crisis—along with tighter monetary conditions and higher costs of funds for, as well as the greater risk aversion of, banks—would once again restrict risk-taking by banks, creating an opportunity for less regulated, non-bank fintech lenders to lend to higher-risk, marginalized consumers. As examined further below, these conditions helped to incentivize investment by fintech lenders in alternative statistical credit scoring. At the same time, the heightened burden of prudential regulation post-2008 incentivized investment by *banks* in new credit scoring techniques, including ML methods, and digital technology more generally, to increase the efficiency of regulatory compliance (a phenomenon referred to in recent years as 'RegTech').[356]

---

financial services—and arguing that the FSA Handbook already offers *greater* consumer protection than that afforded by general consumer law); FCA, 'Reforming Conduct of Business Regulation' (Consultation Paper 06/19, 2019, chapter 28) (similarly arguing that the Handbook gold-plates consumer law). More generally, consumer credit regulation in the UK, and financial regulation more broadly, are a hybrid between public regulation and private law. *See e.g.* Hans Micklitz, 'The Public and the Private—European Regulatory Private Law and Financial Services' (2014) 10(4) European Review of Contract Law 473.

[355] Bank for International Settlements, 'Countercyclical Capital Buffer Proposal' (2010) <https://www.bis.org/publ/bcbs172.htm>; Bank of England, 'The Role of Macroprudential Policy—A Discussion Paper' (2009) <https://www.bankofengland.co.uk/-/media/boe/files/paper/2009/the-role-of-macroprudential-policy.pdf>; The Capital Requirements (Capital Buffers and Macro-Prudential Measures) Regulations 2014, SI 2014/894; Mark Carney (former Governor of the Bank of England), 'The Grand Unifying Theory (and Practice) of Macroprudential Policy' (5 March 2020) <https://www.bankofengland.co.uk/-/media/boe/files/speech/2020/the-grand-unifying-theory-and-practice-of-macroprudential-policy-speech-by-mark-carney.pdf>, 7 ('Macroprudential policy addresses risks arising from interactions between institutions and sectors within the financial system, and between the financial system and the real economy.').

[356] *See generally* Arner et al, n 116.

4.2.2.2 Consumer credit regulation

The GFC provided a stark reminder that, in the absence of regulation, lenders will tend to take on more credit risk and extend more unaffordable debt than is optimal, for both individuals borrowers and society.[357] As discussed earlier, a lender may be willing to lend to borrowers who are a high credit risk because it can compensate itself ex ante by charging more to lend, diversifying its exposure across many similarly situated borrowers and/or passing on the risk through practices such as debt securitization, thereby lowering its overall portfolio risk.[358] From the borrower's perspective, however, the risks of high-cost, potentially unaffordable debt are less well diversified.

Importantly, credit risk (PD and LGD) does not always capture the *affordability* of credit for borrowers, even though they are strongly correlated.[359] For example, a borrower may be deemed 'willing and able' to make timely repayments under the specific credit agreement that an individual lender is exposed to, i.e., they have a low credit risk. Nevertheless, the debt could be unaffordable. For example, the borrower may have to forgo other essential expenditure, such as housing and food, and potentially default on other debts to meet repayments. The borrower may take on unaffordable debt because they do not understand the true cost (due to behavioural biases and cognitive limitations) and/or need credit to finance emergency consumption, despite being aware of the future disutility due to the high costs of servicing the debt.[360]

---

[357] *See* ch 5 (examining the distributional effects of unaffordable lending).

[358] FCA, *Preventing Financial Distress*, 13-14. As discussed above, regulatory capital requirements are calculated based on the overall credit risk on the bank's balance sheet.

[359] FCA, *Preventing Financial Distress*, 6 ('Without affordability rules, firms may be incentivised to offer predictably unaffordable credit agreements to applicants who are expected to be profitable even if these people have a high risk of suffering financial distress which can be predicted').

[360] *See* n 328 et seq and associated text, and ch 5 infra (examining the welfare and distributional effects of consumer credit).

The overriding objective of prudential (micro and macro) regulation, examined above, is to reduce the probability of bank failure(s) and the consequent threat to (global) financial stability. Capital adequacy ratios seek to limit credit risk on banks' balance sheets. They focus on aggregate credit risk in banks' loan portfolios—for example, micro- and macro-prudential capital requirements, such as the countercyclical capital buffer, and capital conservation buffer, are calculated as a percentage of a bank's 'total risk exposure amount'.[361] These rules are not motivated, at least in the first instance, by the need to protect *individual* borrowers from the financial and non-financial costs of debt they can't repay, affordably, except to the extent that unaffordable debt threatens the stability of individual firms and/or the financial system. They are certainly not motivated by an independent distributional objective of protecting low-income borrowers from the regressive effects of unaffordable borrowing.[362]

Thus, unaffordable lending may still be optimal at the level of individual firms, even though it is likely to be suboptimal for the borrower, to the extent that it causes them financial or non-financial distress, and suboptimal for the broader economy, to the extent that it increases systemic non-performing loans, consumer bankruptcies, and demand for welfare support, the costs of which are partly borne by the state.[363] Unaffordable borrowing is also more likely to harm less well-off, vulnerable consumers who typically have less disposable income and lower levels of financial literacy, and are thus more susceptible to financial (and non-financial) distress.[364] In particular, these consumers are less likely to be

361 PRA rulebook, rules 2 and 3 <https://www.prarulebook.co.uk/rulebook/Content/Part/211272/23-12-2022>.

362 *See* ch 5.

363 As examined further in ch 5.

364 FCA, 'FG21/1 Guidance for Firms on the Fair Treatment of Vulnerable Consumers' (2021) <https://www.fca.org.uk/publication/finalised-guidance/fg21-1.pdf>.

able to assess the affordability of debt before entering into a loan, to the extent that unaffordability is foreseeable, and are more susceptible to unexpected shocks that could make their debts unaffordable ex post.[365]

The experience of the GFC motivated the adoption, in 2010, of more stringent rules requiring lenders to assess the creditworthiness of prospective borrowers.[366] Pursuant to this regime, authorized credit providers are required to assess a borrower's creditworthiness prior to entering into a credit agreement, and prior to significantly increasing the amount of credit or credit limit. Importantly, credit providers must take account of both whether the borrower will repay credit by the due date—i.e., credit risk—as well as the borrower's ability to do so without incurring financial or non-financial distress—i.e., credit affordability.[367] Whereas prudential regulation under the PRA regime is concerned primarily with the lender's balance sheet—where, as noted, credit risk can be diversified within the lender's loan portfolio—the FCA creditworthiness regime, and particularly the affordability criteria, are concerned with the individual, household balance sheet—where the risks due to borrowing are less well diversified.

---

365 *See* n 327 et seq and associated text.

366 CONC, s 5.2A (Creditworthiness Assessment). *See also* FCA, 'Assessing Creditworthiness in Consumer Credit—Feedback on CP 17/27 and Final Rules and Guidance' (Policy Statement PS18/19, July 2018) <https://bit.ly/2SS9ijA>. *See* original section 55B CCA (now replaced by CONC s 5.2A), and previous guidance from the Office of Fair Trading (OFT), 'Irresponsible Lending—OFT Guidance for Creditors' (2011) <https://webarchive.nationalarchives.gov.uk/ukgwa/20140402162813/http://www.oft.gov.uk/OFTwork/publications/publication-categories/guidance/consumer_credit_act/oft1107>. This implements changes to EU law on unsecured credit agreements (Directive (EC) No 2008/48/EC of the European Parliament and of the Council of 23 April 2008 on Credit Agreements for Consumers and Repealing Council Directive 87/102/EEC [2008] OJ L133/66 (CCD 2008)).

367 CONC, s 5.2A.10ff and s 5.5A.11ff (for p2p lending agreements). Since 2019, p2p lending platforms are also subject to creditworthiness assessment and model risk management requirements under the FCA regime. *See* CONC s 5.5A (Creditworthiness assessment: P2P lending agreements); COBS s 18.12; SYSC s 7.1 (*see* FCA, 'PS19/14 Loan-Based ('Peer-to-Peer') and Investment-Based Crowdfunding Platforms: Feedback to CP18/20 and Final Rules' (Policy Statement PS19/14, June 2019) <https://www.fca.org.uk/publication/policy/ps19-14.pdf>. Note, the CCD 2008 leaves open the definition of creditworthiness. The UK implemented it as a requirement to assess both credit risk (to the lender), as well as affordability of credit (for the borrower).

Authorized credit providers are required to base their assessment of consumer creditworthiness on 'sufficient' information obtained from the consumer 'where appropriate', and a CRA 'where necessary'. The creditworthiness assessment should also be 'proportionate' in extent and scope, having regard to factors such as the type of credit, and the financial position and 'vulnerability' of the borrower. The requirement for proportionality extends to the types and sources of information that the credit provider relies upon in making its assessment, which may include a credit score and a credit report.

In 2014, the creditworthiness assessment regime was extended to include HCSTC, such as payday lending. Together with the introduction of an interest rate cap on HCSTC—examined below—this would directly contribute to the demise of Wonga, the infamous high-cost payday lender.[368] The creditworthiness assessment rules were extended to p2p lenders in 2019.[369]

4.2.2.2.1 Responsible lending

More broadly, the years following the GFC saw a more concerted push for 'responsible lending' and the protection of vulnerable consumers from the burden of high-cost and unaffordable debt.[370] This more consumer protection-minded approach of consumer credit regulation post-2008—in the UK as well as in other jurisdictions, such as the EU and US—

---

[368] n 130.

[369] The FCA brought p2p lending platforms within its regulatory perimeter in 2014. *See* FCA, 'FCA's Regulatory Approach to Crowdfunding Over the Internet, and the Promotion of Non-Readily Realisable Securities by Other Media' (Policy Statement PS14/4, March 2014) <https://www.fca.org.uk/publication/policy/ps14-04.pdf>; FCA, n 367.

[370] Although the FSA initiated various consumer protection-oriented reforms in the late 90s and early 2000s, in practice, its approach to supervision remained light-touch. This includes the establishment of the Financial Ombudsman Service (FOS), and a new 'Treating Customers Fairly' initiative (*see* s225ff FSMA, establishing the FOS; FSA, 'Treating Customers Fairly—Towards Fair Outcomes For Consumers' (2006) <https://www.fca.org.uk/publication/archive/fsa-tcf-towards.pdf>). The early 2000s also saw reforms to the CCA to strengthen the protection of credit consumers.

was partly influenced by the popularisation of behavioural (law and) economics.[371] Insights from behavioural economics offered a more systematic explanation for why individualised informational and contractual remedies—which had characterised consumer financial regulation in the years prior to the GFC, as discussed earlier—had been ineffective in protecting vulnerable consumers.[372]

Of course, the crisis had also highlighted the macro-economic, financial stability costs of excessive household debt.[373] Arguably then, from a normative perspective, the goals of protecting vulnerable consumers and preventing over-indebtedness through more responsible lending are primarily rooted in welfarist (allocative efficiency) norms, and the goal of maintaining efficient and competitive financial markets—rather than direct concern to protect vulnerable consumers, or associated distributional fairness concerns.[374]

In addition to the introduction of mandatory creditworthiness assessment, examined above, the more consumer-protection oriented approach of consumer credit regulation post-2008 is reflected in the FCA's new statutory consumer protection objective, which explicitly

---

371 *See supra* section 4.2.1.2; Ferran, n 354, 419-420 (discussing the FCA's intention to take a more 'behaviourally informed approach' and noting that its 'more paternalistic style of supervision is rooted in a well-meant desire to promote fairness'). In the US, the GFC led to the creation of a unified consumer financial regulator, the CFPB. *See* Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, 124 Stat. 1376 (2010), § 1011 (codified at 12 U.S.C. § 5491) (creating the CFPB). *See also* Elizabeth Warren, 'Unsafe at Any Rate' (2007), https://democracyjournal.org/magazine/5/unsafe-at-any-rate/; Oren Bar-Gill and Elizabeth Warren, 'Making Credit Safer' (2008) 157(1) University of Pennsylvania Law Review 1.

372 Ramsay, *Changing Policy Paradigms*, 173; Julia Black 'Financial Markets' in Herbert M Kritzer and Peter Cane (eds) *Oxford Handbook of Empirical Legal Research* (OUP 2010), cited in Ferran, n 354, at 419.

373 G20, '2008 G20 Communique' <http://www.g20.utoronto.ca/2008/2008communique1109.html>; Iain Ramsay and Toni Williams, 'Peering Forward, 10 Years After: International Policy and Consumer Credit Regulation' (2020) 43 Journal of Consumer Policy 209. *See further* ch 5, section 5.2.2 (examining the relationship between credit and the macroeconomy).

374 *See e.g.* Zanna Iscenko et al, 'Economics for Effective Regulation' (FCA Occasional Paper No. 13, March 2016) <https://www.fca.org.uk/publication/occasional-papers/occassional-paper-13.pdf> (setting out the FCA's welfarist approach to regulation focused on mitigating 'economic harm'); Starks et al, n 307, 4 (noting that 'Our Mission sets out a clear framework for identifying, assessing, and scaling economic harm…Traditionally our work has focussed less on issues relating to distributive fairness.'; and setting out a framework for thinking about distributive harms). *See also* Coffee and others, n 242 (discussing private interest theories and evidence of financial regulation).

puts an onus on firms to behave responsibly, including by having regard to the 'capabilities of the consumers'.[375] Relatedly, the FCA's operational objective to promote competition is now defined in terms of a consumer welfare standard ('promoting effective competition in the interests of consumers'), which could be interpreted as embracing not only an orthodox allocative efficiency goal, but also (distributional) fairness and consumer dignity/autonomy goals.[376]

The normative rebalancing of consumer credit regulation post-crisis is perhaps most evident in the new 'product intervention' powers given to the FCA to, inter alia, ban financial products[377] and limit the cost of credit[378]—the latter a response to the growth of the high-cost payday lending market.[379] In 2015, the FCA introduced a new regime restricting HCSTC, including a price cap.[380] Pursuant to this regime, the total cost of interest, fees and charges is limited to 100 percent of the amount borrowed. Additionally, default fees are

---

[375] FSMA, s 1C. In contrast, the statutory consumer protection objective under the prior FSA regime only recognized the duty of *consumers* to act responsibly. *See* FSMA (as originally enacted), s 5(2)(d).

[376] Ferran, n 354, 431.

[377] FSMA, s 137C; FSA, 'Product Intervention' (Discussion Paper DP11/1, 2011) <https://www.fca.org.uk/publication/discussion/dp11_01.pdf>. On parallel proposals in the US, *see* Bar-Gill and Warren, n 371.

[378] FSMA, s 137D. FSMA also gave the FCA new rule-making powers to protect consumers from misleading financial promotions (FSMA, s 137R). *See also* developments in general consumer protection law, notably the Consumer Rights Act 2015, a key aim of which was to make it easier for consumers to understand and challenge unfair terms, and pursuant to which the FCA can consider complaints and challenge unfair terms.

[379] In 2013, parliament imposed a statutory duty on the FCA to cap the cost of HCSTC to 'secure (sic) an appropriate degree of protection for borrowers against excessive charges'. *See* s 137C(1A), as amended by the Financial Services (Banking Reform) Act 2013, s 131(1). This followed a campaign by the Church of England, dubbed the 'War on Wonga'. *See e.g.* Andrew Grice, 'War on Wonga: We're Putting You Out of Business, Archbishop of Canterbury Justin Welby Tells Payday Loans Company' *Independent* (25 July 2013) <https://www.independent.co.uk/news/uk/home-news/war-on-wonga-we-re-putting-you-out-of-business-archbishop-of-canterbury-justin-welby-tells-payday-loans-company-8730839.html>.

[380] FCA, 'Detailed Rules for the Price Cap on High-Cost-Short-Term-Credit' (2014) PS 14/16 <https://www.fca.org.uk/publications/policy-statements/ps14-16-detailed-rules-price-cap-high-cost-short-term-credit> (as reviewed in 2019): <https://www.fca.org.uk/firms/high-cost-credit-consumer-credit/high-cost-short-term-credit>); CONC 2.5A and 5A.

capped at £15; interest and fees are capped at 0.8 percent of the outstanding principal, per day; and extensions of the credit term are limited to two rollovers.

***

Part Two will examine the distributional effects of the FCA's consumer credit regime, particularly for creditworthiness assessment. For now, the main takeaway is that this regime may have helped to construct alternative credit scoring, and its distributional promise, in two related ways. First, the introduction of the creditworthiness assessment regime increased the regulatory demand for statistical credit scoring by authorized credit providers, particularly non-banks that were not subject to credit risk management requirements under prudential regulation. Second, the stricter rules on creditworthiness, particularly the requirement to assess credit *affordability*, together with the price caps on HCSTC, restricted firms within the FCA's regulatory perimeter from lending to higher risk consumers.[381] In turn, this increased the opportunity for firms outside the regulatory perimeter—notably, p2p lending platforms—to lend to marginalized, higher risk borrowers, leveraging practices such as alternative credit scoring. As noted earlier, the mandatory creditworthiness assessment rules were not extended to p2p lenders until 2019. The light-touch regulation of p2p lenders between 2014 and 2019—intended to 'foster fintech innovation'[382]—thus helped to incentivize investment in, and the development of, alternative credit scoring technology by less regulated lenders, as they sought to profit from lending to higher risk borrowers, including credit invisibles.

---

[381] *See further* ch 5, section 5.3.4 (discussing the weaknesses of the FCA's creditworthiness assessment regime).

[382] *See* n 125 and associated text.

4.2.3 Data protection regulation

Since at least the mid-1990s, UK data protection regulation has been influenced significantly by EU data protection and fundamental rights law. The DPA 1984, examined earlier, was superseded in 1998 by a new Data Protection Act (DPA 1998), which implemented the first EU Data Protection Directive (DPD 1995) under English law.[383] More recently, this regime has been superseded by the EU General Data Protection Regulation (GDPR)[384] and UK Data Protection Act 2018 (DPA 2018), which entered into force in 2018.[385] The DPA 2018/GDPR—as the data protection regulatory framework governing alternative credit scoring in the UK today—will be examined in Chapter 7. For now, the focus will be on its antecedent—the DPA 1998—and its influence on the development of alternative credit scoring.

The DPA 1998 established duties for firms (as 'data controllers' and 'data processors'), rights for consumers (as 'data subjects'), and regulatory enforcement powers with respect to the processing of personal data, overseen by a dedicated regulator, the Data Protection Authority. Importantly for present purposes, it perpetuated the DPA 1984's relatively permissive, market-based approach to data protection regulation. Pursuant to the DPA 1998, the processing of personal data was presumed to be prohibited unless permitted under one of six 'lawful' grounds for processing. They include, for example, where the

---

[383] European Parliament and Council Directive 95/46/EC of 24 October 1995 on the Protection of Individuals Regarding the Processing of Personal Data and on the Free Movement of Such Data [1995] OJ L281/23.

[384] Regulation (EU) No 2016/679 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data [2016] OJ L119/1.

[385] Reference will be made to the GDPR/DPA 2018 regime, which represents the current data protection regime in the UK. It should be noted, however, that these regimes could diverge in the future. *See* n 16 and UK Department for Digital, Culture Media & Sport, 'National Data Strategy' (2020) <https://www.gov.uk/government/publications/uk-national-data-strategy/national-data-strategy> ('data and data use are seen as opportunities to be embraced, rather than threats against which to be guarded.'); UK Department for Digital, Culture Media & Sport, 'Data: A New Direction' (2021), and Response to Consultation (2022) <https://www.gov.uk/government/consultations/data-a-new-direction> ('This government's ambition on data is clear: we will establish the UK as the most attractive global data marketplace.').

consumer has given their consent to processing, where the processing is necessary for the controller's 'legitimate interests', where the data processor has a 'legal obligation' to process personal data, or where the processing is necessary for the performance of a contract with the data subject.[386] However, these grounds still gave data processors and controllers considerable freedom to process personal data. Inter alia, the consent ground was thinly defined and, in practice, assumed to be given if the data subject had notice of a proposed data processing and did not actively 'opt out'.[387] Various market failures mean that, in practice, consumers often do not, and cannot, actively manage the processing of their personal data.[388]

CRAs rely primarily on the legitimate interest ground and, to a lesser extent, the legal obligation ground—rather than consumer consent—as the legal basis to support the wide-scale collection, processing, and sharing of consumer data.[389] This includes, but is not limited to, their 'legitimate interest' in promoting responsible lending and the prevention of consumer over-indebtedness.[390] Similarly, credit providers rely heavily on the legitimate interest, contractual necessity, and legal obligation grounds—rather than consumer consent.

---

386 DPA 1998, Schedule 2. Several of these grounds mirror the qualifications to the common law duty of bank confidentiality (*see* section 4.1.2.1).

387 As discussed further in ch 7, the GDPR attempts to strengthen the consent ground.

388 Daniel J Solove, 'Privacy Self-Management and the Consent Dilemma' (2013) 126 Harvard Law Review 1880. *See further* ch 6, section 6.4 and ch 7.

389 *See further* section 4.2.4.

390 Examined further in sub-section 4.2.4, below. *See* Experian, n 107, 10 (explaining that 'Credit reference agencies facilitate responsible lending by providing services that allow lenders to access information about a person (and anyone with whom they have a financial association, such as a joint account), including how they are managing current debt, have managed debt in the past and whether they have sufficient income to repay the debt.'); ('the majority of credit reference agencies' activity is on the basis that: the processing is necessary to pursue the legitimate interests of the credit reference agencies and third parties (such as their clients), and those interests do not unduly prejudice the rights and freedoms of individuals; or the processing is necessary to comply with a legal obligation binding on the credit reference agencies.'). Note that all CRAs rely on virtually identical grounds. *See* Equifax, 'Credit Reference Agency Information Notice' (Version 1.1, March 26 2020) <https://www.equifax.co.uk/crain/>; TransUnion, 'Credit Reference Agency Information Notice' <https://www.transunion.co.uk/legal/privacy-centre/pc-credit-reference>.

As Part Two will examine, the extensive, broad-brushed reliance—by both CRAs and credit providers—on non-consent grounds for personal data processing raises questions about the appropriate limits of these grounds and whether a narrower interpretation is warranted.[391]

The permissive, market-oriented approach of the DPA 1998—and the EU DPD 1995 on which it is based—reflects the economic orthodoxy of the time, as well as the relatively narrow competences and objectives of the EU. As with EU consumer credit law, examined earlier, the DPD 1995—which predates the adoption of the EU Charter[392]—was based on the EU's internal market competence.[393] Although the DPD 1995 alludes to the protection of fundamental rights and freedoms, including the fundamental right to privacy under Article 8 of the European Convention on Human Rights,[394] its primary goal was to facilitate the integration of the internal market by harmonising data protection laws in the EU and enabling the 'free flow of personal data'.[395] Fundamental rights and fairness-related concerns were thus addressed only indirectly.

The perpetuation of a relatively permissive data protection regime pursuant to the DPD 1995/DPA 1998 continued to enable the use of personal data in consumer credit markets, and thus the development of credit referencing systems, CRAs, data-driven practices such as (alternative) statistical credit scoring, and in turn the growth of consumer credit markets during the early 2000s and 2010s.[396] As Part Two will argue, despite its

---

[391] *See further* ch 7, section 7.2.

[392] Charter of Fundamental Rights of the European Union [2012] OJ C326/391.

[393] Pursuant to Article 114 TFEU (Article 100a TEC). *See* DPD 1995, introductory text.

[394] DPD 1995, recital 10.

[395] Schwartz and Peifer, n 298, 130; DPD 1995, recitals 7 to 9.

[396] *See also* Giuseppe Bertola, Richard Disney and Charles Grant, 'The Economics of Consumer Credit Supply and Demand' in Giuseppe Bertola, Richard Disney and Charles Grant (eds) *The Economics of Consumer Credit* (MIT Press 2006), 1 ('Privacy rules and the regulation of contractual responsibilities bear importantly on the functioning of consumer credit markets and are an important political concern in all countries').

increased emphasis on the protection of fundamental rights, the data protection regime pursuant to the DPA 2018/GDPR remains relatively permissive. This is partly a function of its design, including the continued emphasis on contractual, private mechanisms such as user consent. It is partly a function of weak enforcement.[397] It is also partly a function of the political economy and private interests—notably, the outsize role that data, and data-rich tech firms play in the modern economy, and consequently the powerful commercial interests that continue to lobby against data protection regulation, and digital regulation more broadly.[398]

4.2.4 Credit referencing regulation

Credit providers are not mandated by law to participate in the credit referencing system, i.e., to share information about borrowers inter se via CRAs. However, most credit providers have strong private and regulatory incentives to participate in this system.[399] This includes private and regulatory incentives to manage credit risk and affordability, as discussed earlier. In addition to helping credit providers assess the creditworthiness of a prospective borrower ex ante, and thereby manage credit risk, credit referencing also supports credit risk management ex post by disciplining borrowers, given that a negative mark on a credit file could adversely impact a consumer's future ability to access credit on favourable terms.[400] Consumer credit regulation encourages credit providers to consult CRAs for the purposes of

---

[397] However, the higher penalties under the DPA 2018/GDPR go some way to substituting for this. Pursuant to the DPA 2018/GDPR, the ICO can impose fines up to 4% of revenue (or EUR 20 million, whichever is higher). Note also that the FCA can impose fines of up to 20% of a firm's revenue (plus disgorgement).

[398] Max Bank et al, 'The Lobby Network: Big Tech's Web of Influence in the EU' (2021) <https://corporateeurope.org/en/2021/08/lobby-network-big-techs-web-influence-eu>. On private interest theories of regulation, *see* n 242.

[399] *See generally* Pagano and Jappelli, n 67.

[400] *See generally* Jorge Padilla and Marco Pagano, 'Sharing Default Information as a Borrower Discipline Device' (2000) 44 European Economic Review 1951-80; Stiglitz and Weiss, n 317.

carrying out a creditworthiness assessment (but does not mandate them to do so).[401] As such, the voluntariness of participation in this system is largely illusory.[402]

Credit providers and CRAs that participate in the credit referencing system are subject to various obligations under consumer credit and data protection regulation, as well as self-regulatory industry standards.[403] There is considerable overlap between data protection and consumer credit regulation in this area. Chronologically, credit referencing was regulated first by consumer credit regulation, and latterly by data protection regulation.[404] Today, data protection regulation imposes a much broader set of obligations and rights with respect to the processing of personal data for credit referencing, relative to consumer credit regulation.

To elaborate, the CCA established, as early as 1974, that credit providers have an obligation to notify customers about any CRA from which they have obtained information about the customer's financial standing.[405] This is required when a creditor decides not to

---

401 CONC 5.2A.7 states that 'A firm must base its creditworthiness assessment on sufficient information…obtained, where appropriate, from the customer, and where necessary from a credit reference agency' (see also CCD 2008, art 7). *See also* CONC ss 2.4.3 and 2.5.7 (encouraging lenders to carry out a 'quotation search', also known as a 'soft' credit check). In addition, many credit providers are subject to fraud, KYC, and AML/CFT prevention obligations, which make participation in the credit referencing system unavoidable. *See e.g.* Natwest, n 181, 6 (describing reasons for sharing consumer data with third parties, including CRAs); 8 (describing reasons for accessing and using information from CRAs, including creditworthiness assessment, fraud and AML prevention, identity verification, debt recovery and tracing). The FCA Handbook previously included a statement that the FCA 'encourages' credit providers to share data with each other, and through CRAs, 'about the performance of a customer's account and the settlement of outstanding debts' (formerly CONC s 5.3.1(12)). However, this statement was removed in 2019 pursuant to amendments to CONC (*see* n 367).

402 Nevertheless, not all credit providers participate in the credit referencing system. *See* n 87 and associated text (discussing payday lenders).

403 The US takes a similar approach. To the extent that entities provide or use credit reports, they are subject to various obligations (and consumers have various rights) under FCRA. *See generally*, Chi Chi Wu et al, *Fair Credit Reporting* (10th edition, National Consumer Law Center 2022).

404 As noted earlier, the CCA was in effect the first instance of data protection regulation in the UK. *See* n 267 and associated text.

405 CCA, s 157. Further rules and guidance are now set out under the FCA's conduct regime (*see* CONC ss 2.4.2, 2.5.5 and 2.5.6). Note that this is mirrored in data protection regulation, which creates a presumption that any subject access request for data from a CRA is limited to personal data relevant to the consumer's 'financial

extend credit on the basis of information obtained from a CRA and/or when a customer makes a written request for information. In turn, consumer credit and data protection regulation collectively create a set of rights for consumers with respect to their credit files. Notably, consumers have rights to request their credit files from CRAs and to seek amendment of any errors.[406] The credit file is defined as 'all the information about him [the customer] kept by a credit reference agency, regardless of how the information is stored'.[407] Consumers also have a right to request the removal or correction of any erroneous entries in their credit files, where they believe that a failure to do so will prejudice them.[408] Unless the entry is removed, the consumer has a right to request that a notice of correction, drawn up by the consumer, be added to their credit file.[409]

Finally, CRAs have an obligation to disclose a consumer's credit file upon receipt of a written request,[410] as well as to respond to any objections by removing or amending an erroneous entry or attaching a notice of correction. However, a CRA has the right to seek an order from the FCA where it thinks that it would be improper for it to publish a notice of correction (e.g., because the notice is incorrect).[411] CRAs also have a duty to bring to the consumer's attention how they use their personal data.[412] CRAs are authorized and

standing', unless the consumer specifically requests access to additional data. *See also* DPA 2018, s 13(2) (as discussed further in ch 7, section 7.2).

406 CCA s 158.

407 CCA, s 158(5).

408 CCA, s 159(1).

409 CCA, s 159(3).

410 CCA, s 158. However, *see* n 405 (presumption that a subject access request is limited to data relevant to the consumer's financial standing). Note that, although the CCA still refers to payment of a fee for receipt of the report, since the entry into force of the GDPR/DPA 2018, consumers can receive their Statutory Credit Reports at no cost. CRAs also offer more detailed credit reports at an extra cost.

411 CCA, s 159.

412 CONC s 2.6.2.

supervised by the FCA for the activity of providing information to credit providers about the financial standing of prospective borrowers.[413] This includes sharing data with 'subscribed' credit providers through 'closed user groups' (examined below), and the provision of credit information products such as credit scores.[414]

4.2.4.1 Industry self-regulation

Since the 1990s, the credit referencing system in the UK has been governed additionally by a set of self-regulatory industry standards known as the 'Principles of Reciprocity' (hereinafter, the 'Principles').[415] These standards were developed by financial industry participants motivated to establish a 'more formalised approach' to the use of consumer information in credit and marketing decisions.[416] Pursuant to the Principles, credit providers (also known as 'subscribers') agree on a voluntary, contractual and reciprocal basis to share and purchase financial data about consumers with/from other credit providers, through the closed user groups of the three main CRAs (Equifax, Experian, and TransUnion). Data is typically shared in monthly batch files, on a lagging basis.[417]

The 'Governing Principle' is that data should be shared only for the 'prevention of over-commitment, bad debt, fraud and money laundering, and to support debt recovery and debtor tracing, with the aim of promoting responsible lending'. This overarching principle is

---

[413] FSMA 2000 (Regulated Activities) Order 2001, as amended by the FSMA 2000 (Regulated Activities) (Amendment) (No. 2) Order 2013, ss 89A and 89B(1) ('provision of credit references').

[414] Note, CRAs offer a broad range of credit-related products and services that involve the processing of consumer data. Among other things, CRAs produce consumer-facing credit reports and credit scores, as well as provide identity verification services and products to landlords, employee and tenant vetting firms, marketing companies, and government authorities. *See* Experian, n 107, 17 (listing the wide range of entities they share credit reference data with). *See also* SCOR, 'Principles of Reciprocity', n 162.

[415] n 162. Note, these principles apply to both consumer and commercial credit performance data.

[416] n 162, 1.

[417] Note, participating credit providers include both financial institutions, such as banks, as well as non-financial credit institutions, such as utility and telecom companies.

supplemented by five 'General Principles'. They include the principle of reciprocity (subscribers receive the same data that they contribute), and prohibitions on using shared data to 'target any customers of other specific subscribers' or 'to identify and select new prospects'.

In addition to these high-level principles, the Principles include more detailed standards on the types of data that can be shared, as well as the purposes for which they can be used. Importantly, the Principles permit the sharing of both positive and negative customer data (delinquencies and defaults).[418] They also permit the sharing of both financial and non-financial data. The Principles focus, however, on the sharing of *financial* data—particularly current account turnover (CATO) data and credit account performance data (e.g., CAIS).[419]

In all instances, the sharing and use of data is subject to the Governing Principle, described above. Thus, whereas the Principles permit the use of credit reference data for applicant risk screening purposes, they advocate much more limited use of the same data for 'new prospect screening'. Likewise, the use of 'positive customer characteristics' for existing customer account management should be limited to the purpose of preventing over-indebtedness and should not be used to 'promote customer retention and drive product penetration'.[420]

Consistent with the voluntary nature of this framework and participation in the credit referencing system more generally, credit providers typically do not share customer

---

[418] This contrasts with countries, such as France, that operate negative-only credit registries. *See* Nicola Jentzsch, *Financial Privacy: An International Comparison of Credit Reporting Systems* (2nd Edition, Springer 2007), 104 ("The French Data Protection Authority CNIL states that positive information is susceptible of being diverted from its original purpose, because the richness of the data might lead to usage for other purposes such as marketing or employment screening"); and relatedly, Trumbull, *Regulating for Legitimacy*, 23 ('France's lack of centralized credit rating would appear to reflect different national approaches to personal privacy.').

[419] *See* ch 3, Table 1.

[420] n 162, 4-6. Although beyond scope, an interesting avenue for follow-up investigation is the interaction between these self-regulatory information standards and data protection regulation. *See further* ch 8.

data with all three CRAs (nor participate in all CRA user groups). Relatedly, different CRAs have different policies and periods for retaining data.[421] For example, Equifax and TransUnion retain credit account performance data for a total of 10 years, Experian for 11 years. There is also variation in the basis on which the data retention period is calculated—for example, whether insolvency data is retained from the date of insolvency filing or discharge—as well as the purposes for which the data can be used. Typically, CRAs permit retained data to be used for a shorter period for 'live decision-making', and a longer period for 'profiling and statistical analysis'. To illustrate, Equifax retains insolvency data for 6 years from the date of discharge. Experian retains insolvency data for 6 years 'or until [the insolvency] is settled'. Meanwhile, TransUnion retains insolvency data for 10 years from the date of insolvency—where only the most recent 6 years can be used for live decision-making, and a further 4 years can be used for profiling and statistical analysis. There is further variation in the categories of data retained by different CRAs.[422] Combined with the fact that consumer data is shared with CRAs on a lagging, monthly basis, the result is that each CRA typically has a different, and often incomplete, picture of an individual consumer's creditworthiness.

4.2.4.2 Implications

Changes in the regulatory framework for credit referencing, examined above, helped to shape the emergence of (alternative) credit scoring and the development of consumer credit

---

[421] Experian, <https://www.experian.co.uk/legal/crain/data-retention-periods/>, Equifax, <https://www.equifax.co.uk/crain/retention>, TransUnion <https://www.transunion.co.uk/legal/crain-retention>.

[422] These categories and retention periods also change frequently, partly reflecting developments in (alternative) credit scoring, and technological development more broadly. To illustrate, version 1 of Experian's CRAIN (dated 23rd October 2017) included a much more limited list of data types as well as shorter data retention periods, e.g., financial account and repayment data was previously retained for 6 years, whereas it is now retained for 11 years. *See* Experian, 'Credit Reference Agency Information Notice' (version 1, 23rd October 2017) (copy on file with author).

markets more generally. Crucially, the voluntariness of participation in the credit referencing system, the heterogeneity in the types of and purposes for which data are shared between credit providers and CRAs, and retained by CRAs, and the resulting non-comprehensive and asymmetric sharing of information between participating credit providers and CRAs, collectively created informational gaps and asymmetries in consumers' credit files, which in turn created disparities in credit market access for different consumers. Among other things, the retention of insolvency data on credit files constrains access to credit for previously insolvent consumers. At the same time, the choice to prohibit use of that data after a defined period—between 6 and 10 years for the 'big three' CRAs, as noted earlier—also *facilitates* access to credit, by ensuring that consumers who have been insolvent are not permanently cut off from accessing consumer credit markets.[423]

Furthermore, the focus on sharing *financial*, *credit* data helped shape the contours of conventional statistical credit scoring (credit scoring 1.0), particularly the emphasis on a consumer's financial credit history in the assessment of their creditworthiness.[424] In turn, this helped to constitute the credit invisible population—defined as consumers who lack conventional credit data, notably a credit history. As discussed in Chapter 3, the credit invisible population is an important driver of alternative credit scoring.

More generally, by institutionalising the shared databases of the big three CRAs, the self-regulatory framework for credit referencing—combined with the permissiveness of the 'legitimate interest' ground for data processing under data protection regulation, discussed earlier—helped to consolidate their market power, and thus concentration in the credit

---

[423] *See also* Bertola, Disney, and Grant, n 396, 14 ('The ability of the financial market to punish default is limited by its competitive and information-sharing structure…as well as by legal restrictions: For example, bankruptcy cannot be recorded in credit files for more than ten years in the United States').

[424] Of course, as discussed in Chapter 3, the focus on financial/credit data under conventional statistical credit scoring is also a function of the state of the art in technology. The technologies necessary to produce, collect, and process non-financial data (such as geo-location and other tracking data) have mostly advanced over the last twenty years or so.

information market.[425] The lack of effective competition in retail financial markets—including the credit information market—partly drove regulatory and market developments in Open Banking, an alternative and much more extensive framework for sharing consumer data that bypasses the mainstream credit referencing system centred in the big three CRAs. As discussed in Chapter 3, alternative credit scoring and the fintech ecosystem are increasingly driven by data shared and collected through Open Banking.

[425] FCA, 'Credit Information Market Study: Interim Report and Discussion Paper' (MS191.2, 2022) <https://www.fca.org.uk/publication/market-studies/ms-19-1-2.pdf>.

PART TWO

5 UNPACKING THE CREDIT PROMISE

Part One examined the rise of alternative credit scoring and its distributional promise. It demonstrated how co-evolving changes in consumer credit markets, technology, law, social norms, and the political economy over the course of the last half a century, spurred in recent years by the GFC, facilitated the environment in which alternative credit scoring emerged. Alternative credit scoring has been promoted by the credit industry—and embraced by policymakers—with the implicitly distributional promise of improving access to credit for marginalized consumers, particularly credit invisible consumers excluded from mainstream credit markets due to a lack of conventional credit data.

The contours of this promise, however, and whether and to what extent it can be delivered, remain unclear. Certainly, the history of consumer credit markets, and innovation therein, gives us reason to be sceptical. We learnt in Part One that successive governments, particularly over the last half a century, actively promoted liberal credit market policies to satisfy short-term political goals. We also learnt that investment and innovation in statistical credit scoring were driven in large part by lenders' profit-maximising interests. Distributional concerns—for example, mitigating regressive effects due to unaffordable borrowing by low-income consumers—were not the priority in these developments.

This Part critically examines the distributional promise of alternative credit scoring. It begins, in this chapter, by (i) defining the parameters that will guide the distributional analysis of alternative credit scoring, and (ii) examining the economic functions and distributional effects of consumer credit allocation and pricing. The chapter proceeds as follows. Section 5.1 defines poverty and inequality—of consumption, income, and wealth—as non-ideal 'benchmarks', or ways of measuring, distributive justice that will guide the ensuing distributional analysis. Section 5.2 examines the micro and macro-economic functions of consumer credit allocation, and its welfare effects. Section 5.3 examines the distributional effects of consumer credit allocation, distinguishing the effects due to credit allocation to low- and high-income consumers, respectively, through both micro- and macro-economic channels. It also situates the distributional analysis of credit allocation within the broader relationship between consumer credit markets and distributive justice.

5.1 Poverty, inequality, and distributive justice

There are many theories of distributive justice: different ways of thinking about the fairness, or justice, of the distribution of benefits and burdens in society.[426] It follows that there are different ways of evaluating the distributional effects due to alternative credit scoring and consumer credit. Rather than beginning with the abstract question of what a distributionally fair society should look like, and without committing to any ideal theory of distributive justice, this thesis has taken as its point of departure the manifest and widely recognized distributive injustice in the UK due to high levels of inequality and relative poverty (of income, wealth, and consumption); the goals of policymakers to reduce poverty and inequality so defined; and the expectations of policymakers that access to consumer credit,

[426] *See* n 99.

and technological development in consumer credit markets, can contribute towards achieving these distributional goals.[427]

As such, the thesis focuses on a more specific distributional question, namely, whether alternative credit scoring can ameliorate actual distributive injustice in the UK due to high levels of inequality and relative poverty. Before we can begin to address this question, it is necessary to briefly expand upon poverty and inequality as benchmarks of distributive justice, and to define the metrics of poverty and inequality that will be relied upon in the distributional analysis in the rest of this chapter and the next.

5.1.1 Inequality and poverty

Poverty, as a benchmark of distributive justice, is rooted in 'sufficientarian' distributional principles. The principle of sufficiency advocates that everyone should have at least enough, or no less than a *de minimis* level of goods and services considered sufficient for wellbeing.[428] As such, sufficientarian distributional principles foreground a person's *absolute* (material) position, rather than their relative position (as articulated further below). A person's absolute position is considered to be both intrinsically valuable, as well as instrumentally valuable due to the economic and social costs of destitution.

As a matter of public policy, poverty, in the UK, is generally measured in terms of the number of households living below a specified income level (known as the 'poverty line').[429] *Relative* poverty, which is the more salient official measure of poverty, refers to the

---

[427] *See* n 3 (discussing non-ideal approaches to distributive justice), and n 100 and associated text (discussing inequality and poverty as policy goals). *See also* Appendix 1 (discussing poverty and inequality in the UK).

[428] Harry Frankfurt, 'Equality as a Moral Ideal' (1987) 98(1) Ethics 21; Harry Frankfurt, *On Inequality* (Princeton 2016). There are thicker and thinner versions of sufficientarianism—and thus poverty as a 'benchmark' of distributive justice—varying according to which resources or rights are distributed, to whom, and when. *See generally* Lamont, n 99.

[429] *See further* Appendix 1.

share of the population receiving less than the *current* median household income.[430] Formally, a household is categorized as 'low-income' if it is living in relative poverty. The levels and metrics of poverty in the UK are explored further in **Appendix 1**.

Inequality, in contrast, foregrounds a person's *relative* position. It is rooted in egalitarian distributional principles that view a person's relative position as both intrinsically as well as instrumentally valuable.[431] As a matter of public policy, inequality is typically measured by the distribution of income in the population, and, to a lesser extent, the distribution of consumption and wealth—as examined further below and in Appendix 1.

Inequality and poverty reduction in the UK—as well as in countries such as the US—are generally implemented through policies that both redistribute material resources directly (e.g., through tax and transfer), and that seek to increase peoples' *opportunities* to improve their material positions. As such, inequality reduction is informed by the distributional principles of both 'equality of outcome' and 'equality of opportunity'.[432] That is, distribution-minded policymakers seek to reduce existing high levels of inequality, i.e., move society towards more equal outcomes, including by providing more equal opportunities. However, they tolerate a degree of inequality of outcome, i.e., they are not aiming for perfect equality, or 'strict egalitarianism'.

Among others, policies to improve access to credit, and access to financial services more generally under the rubric of financial inclusion, are informed by the principle of equality of opportunity—whereby improving access to credit gives people a more equal

---

[430] *Cf.* 'absolute poverty', which refers to median income in an earlier base year. *See* Appendix 1.

[431] *See further* Amartya K Sen, *Inequality Re-examined* (Harvard 1992); Rawls, n 3; Robert Nozick, *Anarchy, State, and Utopia* (Basic Books 1974); Raghuram G Rajan and Luigi Zingales, 'The Tyranny of Inequality' (1995) 76(3) Journal of Public Economics 521 (describing economic inefficiency due to economic inequality); Richard Wilkinson and Kate Picket, *The Spirit Level: Why Greater Equality Makes Societies Stronger* (Bloomsbury 2011) (discussing the 'social harms due to income inequality'); Thomas Piketty, *Capital in the 21st Century* (Harvard 2014) (arguing that 'wealth inequality causes social and economic instability'). As with sufficientarianism, there are thicker and thinner versions of egalitarianism, and thus inequality as a 'benchmark' of distributive justice.

[432] *See* Rawls, n 3; Lamont, n 99.

opportunity to improve their material positions.[433] As the rest of this chapter will illustrate, however, the conditions under which access to credit can achieve this outcome are highly stringent, particularly where unsecured, small sum, short-term borrowing by low-income consumers is concerned.[434]

5.1.2 Income, consumption, and wealth

The focus on measuring poverty and inequality of income, and to a lesser extent wealth and consumption, has some methodological benefits insofar as there is more detailed data available on these measures, particularly income. Nevertheless, there remain methodological challenges. They include definitional challenges such as what counts as income (social welfare? credit?) and the time frame during which it should be measured.[435] Since data on income, wealth, and consumption is mostly gathered from household surveys, there are also gaps and errors due to limited survey coverage, and under- or over-reporting, among other constraints.

Evidence of underreporting of income by low-income households, specifically, has motivated greater focus on measuring consumption. Indeed, economic theory suggests that consumption is a more accurate proxy for consumer welfare, relative to current money income, in part because it accounts for the welfare effects of income smoothing due to

[433] There are thinner and thicker versions of equality of opportunity. Thin, or formal, equality of opportunity might entail giving everyone the same formal opportunity to acquire resources, such as the same credit eligibility criteria. Thicker, or more substantive, equality of opportunity advocates adjusting for historical and structural disadvantage, for example by allocating more resources to, or lowering the barriers to entry for, less advantaged individuals or groups, to give them a more substantial equal opportunity to compete for resources. *See e.g.* Deborah Hellman, 'Indirect Discrimination and the Duty to Avoid Compounding Injustice' in Collins and Khaitan, n 305; John Gardner, 'Liberals and Unlawful Discrimination' (1989) 9(1) Oxford Journal of Legal Studies 1-22; Hugh Collins, 'Justification of Indirect Discrimination', in Collins and Khaitan, n 305, 249-278.

[434] *See* section 5.3.

[435] *See* Appendix 1 (discussing definitions of income for the purposes of measuring income inequality and poverty).

borrowing (as articulated further below).[436] There are, however, data limitations that also impede the accurate measurement of consumption, and thus the reliability of consumption estimates.[437] The measurement of wealth levels is similarly impeded by data constraints.[438]

More broadly, to the extent that income, consumption, and wealth focus on a person's material position, they are not necessarily adequate proxies for consumer wellbeing, and thus adequate benchmarks for measuring distributive justice.[439] Indeed, capability theorists have long argued that capabilities, including a person's health and the ability to reason, rather than income and wealth, are more suitable measures of wellbeing. In the language of the capabilities approach, increasing a person's income and/or wealth levels will

---

[436] David M Cutler and Lawrence F Katz, 'Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980's' (1992) 82 American Economic Review 546, 546 (applying the permanent income hypothesis, '[e]conomic theory suggests that permanent income or consumption is a more accurate measure of the distribution of resources than is current money income.'); Pascale Bourquin, Mike Brewer and Thomas Wernham, 'Trends in Income and Wealth Inequalities' (Institute for Fiscal Studies Deaton Review of Inequalities, 9 November 2022) <https://ifs.org.uk/sites/default/files/2022-11/Trends-in-income-and-wealth-inequalities-IFS-Deaton-Review-of-Inequality%20%286%29.pdf> (hereinafter, 'Bourquin et al, *IFS Deaton Review*'), 5 ('[d]isposable income serves as a proxy for living standards… But a more rounded impression of inequalities in resources can be obtained by studying the distributions of (net) income, consumption, and wealth… although future income and current wealth determine the future consumption possibilities of households, current levels of income and wealth do not need to be related at all to levels of consumption today.'); Mike Brewer, Ben Etheridge, Cormac O'Dea, 'Why are Households That Report the Lowest Incomes So Well-Off?' (2017) 127 The Economic Journal F24 (cited in Bourquin et al, *IFS Deaton Review*); Krueger and Perri, n 52, 1 ('several authors have moved beyond income and earnings as indicators of well-being and have studied the distribution of individual or household consumption'). *See further* section 5.2 (discussing consumption smoothing due to borrowing).

[437] Bourquin et al, *IFS Deaton Review*, 6 ('[t]he main household survey used to estimate consumption in the UK has a low sample size, and there appears to be a growing problem of undercoverage of expenditure.').

[438] *See* ONS, 'Wealth and Assets Survey QMI' <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/debt/methodologies/wealthandassetssurveyqmi> ('Quality and Methodology Information for the Wealth and Assets Survey, detailing the strengths and limitations of the data, methods used, and data uses and users.'); and *generally* Emmanuel Saez and Gabriel Zucman, 'Wealth Inequality in the United States Since 1913: Evidence From Capitalized Income Tax Data' (2016) 131(2) Quarterly Journal of Economics 519; Gabriel Zucman, 'Global Wealth Inequality' (2019) (11) American Economic Review 109; Bourquin et al, *IFS Deaton Review*, 16 ('Wealth inequality in the UK has been studied less than income inequality because of the lack of accurate and consistent data.').

[439] *See e.g.* Ruth Lister, *Poverty* (Polity Press 2004) (conceptualizing poverty broadly and distinguishing 'material poverty', which is captured by official statistics, from the broader experience of 'nonmaterial poverty' which has cultural, relational, symbolic, and discursive aspects); Amartya Sen, 'Equality of What?' in McMurrin (ed), *Tanner Lectures on Human Values* (CUP 1979), 197–220.

not ensure that they achieve human flourishing if they lack the capabilities to convert those resources into 'functionings', or 'realized capabilities'.[440]

To facilitate analysis whilst remaining cognizant of these critiques and limitations, the distributional analysis in the rest of this chapter and the next focuses on how changes in credit allocation influence people's absolute and relative positions, and thus poverty and inequality, as measured by their levels of consumption, income, and wealth *only*.

5.2 The economic functions and welfare effects of consumer credit

Consumer credit has both micro- and macroeconomic functions and effects. At the microeconomic level, consumer credit is a mechanism for the inter-temporal, intra-personal redistribution of income between a consumer's future and present self.[441] In this function, credit enables liquidity-constrained consumers to fill financial shortfalls and achieve a more desirable consumption pattern—referred to as income or consumption 'smoothing'[442]—as well as, under more stringent conditions, to invest—whether in financial assets, such as stocks and bonds, or non-financial assets, such as education and housing.[443]

440 *See generally* the capabilitarian critique of resourcism, e.g., Sen, ibid; Ingrid Robeyns, 'The Capability Approach' <https://plato.stanford.edu/entries/capability-approach/>. The capabilities approach is itself subject to criticism, particularly on the grounds that it is more difficult to measure and implement than, for example, an approach based on measuring levels of income. *See also* critiques of meritocracy, e.g., Michael J Sandel, *The Tyranny of Merit: What's Become of the Common Good?* (Macmillan 2020).

441 Bertola, Disney, and Grant, n 396, 6 ('Lending and borrowing make it possible to redistribute spending from periods in the life cycle in which income is high to periods in which income is low.'); Wiedemann, *Social Policy Theory*, at 3; Abbye Atkinson, 'Rethinking Credit as Social Provision' (2019) 71(5) Stanford Law Review 1093, 1098 ('At its best, credit is a form of intertemporal and intrapersonal redistribution—credit shifts an individual's future capital to facilitate present consumption.') Recall that, for the purposes of this thesis, consumers are taken to be individuals transacting in their personal capacity, typically dealing with relatively modest sums of money (*see* n 14).

442 *See generally* Bertola, Disney, and Grant, n 396, 2-12, at 8 ('households may be "liquidity-constrained," that is, unable to borrow as much as would be implied at the observed interest rate by unconstrained optimization.'), at 12 ('Theory and evidence indicate that individuals and households do wish to borrow (as well as save) in order to make consumption smoother than labor income.'); Hartfree and Collard, *Poverty, Debt and Credit*, 21 (noting that credit use is associated with low to moderate savings rates, as well as changes in income, with those with stable incomes having lower than average borrowing rates).

443 As discussed further below, most investment also has consumption aspects.

The extent to which credit can be used for consumption and/or investment necessarily varies according to the type, duration, and quantum of credit. For example, short-term unsecured credit card borrowing, in modest sums, primarily enables consumption smoothing rather than investment (in contrast to, for example, mortgage credit, or indeed business credit). Given that this thesis focuses primarily on unsecured consumer credit markets, the welfare and distributional effects due to credit allocation are expected to flow primarily through the consumption channel, as articulated further below.[444]

In the consumption category, a distinction is often drawn between discretionary and non-discretionary ('essential') consumption. Credit is increasingly used by low-income households to finance non-discretionary, essential consumption, such as food and electricity—a phenomenon often referred to as 'credit as welfare' or 'privatized welfare'.[445] Of course, the empirical observation that credit increasingly substitutes for welfare income, does not imply that credit is welfare, nor that it should substitute for welfare. Among other things, credit needs to be repaid, typically at an additional cost, whereas income from welfare (and labor wage earnings) does not. As section 5.3 will demonstrate, credit is only a viable substitute for welfare—that is, a way of financing the consumption of essential goods and services—if it allows consumers to address temporary illiquidity, or short-term volatility in cashflows. If a borrower is insolvent—i.e., their net income is insufficient—relying on credit as a substitute for welfare will only make them worse off.

5.2.1 Effects of borrowing, consumption, and investment on consumer welfare

Borrowing to smooth consumption gives consumers the opportunity to maximise their lifetime utility (welfare). That is, due to the diminishing marginal utility of income and

[444] *See also* n 14.

[445] *See* n 53 and associated text; Appendix 1 (examining credit usage by low-income households).

consumption, transferring consumption from periods of high income (where the marginal utility of an additional unit of consumption is low) to periods of low income (where the marginal utility of an additional unit of consumption is high) offers to maximise a consumer's lifetime utility.[446] It follows that low-income households have a higher marginal propensity to (borrow to) consume relative to high-income households.

Borrowing to smooth consumption in this way can, however, only be utility maximising if it is affordable. As discussed in Part One, affordability refers to the borrower's ability to repay debt (including interest and other fees) *in a sustainable manner*, i.e., on time and without experiencing financial or non-financial distress. This implies that the borrower is not only 'solvent' but also 'liquid', i.e., they have sufficient liquid assets to make up for interruptions to income and repay debt. It also implies that the borrower has adequate income and assets to service their debt while continuing to meet their basic needs. The affordability of credit depends on the terms of credit—particularly the quantum and price, including interest and fees[447]—and various individual and structural factors (which also influence credit terms). The latter include the borrower's projected disposable/discretionary income and liquid assets during the credit term, the opportunities that the borrower has for investment, employment, and education, their informedness (myopia), the competitiveness of credit markets, and policy interest rates, among other factors.[448] As noted previously, low-income consumers are more susceptible to credit becoming unaffordable ex post, particularly due to their lower levels of income and wealth and thus thinner financial safety nets, as well as lower levels of financial literacy.

---

[446] Bertola, Disney, and Grant, n 396, 4 ('The household's problem is to choose consumption *c* in each period so that utility is maximized subject to the intertemporal budget constraint.'); Jonathan Macey, 'Fair Credit Markets: Using Household Balance Sheets to Promote Consumer Welfare' (2022) 100 Texas Law Review 683 (hereinafter, Macey, *Fair Credit Markets*), 697 (and references therein).

[447] At least for unsecured credit. *See* ch 4, section 4.2.1 (discussing the determinants of credit pricing).

[448] *See further* FCA, *Preventing Financial Distress.*

Of course, the condition that credit must be affordable to be welfare-enhancing does not imply that affordable credit (and consumption smoothing) *will be* welfare-enhancing. Among other things, the welfare gains due to borrowing and consumption may be offset by welfare losses due to an increase in hours worked (decline in leisure time), or more broadly, aggregate loss of welfare due to income and wealth inequality.[449] Conversely, if credit is *un*affordable, borrowing to smooth consumption is much more likely to be welfare-diminishing. That is, the gain in utility to the consumer from borrowing and consumption smoothing is likely to be outweighed by the disutility to the consumer due to the costs of managing and repaying the debt.[450] Inevitably, borrowing to finance current, essential or emergency consumption—which as discussed above has become more prevalent among low-income households—has a higher likelihood of being unaffordable.[451]

The welfare effects of borrowing for *investment* follow a similar logic. Consumers could realise a gain in income and/or wealth from borrowing and investment. Given that many goods have both investment and consumption aspects,[452] in addition to the pecuniary gains and losses from investment a borrower also incurs non-pecuniary gains and losses in

---

[449] Dirk Krueger and Fabrizio Perri, 'On the Welfare Consequences of the Increase in Inequality in the United States' (2003) 18 NBER Macroeconomics Annual 83 (finding that consumption inequality has not increased in tandem with income inequality due to the availability of credit; overall, however, the rise in income inequality is welfare-diminishing). *See further* section 5.3.3 (discussing the distributional effects of credit allocation).

[450] Note that, in addition to the *pecuniary* costs of borrowing and consumption, there are psychological, *non-pecuniary* costs such as the mental distress of having and repaying debt. *See e.g.* John Gathergood, 'Debt and Depression: Causal Links and Social Norm Effects' (2012) 122 The Economic Journal 1094; Offer Zellermayer, 'The Pain of Paying' (PhD thesis, 1996) <https://www.researchgate.net/publication/280711796_The_Pain_of_Paying>; Drazen Prelec and George Loewenstein, 'The Red and the Black: Mental Accounting of Savings and Debt' <https://www.cmu.edu/dietrich/sds/docs/loewenstein/redblack.pdf>. Although the pecuniary costs could be mitigated through ex post debt forgiveness (and thus depend, at least in part, on the relative permissiveness of the bankruptcy regime), the non-pecuniary costs of unaffordable borrowing are less likely to be mitigated.

[451] Macey, *Fair Credit Markets*, 687 (generally arguing that credit for non-emergency current consumption should be given special regulatory treatment and credit for emergency current consumption should be replaced by central bank emergency liquidity assistance); Hartfree and Collard, *Poverty, Debt and Credit*, 14 (noting that, whereas high-income households can cut back spending on non-essential items, in order to meet debt servicing costs, low-income households need to cut back on necessities such as food). *See further* Appendix 1.

[452] Bertola, Disney, and Grant, n 396, 11.

consumption utility—in the case of mortgage credit and housing, for example, due to having a roof over their head and the signalling/status value of living in a particular neighbourhood.[453] As before, however, if credit is unaffordable, credit-financed investment is much more likely to be welfare-diminishing. Furthermore, the conditions under which consumers may borrow to support investment are more stringent for unsecured and short-term borrowing, in modest sums, and for low-income households, given their higher consumption needs and lower average levels of financial sophistication relative to high-income households.[454]

5.2.2 Credit and the macroeconomy

Related to its microeconomic functions and effects, consumer credit also has macroeconomic functions and effects.[455] By channelling the economy's savings into more productive uses through investment—i.e., increasing the net return to savings—credit can increase output. The primary macroeconomic effect of *consumer* credit, however—that is, unsecured, often short-term borrowing by households, typically in modest sums—is to increase short run output by boosting household consumption and aggregate demand.[456] As

---

[453] Michael Spence, 'Job Market Signaling' (1973) 87(3) The Quarterly Journal of Economics 355. *See also* Fred Hirsch, *The Social Limits of Growth* (HUP 1976) (describing 'positional' competition for scarce status goods such as private schooling and suburban homes); Philip Oreopoulos and Kjell G Salvanes, 'Priceless: The Nonpecuniary Benefits of Schooling' (2011) 25(1) Journal of Economic Perspectives 159 (discussing the non-pecuniary value of investment in education); John P Anderson, Jeremy Kidd, George A Mocsary, 'Social Media, Securities Markets, and the Phenomenon of Expressive Trading' (2022) 25 Lewis & Clark Law Review 1223 (examining 'the emerging phenomenon of "expressive trading"—securities trading for the purpose of political, social, or aesthetic expression'—and thus the non-pecuniary value of investment in financial assets).

[454] Appendix 1, Figure 8 and associated text (low-income households have a higher debt to income ratio, higher levels of problem debt, and less disposable income).

[455] *See generally* Ben S Bernanke, 'Credit in the Macroeconomy' (FRBNY Spring Quarterly Review, Spring 1992-93) <https://www.newyorkfed.org/medialibrary/media/research/quarterly_review/1993v18/v18n1article6.pdf>.

[456] Marco Lombardi, Madhusan Mohanty, and Ilhyock Shin, 'The Real Effects of Household Debt in the Short and Long Run' (BIS Working Paper no. 607, January 2017) <https://www.bis.org/publ/work607.pdf>, 3 ('Our results suggest that debt boosts consumption and GDP growth in the short run, with the bulk of the impact of increased indebtedness passing through the real economy in the space of one year.'); Mian and Sufi, n

noted earlier, low-income households have a higher marginal propensity to consume relative to high-income households.

Conversely, the over-expansion of credit—or too rapid credit expansion (a credit 'boom' and 'overheating' of the economy)—can undermine growth over the medium to long run, particularly if it causes a wage-price spiral, asset price bubble and/or overindebted households, systemic non-performing loans and bankruptcies, and a financial crisis, the latter as highlighted by the GFC.[457] Inter alia, the fall in asset prices, drop in household (and firm) consumption due to a debt overhang and/or credit contraction following a credit boom, and the fall in government spending due to restricted fiscal space (for example, where the state is called upon to provide financial support to failing firms), reduces output.[458]

Importantly, the reduction in output over the medium to long-run due to household overindebtedness usually *exceeds* the short term gains in output due to household borrowing and consumption, particularly if it is accompanied by a banking/financial crisis.[459] Relatedly, the exploitation of low-income, less sophisticated consumers based on their misperceptions

---

109 ('credit-supply expansions affect the real economy by boosting household demand, rather than the productive capacity of firms.').

457 Rajan, *Fault Lines*; Mian and Sufi, n 109; Atif Mian, Amir Sufi, and Emil Verner, 'Household Debt and Business Cycles Worldwide' (2017) Quarterly Journal of Economics 1755.

458 International Monetary Fund, 'Global Financial Stability Report October 2017: Is Growth at Risk?' (October 2017) <https://www.imf.org/en/Publications/GFSR/Issues/2017/09/27/global-financial-stability-report-october-2017>, Chapter 2 (finding 'a trade-off between the short-term benefits of rising household debt to growth and its medium-term costs to macroeconomic and financial stability. In the short term, an increase in the household debt-to-GDP ratio is typically associated with higher economic growth and lower unemployment, but the effects are reversed in three to five years.'); Lombardi et al, n 456 (finding that 'a 1 percentage point increase in the household debt-to-GDP ratio tends to lower growth in the long run by 0.1 percentage point. Our results suggest that the negative long-run effects of consumption tend to intensify as the household debt-to-GDP ratio exceeds 60%.'). As discussed further in section 5.3, overindebtedness of lower income households, specifically, reduces consumption by those households that have the highest marginal propensity to consume.

459 David Aikman, Andrew G Haldane, and Benjamin D Nelson, 'Curbing the Credit Cycle' (2015) 125(585) The Economic Journal 1072, 1086-1087 (finding that 'The median cumulative gain in GDP in the decade running up to a crisis is around 21.5%. But the median cumulative loss over the subsequent decade is over twice as large at around 48%... the net impact on GDP of a credit boom that eventually results in a banking crisis is negative.'). Lombardi et al, n 456, 3 ('However, the long-run negative effects of debt eventually outweigh their short-term positive effects, with household debt accumulation ultimately proving to be a drag on growth.')

as to the true cost of credit is welfare-diminishing to the extent that it reflects investment by firms seeking to transfer wealth from consumers, without increasing economic output (i.e., 'rent seeking').[460]

5.3 The distributional effects of consumer credit

Building on the prior exposition of the economic functions and welfare effects of consumer credit allocation, this section examines the distributional effects due to credit allocation, and the mechanisms that produce these effects. It focuses on the effects of credit allocation on the absolute and relative levels of consumption, income, and wealth of low and high-income consumers, respectively, and thus poverty and inequality measured in terms of consumption, income, and wealth.[461] Having identified these effects, the next chapter will focus on which of them are affected by the advent of alternative credit scoring, and how.

The section proceeds as follows. Sub-section 5.3.1 begins by situating credit allocation (and pricing) as one of several institutions for (re)distribution in consumer credit markets. Sub-section 5.3.2 examines the distributional effects due to the allocation of credit to *low-income* consumers. Sub-section 5.3.3 examines the distributional effects due to the allocation of credit to *high-income* consumers. Finally, sub-section 5.3.4 examines how consumer credit regulation—specifically, the FCA's regime for mandatory creditworthiness (affordability) assessment, and the interest rate caps on high-cost credit—mitigates regressive distributional effects due to consumer credit allocation.

---

460 Armour et al, *Principles*, 222-223. *See* ch 4, section 4.2.1.2 (discussing credit price discrimination based on consumer myopia). As examined further in Chapter 6, alternative credit scoring, and related data-driven innovations, could cause lenders and other firms to over-invest in gathering private information in a way that is socially wasteful and inefficient. *See generally* Jack Hirshleifer, 'The Private and Social Value of Information and the Reward to Inventive Activity' (1971) 61(4) American Economic Review 561, and *further* ch 6.

461 There are of course many variables that influence levels of poverty and inequality. The analysis in this section (and the next chapter) focuses only on the effects of credit allocation on poverty and inequality, *ceteris paribus*. *See also* n 4 (noting the coarse categorization of 'low-income' and 'high-income' consumers for the purposes of this distributional analysis).

5.3.1 Locating distribution in consumer credit markets

Although the analysis in this chapter focuses on the distributional effects due to credit allocation and credit pricing, it is important to appreciate that several institutions shape these effects, and the distributional effects due to consumer credit markets more broadly.[462] In order to contextualise the analysis of the distributional effects due to credit allocation and pricing, this section maps out the main loci and institutions of distribution due to consumer credit markets. As summarized in **Table 2** (columns 1 and 2), a distinction is made between three principal loci of distribution: (1) within the duration of a credit agreement, before credit is extended; (2) within the duration of a credit agreement, after credit is extended; and (3) outside the duration of the credit agreement. Each of these loci encapsulate multiple, interrelated institutions, as summarized in column 3 of Table 2. The fourth column in Table 2 provides an illustrative list of institutional design questions. Different institutional interventions yield different degrees of (re)distribution. In designing these interventions, firms and policymakers are making a normative choice between different degrees of distribution due to consumer credit markets. Indeed, the distributional promise of alternative credit scoring is premised on the hypothesis that the types of credit data and data analytic techniques used in credit decision-making can positively influence the distributional effects due to consumer credit allocation and pricing.

---

[462] *See generally* Jeremy Waldron, 'Locating Distribution' (2003) 32(1) The Journal of Legal Studies 277. To the extent that lending is a market-based activity, the actual volume of credit supplied is at least partly endogenous to the institutional environment. *See* Nicholas Kaldor, 'Marginal Productivity and the Macroeconomic Theories of Distribution: Comment on Samuelson and Modigliani' (1966) 33 Review of Economic Studies 309 (presenting an institutional theory of income distribution); Nicholas Kaldor, *The Scourge of Monetarism* (OUP 1982) (on endogenous money supply theory). However, *see* Robert C Hockett and Saule T Omarova, 'The Finance Franchise' (2017) 102 Cornell Law Review 1143 (arguing that 'contrary to contemporary orthodoxy, modern finance is not primarily scarce, privately provided, and intermediated, but is, in its most consequential respects, indefinitely extensible, publicly supplied, and publicly disseminated.').

Table 2. Loci and Institutions for Distribution in (Digital) Consumer Credit Markets

Primary location	***Secondary location***	***Distributional institutions***	***Illustrative institutional design questions***
Internal (within the duration of the credit agreement)	*Ex ante (before credit is extended)*	Credit allocation and terms of credit contracts (e.g., interest rate and other repayment charges, quantum of credit/credit limit, pre-contract disclosure).	- How should credit affordability be defined? - Should credit charges and quantum be capped, and if so at what level?
		Data and data analytic techniques used in credit decisions.	- What types of data and data analytic techniques should be permitted for credit decisioning? - After how many years should (different categories of) data no longer be permitted for use in credit decisions?
	Ex post (after credit is extended)	Forbearance for consumers experiencing financial difficulties.	- How much forbearance should be required?
		Judicial review of unfair/ unconscionable contract terms.	- How should 'unfairness' be defined? - How should 'financial difficulties' be defined?
		Bankruptcy relief.[463]	- At what level should bankruptcy relief be set?[464]

[463] To the extent that low-income consumers seek bankruptcy protection at a higher rate than higher-income consumers, bankruptcy acts as a mechanism for *progressive* redistribution of resources. Sullivan et al, n 41, 6 (describing the distributional fairness goals of bankruptcy law: 'the purpose of bankruptcy law, properly used rather than abused, is to serve as a financial hospital for people sick with debt.'), at 8 ('consumer bankruptcy is an economic and social safety valve that permits debtors to function in an economic system even after their financial collapse.'); Adam Feibelman, 'Defining the Social Insurance Function of Consumer Bankruptcy' (2005) 13 American Bankruptcy Institute Law Review 129; Spooner, n 53 (advocating for the social insurance function of bankruptcy law); Iain Ramsay, 'Bankruptcy and Consumer Credit in the Declining Welfare State' in Thomas Wilhelmsson and Samuli Hurri (eds), *From Dissonance to Sense: Welfare Expectations, Privatisation, and Private Law* (Routledge 1999), 461 ('Bankruptcy law is part of the ground rules of credit markets and it might be useful to place it within a continuum of potential forms of regulation of the credit card market.'); Wiedemann, *Social Policy Theory*, 6 ('[c]redit markets only function as a substitute for social policies because governments create and enable permissive regimes. Interest rate subsidies, loan guarantees, *easier debt discharge through bankruptcy*, and interventions in secondary markets through government-sponsored enterprises entice lenders to offer loans to borrowers who might otherwise be excluded from credit markets.' Emphasis added).

[464] Sullivan et al, n 41, 9 ('The question of when the law says "let go" to the creditor and when it says "pay" to the debtor is the central issue in consumer bankruptcy. Ultimately, this is a moral decision.').

External (outside the duration of the credit agreement)		Tax.[465]	- What should be the tax base and rate? - What are permissible deductions from income?
		Monetary policy (interest rates).[466]	- At what level should interest rates be set?
		Social benefits.	- Who should be eligible for social welfare benefits? What benefits should be provided? At what level? Who should provide them?
		Personal insurance.	-What risks are insurable? Should premia be based on individual risk ('actuarial fairness')?[468] How much should risk be pooled (and how can this be modulated through restrictions on data permitted for insurance decision-making)?
		Credit scores as screening mechanisms for *non*-credit goods and services.[467]	

By focusing on alternative credit scoring, credit allocation and pricing, the inquiry in this thesis focuses primarily on ex ante distributional institutions, within the duration of the credit agreement, i.e., the areas highlighted in orange in Table 2, above. As noted, however, these institutions are necessarily influenced by other institutions of distribution, both within and beyond the duration of the credit agreement, which must be part of a more

[465] *See e.g.* Louis Kaplow and Steven Shavell, 'Why the Legal System is Less Efficient than the Income Tax in Redistributing Income' (1994) 23 Journal of Legal Studies 667; Wiedemann, *Social Policy Theory*, 5 (noting that tax policy can also incentivize consumers to borrow, citing the example of the mortgage interest tax deduction in the US that incentivizes mortgage borrowing and homeownership).

[466] *See e.g.* Desmond King and Lawrence R Jacobs, *Fed Power: How Finance Wins* (OUP 2016).

[467] Foohey and Greene, n 13.

[468] *See e.g.* Arrow, n 235; Kenneth S Abraham, 'Four Conceptions of Insurance' (2012) 161(3) University of Pennsylvania Law Review 653.

comprehensive analysis of the relationship between consumer credit markets, technological development, and distributive justice.[469]

5.3.2 Distributional effects of credit allocation to low-income consumers

To evaluate the distributional effects of credit allocation to low-income consumers, it is helpful to distinguish between the consumption and investment channels, examined earlier. We learned that access to affordable credit enables consumers to maximise their lifetime utility through consumption smoothing. From a distributional perspective, affordable borrowing and consumption-smoothing by low-income households can produce positive distributional effects by increasing their lifetime utility, in both absolute and relative terms, i.e., reducing poverty and inequality in utility terms.[470] These positive distributional outcomes are contingent, however, on the gains in utility to low-income consumers due to consumption smoothing not exceeding corresponding gains to high-income households.[471] Moreover, affordable borrowing and consumption smoothing by low-income households does not per se increase their levels of income and wealth, and thus produce positive distributional outcomes by reducing poverty and inequality in income and wealth terms.

Conversely, *un*affordable borrowing by low-income households is likely to produce regressive distributional outcomes by reducing their already low levels of income and wealth and thereby *exacerbating* poverty and inequality.[472] That is, where credit is unaffordable, low-

[469] *See* ch 8, section 8.2.2 (setting out directions for future research along these lines).

[470] Krueger and Perri, n 449; Krueger and Perri, n 52 (arguing that, in the US context, consumption inequality has not increased as much as income inequality because low-income households have used credit to insure against, and substitute for, lower and more volatile earnings).

[471] Furthermore, consumption smoothing by low-income consumers does not necessarily lead to an increase in welfare inter alia due to a decline in leisure time. *See* n 449 and associated text.

[472] Conditional on higher income households not experiencing a greater decline in income/wealth, which is unlikely (*see* Table 3, below) and the borrower being unable to reduce the cost of debt ex post through debt restructuring or cancellation, including through bankruptcy protection. *See also* Hartfree and Collard, *Poverty, Debt and Credit*, 13-14 ('problem debt can deepen people's poverty, even if it is not the direct cause. As a result of repaying problem debts households have less disposable income to live on and have to cut back on other

income borrowers will need to forego future income, possibly liquidate assets, where available, and incur more debt, in order to service existing debts.[473] As discussed earlier, the disutility to the consumer due to the costs of servicing the debt will generally outweigh the increase in utility due to consumption smoothing. Moreover, the regressive effects due to unaffordable borrowing by low-income households are often self-perpetuating. Low-income households can end up in a 'debt trap', unable to escape the cycle of servicing unaffordable debt, in turn exacerbating their poverty and inequality.[474]

The potential distributional effects of borrowing and *investment* by low-income households follow a similar logic. Affordable borrowing and investment can produce positive distributional effects by increasing the income and/or wealth of low-income households. As a threshold matter, however, and as noted earlier, the lower levels of financial sophistication and higher consumption needs of low-income consumers imply that they are less likely to be able to use credit to support investment in the first place—particularly when dealing with relatively modest sums of short term, unsecured credit. Moreover, as before, for borrowing and investment by low-income households to produce positive distributional outcomes, the increase in income/wealth due to borrowing would

---

areas of spending.'); Yamarik et al, n 108 (arguing that credit usage and income inequality mutually cause each other); Atkinson, n 441, 1099 ('Credit is fundamentally incompatible with the entrenched intergenerational poverty that plagues low-income Americans.').

[473] Hartfree and Collard, *Poverty, Debt and Credit*, 28 ('In order to make credit repayments, lower-income households may have to cut back on expenditure and curtail living standards…The extent to which this exacerbates the experience of poverty depends on the level and affordability of repayments.'); Monica Prasad, *The Land of Too Much: American Abundance and the Paradox of Poverty* (HUP 2012), 238-9 ('for credit to be productive…[it] must be repaid by a much richer borrower to whom that amount of debt is worth less'), cited in Atkinson, n 441, 1098 to 1099. *See also* Robert Jarrow and Phillip Protter, 'Fair Microfinance Loan Rates' (2019) 19(4) International Review of Finance 909 (defining a fair lending rate as one in which the net present value of the loan to the lender, after accounting for the lender's costs of issuing and monitoring the loan, is nil, i.e., the lender cannot earn 'riskless and abnormal profits…at the expense of the borrower.').

[474] Hartfree and Collard, *Poverty, Debt and Credit*, 14-15. On the role of credit scoring in perpetuating these effects, *see e.g.* Luke Herrine, 'Credit Reporting's Vicious Cycles' (2016) 40 NYU Review of Law and Social Change 305; Foohey and Greene, n 13. On (big data and) cumulative injustice generally, *see* Hellman, n 433; Deborah Hellman, 'Big Data and Compounding Injustice', Journal of Moral Philosophy (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3840175>.

need to exceed any increase in the median household income/wealth (to reduce relative poverty) and any increase in the income/wealth of higher-income consumers (to reduce inequality).[475] Conversely, as before, if credit is *un*affordable, credit-financed investment is likely to diminish the income and wealth of low-income households—with regressive distributional effects.

5.3.2.1 Distributional effects due to price discrimination and cross-subsidisation

The analysis thus far has identified the potential distributional effects due to the affordability of borrowing by low-income households. There are, in addition, overlapping distributional effects due to price discrimination and cross-subsidization between (low and high-income) borrowers and credit firms.[476] As discussed in Part One, in allocating credit and setting credit terms, lenders generally seek to not only cover the costs of lending, but also (maximise) profit. As a result, lenders price credit based on both cost (notably, credit risk, or PD and LGD)—referred to as price *differentiation*—as well as consumer demand—referred to as price *discrimination*—where demand may be a function of consumers' preferences and/or misperceptions as to the true cost of credit.[477]

The cumulative effect of credit price differentiation and discrimination is that high risk and low-income consumers generally experience worse access to, and pay more for, credit than low risk and high-income consumers—due to the positive correlation between income, credit risk/scores, and levels of financial sophistication.[478] To the extent that this

---

475 As summarized in Table 3, below. *See also* Appendix 1.

476 *See generally* FCA, 'Price Discrimination and Cross-Subsidy in Financial Services' (Occasional Paper No. 22, Sept. 2016) <https://www.fca.org.uk/publication/occasional-papers/op16-22.pdf>.

477 *See* ch 4, section 4.2.1.

478 *See* n 335 et seq and associated text; Iversen and Rehm, n 57. Note that these effects are not causal of each other. Additionally, there may be distributional effects due to 'taste-based' discrimination in credit pricing and allocation (*see* n 305).

entails payments by more myopic, low-income borrowers cross-subsidizing the cost of credit for less myopic, high-income borrowers (who take steps to avoid the low-visibility, high-cost aspects of credit contracts), the effect from a distributional perspective is regressive.[479] Relatedly, high-income consumers are more likely to participate through investment in the profits generated by lending firms, including profits from lending to low-income consumers.[480] There are also regressive effects due to the transfer of wealth from less-well off borrowers to well-off *lenders*.

To a certain extent, these regressive effects may be mitigated by credit pricing based on credit scoring 'bins', or ranges, rather than personalised credit scores.[481] Lower risk (higher income) consumers effectively cross-subsidize the risk and cost of borrowing for higher risk (lower income) consumers within a given credit scoring range (referred to as 'risk pooling'). To the extent that credit scoring ranges thereby redistribute resources from higher-income to lower-income consumers (who pay less than their actual risk as a result), the effect is distributionally progressive. In theory, the more coarsely partitioned and less personalised the credit scoring range, the greater the scope for progressive redistribution from higher to lower-income borrowers in this way.[482]

---

479 Gabaix and Laibson, n 333.

480 Although not the focus of analysis in this thesis, there are second order distributional effects due to the increasingly central role played by credit scores as a gateway to *non*-credit goods and services, such as employment, housing, and insurance, the widespread use of credit reports for identity verification, as well as identity theft resulting from breaches of CRA data (inter alia). *See* n 107 and associated text; Aitken, n 9; Sara Sternberg Greene, 'Stealing Identity from the Poor' (2021) 106 Minnesota Law Review 51; Foohey and Greene, n 13, 117 (arguing that, for borrowers with very low credit scores, remaining credit invisible is preferable, given that verifiable low scores preclude access to jobs, utilities, and favourable insurance rates).

481 *See* n 86.

482 *Cf.* credit as a mechanism for *intra*personal temporal distribution of resources between our present and future selves (*see* n 441 and associated text) and intragroup risk pooling in the context of group-lending programs, more typical in developing market economies. *See e.g.* Manfred Zeller, 'Determinants of Repayment Performance in Credit Groups: The Role of Program Design, Intragroup Risk Pooling, and Social Cohesion' (1998) 46(3) Economic Development and Cultural Change.

In practice, however, the degree of redistribution due to the use of credit scoring ranges is limited. Credit scoring ranges generally separate high and low risk consumers (such as 'prime' and 'subprime', calibrated to a numerical scoring range).[483] Thus, although risk is pooled between high- and higher-risk borrowers in the subprime category (and low- and lower-risk borrowers in the prime category), low-risk consumers are not generally cross-subsidizing high-risk consumers, in absolute rather than relative terms.

5.3.2.2 Distributional effects through the credit-macroeconomy channel

Credit allocation to low-income households also produces distributional effects through the macroeconomic channel. As examined earlier, borrowing and consumption by consumers boosts aggregate demand and economic output, at least in the short run.[484] Low-income households have a higher marginal propensity to consume relative to high-income households. By increasing output ('growing the pie'), borrowing and consumption by low-income households could increase the resources available for redistribution—whether through markets (for example, higher wages for workers) or the state (for example, through tax and transfer).[485]

---

[483] *See* n 86.

[484] *See* section 5.2.2. The discussion here focuses on the consumption channel. As discussed earlier, the conditions under which unsecured borrowing by low-income households will increase output through investment are highly stringent.

[485] Simon Kuznets, 'Economic Growth and Income Inequality' (1955) 45(1) American Economic Review 1 (presenting the hypothesis that economic inequality decreases in the long run due to industrialization, democratization, and the growth of the welfare state); Kaplow and Shavell, n 465, as discussed in Waldron, n 462 (arguing that it is more efficient to pursue distributional goals through government fiscal and social policy—tax and transfer—rather than legal rules); Rawls, n 3, 106 (it is 'fairer and more efficient to redistribute resources through tax or social security than through the alteration of the terms of consumer contracts'); Ramsay, *Consumer Protection*, 51 (arguing that through the tax system, the costs of redistribution are shared by everyone, rather than just certain producers, particularly 'merchants who deal with low-income consumers, who may themselves be relatively poor.').

For this 'welfarist' approach to produce positive distributional outcomes, however, various conditions need to be satisfied.[486] Most obviously, markets and/or the state need to progressively redistribute the (bigger) pie. This condition is increasingly weakly satisfied in countries such as the UK and US. As discussed in Chapter 2, and examined further in Appendix 1, these countries are characterized by restrictive welfare states and increasingly regressive distributional effects due to the market mechanism (wages)—in part due to automation.[487]

In addition, as discussed earlier, credit- and consumption-driven economic expansions are often unstable over the medium to long-run.[488] As a result, an over-expansion of credit that causes a decline in economic output in the medium to long run will ultimately reduce the resources available for redistribution (i.e., 'shrink' the pie). Moreover, the returns to (credit-fuelled) economic growth tend to accrue disproportionately to the already-well off, whereas the costs of recession accrue disproportionately to the less well-off—particularly low-income, less skilled, and younger households.[489]

---

486 *See* Lamont n 99 (explaining the distinction between welfarist and resourcist distributional principles).

487 Thomas Piketty and Emmanuel Saez, 'Inequality in the Long Run' (2014) 344(6186) Science 838 (dispelling the Kuznets hypothesis and finding support for the Marxist theory that the 'dynamics of private capital accumulation inevitably lead to the concentration of income and wealth'); Acemoglu and Restrepo, n 51; Acemoglu, n 51; Krueger and Perri, n 52; Hyman, *Politics of Consumer Debt*, 48 ('Whereas in the postwar period, the 1 percent paid the 99 percent in wages, after 1970 the 1 percent increasingly just lent the 99 percent money…But unlike in the postwar economy, these borrowers, with their stagnant incomes, had no way to repay the loans.').

488 *See* section 5.2.2.

489 Alessandro Ferrari, 'Losers Among the Losers: The Welfare Effects of the Great Recession Across the Cohorts' (ECB working paper series, December 2020) <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2509~a11c0ce310.en.pdf> (finding that younger households that become economically active during a recession suffer the greater welfare loss, mainly driven by permanent loss of employment).

5.3.3 Distributional effects of credit allocation to high-income consumers

To summarize the analysis thus far, if consumer credit is affordable—i.e., the borrower can meet the costs of servicing debt on time and without experiencing financial or non-financial distress—low-income consumers can realize welfare gains from borrowing and consumption smoothing. They are less likely, however, to observe gains *in income and/or wealth* due to borrowing and consumption smoothing or investment, particularly where unsecured, small value, short-term borrowing is concerned. Low-income consumers may also benefit from higher income (wages and/or social benefits) due to an increase in output resulting from higher consumer spending and redistribution by the state and/or markets—although this effect is limited, and increasingly so. Conversely, where credit is *un*affordable, low-income consumers are likely to experience welfare losses, including a reduction in income and/or wealth—due to both the direct costs of servicing debt and possibly also the indirect costs of a credit-induced recession.[490]

The distributional effects of credit allocation to low-income consumers—in terms of influencing poverty and inequality levels—depend not only on the affordability of credit for individual low-income consumers, but also on the net and relative effects of credit allocation and affordability on the consumption, income, and wealth levels of high and low-income consumers, respectively, and different subsets of these populations.[491] This section extends the analysis to include the distributional effects due to borrowing, consumption, and investment by *high-income* consumers. By enabling high income consumers to smooth consumption, and/or increase their income and wealth through investment—at a higher rate than low-income consumers—affordable credit could exacerbate poverty and inequality. Importantly, the higher levels of financial sophistication and lower consumption needs of

---

[490] As before, assuming that the borrower is unable to reduce the cost of debt ex post through debt restructuring or cancellation, including bankruptcy protection.

[491] *See* Appendix 1 (discussing measurement of poverty and inequality).

high-income consumers mean that they are more likely to be able to use credit for investment (albeit less so for unsecured, short-term, small value credit).[492]

These regressive distributional outcomes could be mitigated through policies that redistribute the income and wealth of high-income consumers. As discussed earlier, (affordable) borrowing and productive *investment* offer to increase long-run economic output.[493] From a distributional perspective, this might favour lending more to consumers who are expected to maximise economic returns to borrowing through investment, in order to maximise the resources available for redistribution.[494] However, under conditions of weakly progressive redistribution—whether through the state or markets, as discussed earlier—affordable borrowing by high-income consumers is more likely to be distributionally regressive.[495]

Conversely, *un*affordable borrowing by high-income households that reduces their income and wealth, could *reduce* inequality and poverty. This assumes, however, that low-income households do not experience commensurate losses—which may be unlikely.[496] Moreover, to the extent that unaffordable borrowing by high-income households leads to systemic bankruptcies, a debt overhang and economic recession, it could have regressive

---

[492] *See also* text at n 444.

[493] *See* section 5.2.2.

[494] This logic also supports lending more to businesses, to the extent that credit enables productivity-enhancing investment. *See further* Ronald M Dworkin, 'Is Wealth a Value?' (1980) 9 Journal of Legal Studies 191 (describing welfare, or wealth maximisation, as instrumental to, or a component of, justice). *Cf.* Richard A Posner, 'Utilitarianism, Economics and Legal Theory' (1979) 8(1) The Journal of Legal Studies 103 (arguing that wealth maximisation (welfare) should be the main organizing principle not only of how law is described, but also how (most domains of) law *should* be made); however, *see* Richard A Posner, 'The Value of Wealth: A Response to Dworkin and Kronman' (1980) 9 Journal of Legal Studies 243, 244 (arguing that wealth is a 'mediate' and intrinsically valuable goal, even if not an ultimate goal'); Eric Posner, 'The Boundaries of Normative Law and Economics' (2021) 38(2) Yale Journal on Regulation 657.

[495] Lucian A Bebchuk, 'The Pursuit of a Bigger Pie: Can Everyone Expect a Bigger Slice?' (1980) 8 Hofstra Law Review 671 (arguing that wealth maximisation leaves the poor worse off); Amartya K Sen, 'The Impossibility of a Paretian liberal' (1970) 78(1) Journal of Political Economy 152 (arguing that rights and distributive justice are external constraints and/or incompatible with orthodox welfare economics).

[496] *See* Table 3, *infra*.

distributional effects through the macroeconomic channel. As discussed earlier, low-income households are generally more adversely affected by recessions—including due to the contraction of credit, unemployment, and reduction of social welfare provision.[497]

***

To summarize, the distributional outcomes due to consumer credit allocation and pricing are contingent on the affordability of the terms of credit, as well as the net and relative effects of credit allocation on the consumption, income, and wealth levels of high and low-income consumers, respectively, and different subsets of these populations.[498] These contingencies and the main potential distributional outcomes due to consumer credit allocation—through both micro- and macroeconomic channels—are summarized in **Table 3**, below.[499]

---

[497] *See* section 5.2.2.

[498] As well as the type of consumer credit, which influences the extent to which borrowing funds consumption and/or investment (*see* text to n 444).

[499] As noted previously, there are many other variables that influence poverty and inequality. Table 3 focuses only on the distributional effects of credit allocation, *ceteris paribus*.

Table 3. Distributional Effects of Credit Allocation to Consumers

		Credit allocation to low-income consumers	
		Affordable	*Unaffordable*
Credit allocation to high-income consumers	*Affordable*	- ***progressive outcome***: affordable borrowing enables low-income consumers, on balance, to increase their utility due to consumption smoothing and/or increase income and wealth due to investment, at a faster rate than high-income consumers, thereby reducing poverty and inequality of consumption, income, and/or wealth (albeit likely limited to consumption in the case of unsecured, short-term, small value borrowing). - ***regressive outcome***: affordable borrowing enables high-income consumers, on balance, to smooth consumption, and/or increase income and/or wealth at a faster rate than low-income consumers, thereby increasing inequality and relative poverty (the latter by increasing the median income level, without increasing the income of households below the poverty line).	- ***regressive outcome***: poverty and inequality are exacerbated through any or all of the following channels: *unaffordable borrowing by low-income consumers* reduces their income, wealth and/or future consumption, on balance; *unaffordable borrowing by low-income consumers* leads to systemic non-performing loans and the resulting credit contraction and economic recession reduce the income, wealth and future consumption of low-income consumers, on balance, more than high-income consumers; *affordable borrowing by high-income consumers* on balance increases their utility due to consumption smoothing, and/or income and wealth due to investment.
	Unaffordable	- ***progressive outcomes***: affordable borrowing enables low-income consumers, on balance, to increase their utility due to consumption smoothing and/or income and wealth due to investment, more than high-income consumers *and/or* unaffordable borrowing by high-income consumers reduces their income and/or wealth, on balance, thereby reducing poverty and inequality. - ***regressive outcome***: unaffordable borrowing by high-income consumers leads to systemic non-performing loans and the resulting credit contraction reduces the consumption, income and/or wealth of low-income consumers, on balance, more than that experienced by high-income consumers (i.e., outweighing any previous gains to low-income consumers due to affordable borrowing or losses to high-income consumers due to unaffordable borrowing), thereby increasing inequality and poverty.	- ***progressive outcome***: unaffordable borrowing by high-income consumers on balance reduces their income, wealth and future consumption levels, and these losses are greater than the corresponding losses to low-income consumers due to unaffordable borrowing—collectively reducing poverty and inequality. - ***regressive outcome***: unaffordable borrowing by low-income consumers, on balance, reduces their income, wealth and/or future consumption more than any corresponding losses experienced by high-income consumers, thereby exacerbating poverty and inequality.

5.3.4 Influence of consumer credit regulation on the distributional effects due to credit allocation

The analysis in this chapter has revealed that the distributional outcomes due to credit allocation are contingent on the affordability of credit, i.e., consumers' ability to repay debt on time and in a sustainable manner, without experiencing financial or non-financial distress. Unaffordable borrowing by *low-income* consumers is especially likely to have regressive distributional effects. As discussed in Chapter 4, credit providers lack strong incentives to ensure that credit is affordable, unless and until it exceeds the level of credit risk that they are willing and able to assume profitably on a portfolio basis. As such, lending that is optimal from the point of view of the lender may be suboptimal from the point of the view of the borrower, and society.[500]

The analysis in this chapter has not yet incorporated the effects of regulation, particularly consumer credit regulation, on the distributional effects due to consumer credit allocation.[501] As also discussed in Chapter 4, rules requiring authorized credit providers to assess creditworthiness (both credit risk and affordability) were introduced into consumer credit regulation in 2010. This regime was extended to HCSTC providers, such as payday lenders, in 2014, and to p2p lenders in 2019.[502] To the extent that this regime is enforced, it offers to mitigate the regressive distributional outcomes due to unaffordable lending, at least by FCA-authorized firms that fall within the perimeter of the creditworthiness assessment regime.

---

[500] *See* ch 4, section 4.2.2.2.

[501] Ibid. Prudential regulation also affects these distributional outcomes (*see* ch 4, section 4.2.2.1). Chapter 7 will examine how information law—specifically, data protection regulation—could mitigate regressive distributional outcomes due to alternative credit scoring and increasingly datafied consumer credit markets. Of course, other legal regimes—such as bankruptcy and anti-discrimination law—also play an important role in regulating the distributional outcomes due to consumer lending. As noted previously, a detailed examination of these laws is beyond the scope of this thesis.

[502] *See* n 369 and associated text.

In terms of enforcement, it is encouraging that the FCA has, in recent years, levied sizeable fines on high-cost lenders, such as the 'rent-to-own' lender Brighthouse, for breaching the credit affordability assessment rules.[503] Indeed, the introduction of the affordability rules and their enforcement by the FCA largely killed the business model of Brighthouse, which has since gone into insolvency.[504] The downfall of Wonga, the excitable data-driven lender that we met in Chapter 1, was similarly triggered by the extension of the affordability rules to payday lenders in 2014, and the large volume of consumer compensation complaints that ensued.[505]

Even with perfect enforcement, however, the effectiveness of the FCA's creditworthiness regime in curbing unaffordable borrowing, particularly by vulnerable, low-income consumers, is limited by its substantive scope. To begin with, certain consumer credit markets are currently outside the perimeter of this regime. This includes the growing market in short-term, nominally interest-free 'pay in three' BNPL credit products.[506] There is growing concern and evidence to suggest that consumers are over-extending themselves with short-term BNPL credit.[507]

---

503 FCA, 'Rent-to-Own Provider BrightHouse to Provide Over £14.8 Million in Redress to Around 249,000 Customers' <https://www.fca.org.uk/news/press-releases/rent-to-own-provider-brighthouse-14-8-million-redress-249000-customers> ('the firm's lending application affordability assessment processes and collections processes did not always deliver good outcomes for customers particularly those who were at a higher risk of falling into financial difficulty.').

504 Zoe Wood, 'Brighthouse Admits Affordability Checks Are Hurting Business Model' *Guardian* (Oct 4 2016) <https://www.theguardian.com/money/2016/oct/04/brighthouse-admits-affordability-checks-are-hurting-business-model>.

505 FCA, 'Wonga to Make Major Changes to Affordability Criteria Following Discussions With the FCA' (Press release, October 2nd 2014) <https://www.fca.org.uk/news/press-releases/wonga-make-major-changes-affordability-criteria-following-discussions-fca>.

506 HM Treasury, 'Regulation of Buy-Now Pay-Later: Consultation' (2021) <https://www.gov.uk/government/consultations/regulation-of-buy-now-pay-later-consultation> (Annex A describing the exemption of short term, interest-free credit from regulation, which was expanded by Treasury in 2015). *See also* Crowther, *Consumer Credit* (noting that they don't address this type of credit because they aren't aware of any harm caused, and exclude it for 'practical reasons').

507 *See generally* Aggarwal, Kaye, and Odinet, n 141.

The UK government and the FCA have recently proposed an expansion of the regulatory perimeter, including the creditworthiness/affordability assessment rules, to include unsecured consumer credit products such as short-term BNPL. A key stated objective of this proposal is to protect vulnerable consumers from unaffordable debt.[508] More broadly, there remain informal, unregulated, high-cost consumer credit markets (so-called 'loan sharks') that are not governed by the FCA regime, including the affordability rules.

Another substantive limitation of the FCA creditworthiness/affordability regime is that it gives firms within the regulatory perimeter considerable discretion in the way that they define and implement the affordability criteria. Furthermore, the requirement to assess creditworthiness only applies at the point of credit origination and upon raising the credit limit. Even if lenders have exercised good faith in assessing credit affordability at the junctures required by the FCA regime, credit could still become unaffordable—although this risk may be reduced to a level deemed acceptable to regulators. Credit affordability (and credit risk) are probabilistic, not deterministic.[509] Debt can rapidly become unaffordable due to unexpected income shocks or changes in the macroeconomic environment (and over-optimistic assumptions on the part of lenders, and borrowers, about both).[510] As such, even very strict affordability rules will not fully mitigate the risk of unaffordable borrowing, and the attendant regressive effects—although they could reduce their magnitude to a level that is *more* in line with a more distribution-minded consumer credit market policy.[511]

---

[508] FCA, 'The Woolard Review—A Review of Change and Innovation in the Unsecured Credit Market' (2021) <https://www.fca.org.uk/news/press-releases/fca-publishes-woolard-review-unsecured-credit-market>; HM Treasury, n 506.

[509] *See* ch 3, section 3.3.2 (discussing the scientific limits of prediction).

[510] Mian and Sufi, n 109, 9-10 (comparing 'fundamentals', 'animal spirits', and 'banking' explanations for severe recessions caused by the build-up of household debt).

[511] *See further* ch 8, section 8.1.1.

Conversely, the affordability rules could be over-inclusive. That is, they may help to mitigate the distributionally regressive and welfare-diminishing effects due to unaffordable borrowing in certain regulated consumer credit markets. However, given that affordability is probabilistic, these rules also risk limiting access to *affordable* credit, and the positive welfare and distributional effects that flow from affordable borrowing, particularly for lower-income consumers. More particularly, they could push these consumers further out of formal, regulated consumer credit markets and into even less affordable, informal consumer credit markets.[512]

Relatedly, the creditworthiness assessment regime is protective rather than affirmative. That is, it encourages lenders within the regulatory perimeter not to extend unaffordable credit. It does not, however, require lenders to affirmatively make credit available on affordable terms—and thus does not directly facilitate the potential positive distributional outcomes that flow from access to affordable credit for low-income consumers.[513]

The relatively light-touch approach of the current creditworthiness assessment regime is partly informed by the FCA's preference for more principles- and outcomes-based regulation.[514] It also reflects the enduring challenge of balancing market access and consumer protection, as discussed above. The FCA thus leaves it to firms to find an appropriate

---

[512] *See further* n 522 and associated text.

[513] Note, this regime also does not mandate consumer credit providers to *deny* credit upon a negative creditworthiness assessment—in contrast to the FCA's mortgage credit regime, which does impose such as duty. *See* FCA Handbook, MCOB 11.6.2(1)(b). This also contrasts with the position in some EU Member States, such as the Netherlands, Belgium, and Germany. *See* European Commission, 'Report From the Commission to the European Parliament and the Council on the Implementation of Directive 2008/48/EC on Credit Agreements For Consumers' (2020) <https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/1844-Evaluation-of-the-Consumer-Credit-Directive>.

[514] *See generally* Armour et al, *Principles*, n 258 and 549-551 (describing the principles, process, and outcomes-based approach to financial regulation, which is favoured by the FCA).

balance based on the principles of 'proportionality', 'necessity', and 'sufficiency'.[515] This approach has, inevitably, also been shaped by the political economy of consumer credit markets and regulation. As discussed in previous chapters, policymakers lean on consumer credit markets to boost consumer spending and aggregate demand—if only in the short term. Stricter affordability criteria limit the potency of consumer credit as a mechanism for boosting the economy in this way.

At the time of writing, the European Commission has published a proposal for a new consumer credit directive (CCD 2021).[516] In light of Brexit, this will not directly impact consumer credit regulation and markets in the UK. However, it could have an indirect impact due to the presence of EU-based credit providers in the UK, and vice-versa. As such, it is worth noting that both the Commission and Council's drafts of the CCD 2021 propose a more protective approach to consumer credit regulation, a shift motivated in part by the accelerating digital transformation of these markets and the COVID-19 pandemic.[517] This includes a positive duty not to lend where the result of a creditworthiness assessment is negative,[518] and a right for consumers to challenge and seek explanation of creditworthiness assessments and profiling that use automated decision-making.[519] The CCD 2021 also limits

---

515 FCA, n 366 (consultation paper on assessing creditworthiness) (paras 1.22 and 2.31); ch 4, section 4.2.2.2; ch 4, section 4.1.1 (discussing the historically light-touch approach of consumer credit regulation).

516 European Commission, 'Proposal for a Directive of the European Parliament and of the Council on Consumer Credits COM/2021/347 final' <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2021:347:FIN>. *See also* European Council, 'Consumer Protection: Council Adopts its Position on New Rules For Consumer Credit', June 9 2022, <https://www.consilium.europa.eu/en/press/press-releases/2022/06/09/consumer-protection-council-adopts-its-position-on-new-rules-for-consumer-credits/>.

517 Commission, ibid, at 1 ('Digitalisation has also brought new ways of disclosing information digitally and assessing the creditworthiness of consumers using automated decision-making systems and non-traditional data.').

518 Draft Article 18(4) (Council and Commission drafts). This brings the consumer credit regime in line with the mortgage regime (*see* n 513).

519 Thereby expanding the corollary rights of consumers under EU data protection regulation. *See further* ch 7.

the types of data that can be used for creditworthiness assessment to information that is 'relevant to their [borrowers'] financial or economic circumstances'.[520]

5.3.4.1 The HCSTC regime and 'Responsible Lending'

In addition to the creditworthiness assessment rules, unaffordable borrowing, and the attendant regressive distributional effects, are also mitigated by specific restrictions on HCSTC.[521] More particularly, the price cap on HCSTC offers to address some of the shortcomings of the affordability criteria—especially the discretion left to lenders to determine whether a loan will be affordable at a given price. As with the debate over the appropriate stringency of affordability criteria, there is an ongoing debate over the effectiveness of this price cap, and the HCSTC regime more generally, as mechanisms for mitigating negative welfare and distributional effects due to high-cost credit.

For some, this regime strikes the appropriate balance between enabling credit market access and protecting the most vulnerable consumers from the harms due to high-cost credit. For others, the regime is too restrictive and has undesirable side effects by pushing the most vulnerable consumers into even more predatory markets, as discussed earlier.[522]

---

520 Draft Article 18(2).

521 *See* ch 4, section 4.2.2.2.1.

522 *See e.g.* Hartfree and Collard, *Poverty, Debt and Credit*, 25 (noting that 'users of illegal money lenders are primarily in the lowest income quintile and concentrated in the most deprived communities', however only 3% of these households—roughly 0.5% of the population in 2014–use them); Jodi Gardner, 'Austerity, Inequality and High-Cost Credit: Understanding the Role of a Social Minimum, in Gardner, Gray, and Moser, *Debt and Austerity*, 298-320 (arguing that austerity-based structural inequality rather than the debtor's behavioural problems is the main cause of the demand for high-cost loans). Empirical studies yield mixed results on the welfare effects of restricting access to high-cost credit. *See e.g.* Zinman, n 324 (finding that the introduction of a price cap on payday lending 'dramatically reduced access to payday loans in Oregon, and that former payday borrowers responded by shifting into incomplete and plausibly inferior substitutes' and 'harmed Oregon respondents, at least over the short-term, by hindering productive consumption smoothing and/or investment (e.g., in job retention).')*;* Paige Marta Skiba, 'Regulation of Payday Loans: Misguided?' (2012) 69 Washington & Lee Law Review 1023, 1026 (concluding that 'most regulations that restrict access to payday loans do not increase consumers' welfare'). *Cf. e.g.* Paige Skiba and Jeremy Tobacman, 'Do Payday Loans Cause Bankruptcy?' (2019) 62 Journal of Law & Economics 485 (2019) (finding that payday loans induce bankruptcy filings by worsening the cash flow position of the household); Brian T Melzer, 'The Real Costs of Credit Access' (2011)

Inevitably, these effects depend on the level at which the price cap is set.[523] For others still, the regime is not restrictive enough. Notably, the existing price cap still leaves room for unaffordable short-term, high-cost lending. The HCSTC regime is also limited in scope. For example, it excludes, by definition, longer term credit products, as well as notionally 'zero interest' short-term unsecured credit products, such as BNPL.[524]

There are additional mechanisms under the FCA regime that offer to mitigate the regressive effects due to unaffordable borrowing, particularly by lower income, more vulnerable consumers. They include: the FCA's 'high level principles', which, among other things, require firms to treat customers fairly and pay due regard to their interests;[525] the FCA's responsibilities and powers under general consumer law to challenge unfair contract terms;[526] and the FCA's recently introduced 'Consumer Duty' for firms in retail financial markets, which purports to strengthen consumer protection.[527]

---

126 The Quarterly Journal of Economics 517 (finding that payday loans increase financial distress). *See also* Ramsay, *Consumer Protection*, 343; Crowther, *Consumer Credit*, chapter 6.6.6.

523 FCA, n 137, 127-128 (finding that substitution to and from other credit markets is sensitive to the level of the price cap. At a cap of 0.8% per day, demand analysis shows a low degree of substitution between HCSTC and other credit markets; below 0.8% consumers are more likely to substitute).

524 'Wonga 2.0? Meet the New Breed of Payday Lenders' (*Guardian*, Apr 14 2018) <https://www.theguardian.com/money/2018/apr/14/wonga-mark-2-new-breed-of-payday-lenders-oakam> (discussing the rise of medium term payday loans that are not caught by the HCSTC regime).

525 FCA Handbook, PRIN 2.1.1(6); FCA, n 328, 9 (describing the high-level principles for business as being 'directly about fairness'). However, *see* Starks et al, n 307, 4 (noting that the FCA's principle of fairness is concerned primarily with procedural fairness—'a firm's conduct in how it treats consumers'—rather than distributional fairness). The FCA has indicated that it intends to take distributional concerns into account more explicitly when regulating price discrimination. *See* Starks et al, n 307; FCA, n 328; FCA, 'Fair Pricing in Financial Services: Summary of Responses and Next Steps' (Feedback Statement FS 19/04, July 2019) <https://www.fca.org.uk/publication/feedback/fs19-04.pdf>, para 3.10 ('[o]ur concern about consumers affected by price discrimination goes wider than vulnerable consumers and includes all consumers. However….we are more likely to intervene if the price discrimination results in harm to vulnerable consumers.'); and paras 3.17-18 (observing that the size of the group harmed does not automatically negate a finding of an unfair pricing practice).

526 *See* FCA Handbook, n 268; FCA, n 328, para 2.11 and 2.12 (discussing the application of the FCA's powers under general consumer protection law to price discrimination and 'unfair' terms in consumer financial contracts).

527 FCA, 'A New Consumer Duty' (Consultation Paper CP 21/36, December 2021) <https://www.fca.org.uk/publications/consultation-papers/cp21-36-new-consumer-duty-feedback-cp21-13-further-consultation>. Among other things, this requires firms to avoid causing foreseeable harm, and to offer

6 UNPACKING THE ALTERNATIVE CREDIT SCORING PROMISE

We have learnt that consumer credit can produce both positive and negative distributional effects. Key determinants of these effects are the affordability of credit for the borrower and the net and relative effects of borrowing on the levels of consumption, income, and wealth of higher and lower-income consumers, respectively. Unaffordable borrowing, particularly by lower-income consumers and/or where it leads to systemic non-performing debt, risks being distributionally regressive. Conversely, affordable borrowing by lower-income consumers can produce positive distributional outcomes, but where unsecured, short-term, small sum borrowing is concerned, these gains will generally be limited to improvements in consumption smoothing.

In deciding whether to extend credit, and at what price, lenders are thus making distributionally consequential decisions. However, in the absence of laws regulating the affordability of credit, (profit-maximising) lenders will tend to over-produce unaffordable debt.[528] Importantly, credit providers can still profit from extending credit that is unaffordable for the borrower, and thus lack strong incentives to ensure that credit is

financial products and services that offer 'fair value' to consumers. *See also* FCA Handbook, CONC 6.7.3A (a firm may be required to waive credit card fees if a customer displays signs of actual or possible financial difficulties) <https://www.handbook.fca.org.uk/handbook/CONC/6/?view=chapter>; FCA, 'Coronavirus: Information For Consumers With Personal Loans, Overdrafts and Other Forms of Credit' <https://www.fca.org.uk/consumers/coronavirus-information-personal-loans-credit-cards-overdrafts>.

[528] *See* ch 4, section 4.2.2.2.

affordable—unless and until it exceeds the level of credit risk that they are willing and able to assume profitably on a portfolio basis. In turn, consumers—particularly lower income, less financially sophisticated consumers—will tend to take on more debt and pay a higher price than is individually and socially optimal. Existing financial regulation—particularly the mandatory requirement for credit providers to assess credit affordability—partly mitigates this risk of excessive, unaffordable borrowing, and the associated negative distributional (and welfare) effects.[529]

This chapter examines how alternative credit scoring stands to influence the distributional outcomes due to consumer credit allocation, and thereby evaluates the strength of its distributional promise. Leveraging theoretical and empirical insights, the chapter argues that the distributional promise of alternative credit scoring is credible yet strictly bounded. Alternative credit scoring enables the expansion of credit to consumers who were previously marginalized from credit markets, particularly credit invisibles. To the extent that this entails the expansion of *affordable* credit to low-income, marginalized consumers, alternative credit scoring could mitigate the existing, regressive distributional effects due to unaffordable borrowing by these consumers—as well as enable positive distributional outcomes due to more affordable borrowing.

These positive distributional outcomes are, however, contingent. First, due to the limits of consumer credit itself as a mechanism for improving distributive justice. As discussed in the previous chapter, although access to affordable credit can increase consumer welfare by enabling consumption smoothing, the conditions under which borrowing—especially unsecured, short-term, small sum borrowing, by lower-income consumers—will enable consumers to increase their income and/or wealth are highly stringent. Second, due to the potential negative distributional effects of alternative credit scoring. Notably, by

[529] *See* ch 5, section 5.3.4.

enabling the *over*-expansion of credit—including too rapid credit expansion—and *un*affordable borrowing, particularly by low-income consumers, alternative credit scoring will tend to produce regressive distributional effects, rendering its distributional promise illusory.

The chapter proceeds as follows. Section 6.1 examines how alternative credit scoring stands to reduce creditor ignorance in consumer credit markets, thereby improving the ability of lenders to assess borrowers' creditworthiness and price differentiate between borrowers based on credit risk. Section 6.2 examines how the reduction of creditor ignorance combined with greater *consumer* ignorance due to alternative credit scoring stands to increase lenders' ability to price *discriminate* based on consumer demand, including where demand is a function of consumers' misperceptions. The analysis in these sections also incorporates the effects of alternative credit scoring, and digitisation more broadly, on automation and competition in consumer credit markets. Section 6.3 examines how these changes due to alternative credit scoring stand to influence the distributional outcomes due to credit allocation. Finally, section 6.4 examines how consumer-helping solutions—particularly those using AI/ML and alternative data—could influence creditor ignorance and consumer ignorance, respectively, and in turn influence the distributional outcomes due to alternative credit scoring and consumer credit allocation.

6.1 Reducing creditor ignorance, increasing price differentiation

We learnt in Chapter 4 that consumer credit markets are characterized by asymmetries of information, understanding, and power between lenders and borrowers.[530] *Creditor* ignorance describes the informational disadvantage of *lenders*, whereby lenders have less information than borrowers about the latter's characteristics, particularly those that influence credit risk

[530] *See* ch 4, section 4.2.1.

(PD and LGD) and affordability. *Consumer* ignorance describes the informational and behavioural disadvantage of *borrowers*, whereby borrowers understand less than lenders about the terms of credit contracts and their performance over time. We also learnt that, in allocating credit and setting credit terms, commercial lenders generally seek to not only cover the costs of lending, but also (maximise) profit. As a result, lenders price credit based on both cost (notably, credit risk, or PD and LGD)—referred to as price *differentiation*—as well as consumer demand—referred to as price *discrimination*—where demand may be a function of consumers' preferences and/or misperceptions.[531] Credit decisions can also be influenced by lenders' non-profit preferences, such as personal animus against certain social groups.[532]

Under conditions of high creditor ignorance, lenders are expected to ration credit to borrowers to mitigate adverse selection and moral hazard effects.[533] Advances in credit referencing and statistical credit risk-scoring technology, particularly since the 1980s, have reduced creditor ignorance in consumer credit markets and therefore credit rationing due to creditor ignorance.[534] With more information about borrowers' characteristics, lenders are better able to screen borrowers based on their credit risk, and price differentiate to compensate themselves ex ante for the cost of lending. More particularly, advances in credit referencing and credit scoring technology have reduced the *cost* and *time* it takes to acquire relevant information about borrowers, particularly 'soft' information, and allocate and price credit accordingly.[535]

---

531 *See* ch 4, section 4.2.1.

532 *See* n 305 (discussing lenders' non-profit preferences and 'taste-based' discrimination; noting, however, that anti-discrimination laws limit the scope for taste-based, as well as statistical, discrimination).

533 n 315 et seq and associated text.

534 As discussed in ch 4, the availability of secondary debt markets and techniques such as securitization to pass on credit risk (as well as changes in the money supply) also reduce credit rationing.

535 Mitchell A Petersen and Raghuram Rajan, 'Does Distance Still Matter? The Information Revolution in Small Business Lending' (2002) LVII(6) The Journal of Finance 2533; Liberti and Petersen, n 65 (distinguishing hard and soft data).

It follows that, by improving lenders' ability to observe borrowers' characteristics—that is, reducing the cost and time it takes to acquire this information—*alternative* credit scoring stands to further alleviate creditor ignorance in consumer credit markets. More particularly, alternative credit scoring enables lenders to acquire a more multi-dimensional, real time and up-to-date view of a consumer's creditworthiness (credit risk and affordability). As discussed in Part One and Appendix 2, certain ML methods can more accurately capture complex, non-linear relationships in data, as well as reflect changes in the population and environment.[536]

In turn, by reducing creditor ignorance, alternative credit scoring enables lenders to more accurately price differentiate between borrowers based on their credit risk.[537] It also enables a more accurate assessment of credit affordability, based on a more accurate prediction of the borrower's likely expenditure and disposable income during the repayment term of a loan and thus their ability to meet credit repayments without experiencing financial and non-financial distress. More precise price differentiation due to alternative credit scoring also stands to reduce the cross-subsidization of credit risk within (coarsely grained) credit scoring 'bins'. As discussed in Chapter 5, to a limited extent, higher income consumers cross-subsidize the credit risk of lower income consumers within a given credit scoring range.[538]

Alternative credit scoring, and its underlying technologies, could also alleviate creditor ignorance ex post, after credit is extended. More specifically, insights about borrowers obtained through ML and alternative data analysis (and leveraging other digital technologies, such as smartphones and apps) could enable lenders to more effectively monitor and control a borrower's actions ex post, thereby reducing inefficiency due to

---

[536] *See* ch 3, section 3.3, and Appendix 2.

[537] Iversen and Rehm, n 57, 3 ('As the data available to lenders improve, they can make more differentiated risk-of-default assessments, which means that interest rates increasingly reflect the underlying risk distribution.')

[538] *See* section 5.3.2.1.

creditor ignorance and moral hazard effects after credit is extended.[539] For example, these technologies could be used to more effectively design penalty pricing provisions or fee waivers that adapt dynamically to the consumer's behaviour during the term of the credit contract.[540]

The reduction of creditor ignorance in these ways is expected to be more pronounced in the credit invisible consumer segment, which is traditionally constituted by high levels of creditor ignorance. As discussed in Chapter 3, due to credit invisibles' lack of conventional credit data, conventional credit referencing and scoring techniques are less effective at estimating their creditworthiness relative to credit visible, thick file borrowers.[541] However, despite their lack of conventional credit data, credit invisible consumers typically have alternative data that can demonstrate their creditworthiness to lenders. It follows that the marginal utility of alternative credit scoring for assessing creditworthiness will be lower in thick file, credit visible consumer segments that are characterized by lower levels of creditor ignorance and greater borrower homogeneity, and in which most of the predictable association with credit risk can be discerned from borrowers' longer credit histories and conventional credit scores.[542]

---

539 Stiglitz and Weiss, n 317.

540 More broadly, the use of data-driven, digital technology offers to reduce creditor ignorance in other parts of the credit lifecycle, such as borrower identity verification, fraud and money laundering detection, and debt collection.

541 *See* ch 3, section 3.1.

542 *See* Edward Golding, Richard Green and Douglas McManus, 'Imperfect Information and the Housing Finance Crisis' (2008) <https://www.jchs.harvard.edu/research-areas/working-papers/imperfect-information-and-housing-finance-crisis> ('Within the realm of the traditional conventional-confirming market, borrowers are relatively homogenous in terms of down payments and credit scores as measured by FICO….By contrast, borrowers in the subprime market are highly heterogeneous and the differences are not fully transparent.'); Leonardo Gambacorta et al, 'How do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm' (2019) <https://www.bis.org/publ/work834.pdf>, 19-20.

6.1.1 *Empirical data on alternative credit scoring, creditor ignorance, and credit risk prediction*

Recent CRA data supports the hypothesis that the incorporation of alternative data reduces creditor ignorance in the credit invisible segment. For example, Experian UK reports that, by incorporating alternative data into credit reports, the number of credit invisibles in the UK fell by 750,000 between 2018 and 2022, a reduction of approximately 13 percent.[543] Similarly, Experian US reports that, by sharing alternative data through Experian Boost, 42 percent of thin file consumers became thick file; 34 percent of previously unscoreable consumers became scoreable; and 88 percent of customers with 'poor' credit scores were able to increase their scores.[544]

Recent empirical data also corroborate the hypothesis that alternative credit scoring enables lenders to more accurately predict credit risk.[545] More specifically, the use of certain types of alternative data in consumer credit scoring has been shown to either match or improve the accuracy of credit risk prediction, and reduce loan default rates, relative to conventional credit data for credit scoring.[546] For example, in a study of Lending Club, a US-based p2p lending platform, researchers at the Federal Reserve Bank of Philadelphia found that 'the rating grades (assigned based on alternative data) perform well in predicting loan

---

[543] Experian, *Making the Invisible Visible*.

[544] Experian, 'Experian ESG Presentation' (June 27, 2022), 24 <https://www.experianplc.com/media/4157/experian_esg_presentation.pdf>.

[545] To the best of my knowledge, at the time of writing there are no empirical studies looking specifically at the use of ML or alternative data for the assessment of credit *affordability* (*see* FCA, *Preventing Financial Distress*, using traditional statistical techniques).

[546] Note, most of these studies are based on simulating credit decisions using historic loan datasets (of credit decisions and/or outcomes) and alternative credit scoring. Other studies observe loan outcomes directly following the introduction of alternative credit scoring by a lender. In both cases, researchers compare the predictive accuracy of alternative credit scoring using different types of alternative data and/or ML methods to the predictive accuracy of conventional statistical credit scoring. Recall that predictive accuracy is measured by the classification error rate and influenced by the 'cut-off' probability for classification (*see* ch 3, section 3.3.2).

performance over the two years after origination'.[547] Research carried out by FinReg Lab, a US-based think tank, found that the use of borrowers' cash flow data for credit scoring was at least as predictive of credit risk and loan performance as conventional credit scores, and more predictive when used in combination with conventional credit scores.[548]

Other studies have produced similar results. For example, it has been shown that borrowers who use Apple iOS devices,[549] have larger and more stable social networks,[550] make fewer spelling mistakes in filling out a loan application form,[551] spend more time scrolling through a lender's terms and conditions,[552] and/or send emails at night[553] are more likely to repay their debts on time (i.e., have a lower credit risk). Some of these variables proxy for conventional credit lifecycle variables, such as income,[554] whilst others proxy for information that is harder to observe or measure, such as the borrower's level of financial sophistication.[555]

---

547 Julapa Jagtiani and Catherine Lemieux, 'The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform' (FRB of Philadelphia Working Paper No. 18-15, 2018) <https://ssrn.com/abstract=3178461>.

548 FinReg Lab, 'The Use of Cash-Flow Data in Underwriting Credit' (2019) <https://finreglab.org/cash-flow-data-in-underwriting-credit-empirical-research-findings>.

549 Berg et al, n 186.

550 Björkegren and Grissen, n 183.

551 Oded Netzer, Alain Lemaire, and Michal Herzenstein, 'When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications' (2019) 56(6) Journal of Marketing Research 960; Michelle S A Lee and Jatinder Singh, 'Spelling Errors and Non-Standard Language in Peer-to-Peer Loan Applications and the Borrower's Probability of Default' (2020) <https://papers.ssrn.com/abstract=3609834>.

552 Quentin Hardy, 'Big Data for the Poor' *New York Times* (July 2012) <https://bits.blogs.nytimes.com/2012/07/05/big-data-for-the-poor/>.

553 Djeundje et al, n 184.

554 Marianne Bertrand and Emir Kamenica, 'Coming Apart? Cultural Distances in the United States over Time' (NBER Working Paper No. 24771, 2018) <https://doi.org/10.3386/w24771>.

555 Agarwal et al, n 185, 5.

Recent empirical studies have also shown that the use of certain types of ML methods match or increase the accuracy of conventional statistical credit scoring in estimating credit risk. For example, a study based on consumer credit markets in the UK found that ML credit scoring models were more accurate than conventional (logit) models in predicting borrowers' likelihood of default, specifically in the credit invisible population.[556] Similar results are reported in other regions. For example, a study based on US housing mortgage markets hypothesised that the use of ML for credit underwriting increases the accuracy of credit risk prediction.[557] The study's authors attribute the expected increase in predictive accuracy to both increased flexibility available to ML to uncover structural relationships between borrower characteristics and default outcomes, as well as better triangulation between unobserved borrower characteristics and default outcomes—with increased flexibility being the dominant mechanism.[558]

It is important to note, however, that available empirical data also indicates that not all forms of alternative credit scoring will yield improvements in predictive accuracy viz conventional statistical credit scoring, and indeed some may be *less* accurate.[559] More

---

[556] Bono et al, n 135.

[557] Andreas Fuster et al, 'Predictably Unequal? The Effects of Machine Learning on Credit Markets' (2022) 77(1) The Journal of Finance 5 ('machine learning technology delivers statistically significantly higher out-of-sample predictive accuracy for default than the simpler logistic models.'). Note that these findings are based on simulating credit decisions using a historic loan dataset, rather than actual outcomes following the introduction of alternative credit scoring by a given lender (*see* n 546).

[558] Fuster et al, ibid, 4 ('the majority of the predictive accuracy gains from the more sophisticated machine learning model can be attributed to the increased flexibility of the model, with at most 30% attributable to pure triangulation.'). *See also* Mark Jansen, Hieu Nguyen, and Amin Shams, 'Rise of the Machines: The Impact of Automated Underwriting' (Fisher College of Business Working Paper No. 2020-03-019, 2021) <https://ssrn.com/abstract=3664708> (finding that algorithmic underwriting outperforms the human underwriting process in auto lending, resulting in 10.2% higher loan profits and 6.8% lower default rates); Agarwal et al, n 185 (finding that the use of alternative data and ML for credit scoring in India 'significantly improved default prediction and outperformed the credit bureau score'); Óskarsdóttir et al, n 183 (finding improvements in performance, or predictive accuracy, of credit scoring models due to the use of alternative data).

[559] *See e.g.* Bono et al, n 135 (finding that the use of interpretable ML techniques in certain contexts reduces the potential accuracy gains due to the use of ML for credit scoring).

generally, there are important limitations to the conclusions that we can draw from available empirical studies on alternative credit scoring. They include:

- *Geography*—most available empirical studies of alternative credit scoring are based on US (mortgage) credit markets and/or developing market economies;[560]
- *Heterogeneity in the definition of alternative credit scoring* (ML and/or alternative data) and thus the subject of study;[561]
- *Heterogeneity in the definition and measurement of predictive accuracy* (including the cut-off classification probability and target variable);[562]
- *Time frame, and controlled/uncontrolled variables*—many of these studies were carried out pre-Covid and thus under relatively benign macroeconomic conditions (including monetary easing). The gains in predictive accuracy and lower rates of credit default observed in these studies may simply be a function of strong macro-fundamentals at the time.[563]

6.2 Exacerbating consumer ignorance, increasing price discrimination

The key lesson from the analysis thus far is that alternative credit scoring offers to ameliorate creditor ignorance in consumer credit markets (particularly in the credit invisible segment) and, as a result, improve the accuracy of creditworthiness (credit risk and affordability) assessment by lenders. However, this is not the only dimension along which changes may be

---

560 *See also* n 16 et seq and associated text (discussing conditions for external validity); Alexandra Ciocanel et al, 'Algorithmic Risk Profiling in Housing: A Literature Review' (June 2022) <https://www.york.ac.uk/media/chp/documents/2022/Code%20Encounters%20Algorithmic%20risk%20profiling%20in%20housing%20a%20literature%20review.pdf>, 5 (noting that the main focus of the existing (empirical) credit scoring literature is the US, 'a country with specific social, political, and economic circumstances.').

561 *See also* ch 3, sections 3.2 and 3.3.

562 *See* ch 3, section 3.3.2.

563 Danielsson, Macrae and Uthemann, n 227.

expected. As discussed, in pricing credit, commercial lenders are not simply looking to cover their costs but maximise profits. As a result, they will generally charge more to borrowers where they can, i.e., where there is greater 'demand' based on borrowers' apparent willingness to pay. Additionally, consumer credit markets are characterized by *consumer* ignorance, due to which consumers commonly misperceive the true cost of credit.[564] Profit maximizing lenders often seek to exploit consumer ignorance. Less financially literate consumers—who may be more likely to come from lower-income groups—are more susceptible to manipulation of their misperceptions regarding the true cost of credit, as compared to more sophisticated, higher-income consumers.

These observations allow us to deepen our analysis in two ways. *First*, by ameliorating *creditor* ignorance, alternative credit scoring—and the use of ML and predictive data analytics more broadly—also affords lenders a more precise knowledge of a consumer's reservation price, whether this is a function of their actual preferences or their misperceptions (consumer ignorance). As a result, alternative credit scoring increases the ability of lenders to price discriminate and maximise profit based on consumer demand.[565]

To illustrate, the analysis of a person's social and behavioural data using ML techniques could indicate that they are more myopic and/or in need of credit—for example, because they are suffering ill health and have an urgent need to pay for medical expenses—and therefore may be 'willing' to pay more to borrow. Based on this analysis, a lender's

[564] *See* ch 4, section 4.2.1.2.

[565] Starks et al, n 307, 3 ('More information through big data and advanced algorithms of artificial intelligence will potentially enhance the ability of firms to identify different types of consumer behaviour.'); Varian, n 61, 12 ('[i]nformation technology allows for fine-grained observation and analysis of consumer behavior. This permits various kinds of marketing strategies that were previously extremely difficult to carry out.'). *See also* FCA, 'Call for Inputs on Big Data in Retail General Insurance' (Feedback Statement FS 16/5, September 2016) <https://www.fca.org.uk/publication/feedback/fs16-05.pdf>. In this sense, alternative credit scoring fits into a broader landscape of increasingly personalised, dynamic pricing in online commercial environments, where pricing algorithms continually adjust prices based on estimates of supply (inventory) and consumer demand. *See e.g.* Zach Brown and Adam Mackay, 'Competition in Pricing Algorithms' (2021) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3485024>.

recommender system, optimised for profit maximisation, could recommend less favourable credit terms to these borrowers, at moments of extreme vulnerability and before they have an opportunity to shop around for a better offer.[566]

Importantly, the scope for data-driven price discrimination in this way is not limited to the individual consumer whose data is collected and processed—whether for alternative credit scoring or other purposes. There are externalities, both negative and positive, to the processing of personal data, particularly networked data.[567] A person's data can also yield detailed and potentially harmful inferences about their friends, as well as other consumers who behave like them, without the latter's consent or knowledge. Detailed yet unforeseeable behavioural inferences can also be obtained by aggregating personal data with seemingly unrelated and/or non-personal data, such as demographic or environmental data, in ways that are unintuitive and opaque to most consumers.[568]

More broadly, lenders can leverage digital technology and data-driven insights about consumers to exploit their ignorance in other parts of the credit cycle, such as debt collection and marketing.[569] For example, new forms of digital marketing, such as social media 'influencing', enable lenders to more effectively target vulnerable, younger consumers with

---

566 Robert Bartlett, Adair Stanton, Richard Morse, and Nancy Wallace, 'Consumer Lending Discrimination in the Fintech Era' (2022) 143(1) Journal of Financial Economics 30, 40 ('An algorithm could naturally discover that higher prices could be quoted to profiles of borrowers or geographies associated with low-shopping tendencies.'); Gerard Wagner and Horst Eidenmüller, 'Down by Algorithms? Siphoning Rents, Exploiting Biases and Shaping Preferences—The Dark Side of Personalized Transactions' (2019) 86 University of Chicago Law Review 581. *See also* Ryan Calo, 'Digital Market Manipulation' (2014) 82 George Washington Law Review 995; ch 4, section 4.2.1.2 and associated text.

567 Omri Ben-Shahar, 'Data Pollution' (2019) 11 Journal of Legal Analysis 104; Alessandro Acquisti, 'The Economics of Personal Data and the Economics of Privacy' at <https://bit.ly/32JAaX6>, 27; Solon Barocas and Helen Nissenbaum, 'Big Data's End Run Around Anonymity and Consent' in Julia Lane et al. (eds.), *Privacy, Big Data, and the Public Good: Frameworks for Engagement* (CUP 2014), 44-75; Madden et al, n 155.

568 Brent Mittelstadt, 'From Individual to Group Privacy in Big Data Analytics' (2017) 30 Philosophy and Technology 475.

569 Antoaneta Roussi, 'Kenyan Borrowers Shamed by Debt Collectors Chasing Silicon Valley Loans' *Financial Times* (September 9 2020) <https://on.ft.com/2FtPY95> (describing data-driven targeting of vulnerable borrowers by debt collectors).

(unfavourable) credit offers.[570] Lenders increasingly deploy virtual assistants ('chatbots') in their communications with consumers.[571] These assistants could be used to improve consumer financial decision-making, inter alia by improving consumer access to financial advice and/or mitigating the biases of human financial advisors.[572] Or, they could be used to manipulate consumers into agreeing to less favourable credit offers.[573] The increasingly human-like conversational capabilities of virtual assistants could give consumers a false sense of familiarity and trust, making it more likely that they enter into an unfavourable credit contract.[574] To the extent that lenders are motivated to maximize profits from lending, and their virtual assistants are optimized for profit maximization, there remain principal-agent risks that are likely to undermine the quality and suitability of any financial advice offered to consumers by lenders' in-house virtual assistants.

Second, and relatedly, the use of alternative credit scoring and related data-driven, digital technologies stands to exacerbate *consumer* ignorance in consumer credit markets. In particular, the use of these technologies could make it harder for consumers to compare consumer credit products and shop around for a better deal. This is due to greater product personalisation and differentiation, as well the increased ability of firms to capture consumers in digital ecosystems—increasing the chance that they commit reflexively to an

---

570 Aggarwal, Kaye, and Odinet, n 141 (discussing the use of social media platforms by BNPL lender Klarna to target young, Gen Z consumers, potentially encouraging them to take on unaffordable debt).

571 For example, Natwest has a virtual assistant named Cora (*see* <https://www.natwest.com/support-centre/cora.html>); Bank of America has a virtual assistant named Erica (*see* <https://promotions.bankofamerica.com/digitalbanking/mobilebanking/erica>).

572 *See further* ch 6, section 6.4.

573 Ariel Ezrachi and Maurice Stucke, 'How Digital Assistants Can Harm our Economy, Privacy, and Democracy' (2017) 32 Berkeley Technology Law Journal 1239. On manipulation by social bots generally *see* Thomas King, Nikita Aggarwal, Mariarosaria Taddeo and Luciano Floridi, 'Artificial Intelligence Crime: An Interdisciplinary Analysis of Foreseeable Threats and Solutions' (2020) 26 Science and Engineering Ethics 89.

574 Yaniv Leviathan and Yossis Matias, 'Google Duplex: An AI System for Accomplishing Real-World Tasks Over the Phone' (*Google Research Blog*, 8 May 2018) <https://bit.ly/2rznYXJ>.

offer before they can shop around, or before another lender can intervene with a more favourable offer.[575]

Collectively, developments in credit scoring and related data-driven technology risk generating a harmful, self-perpetuating cycle in which: (i) the knowledge and power of creditors (firms) increases (i.e., creditor ignorance abates); (ii) the knowledge and power of consumers decreases (i.e., consumer ignorance exacerbates); and (iii) the ability of firms to exploit consumer ignorance increases. Due to greater ignorance, low-income, less-advantaged consumers are more likely to be adversely affected by these effects. These effects are also expected to be more acute in less competitive markets, where firms necessarily have greater control over the services and products used by consumers.

The jury is still out on the competitive effects of digitization and datafication—in consumer credit markets specifically, and in digital markets more generally. On the one hand, high start-up costs and increasing returns to scale from data processing and ML, as well as 'winner-takes-all' effects in platform-based digital markets, have been shown to favour larger lenders and already-data-rich companies, like Amazon and Apple, over smaller firms and new entrants, leading to concentration and anti-competitive pricing.[576] These effects are thus more likely to favour 'TechFins',[577] like Amazon and Apple, relative to incumbent financial

---

575 Wagner and Eidenmüller, n 566.

576 Varian, n 61, 12 ('the high-fixed-cost, low-marginal-cost technologies commonly observed in these [high tech] industries often lead to significant market power, with the usual inefficiencies'); Jason Furman, 'Unlocking Digital Competition: Report of the Digital Competition Expert Panel' (2019) <https://www.gov.uk/government/publications/unlocking-digital-competition-report-of-the-digital-competition-expert-panel>; Erik Feyen et al, 'Fintech and the Digital Transformation of Financial Services: Implications For Market Structure and Public Policy' (BIS Working Paper No. 117, July 2021) <https://www.bis.org/publ/bppdf/bispap117.pdf>; Karen Croxson et al, 'Platform-Based Business Models and Financial Inclusion' (BIS Working Paper No. 986, 2022) <https://www.bis.org/publ/work986.htm>; Brown and Mackay, n 565 (finding that high frequency algorithmic pricing has raised prices and undermined price competition); Ariel Ezrachi and Maurice E Stucke, 'Artificial Intelligence & Collusion: When Computers Inhibit Competition' (2017) University of Illinois Law Review 1775.

577 Dirk W Zetsche et al, 'From FinTech to Techfin: The Regulatory Challenges of Data-Driven Finance' (University of Hong Kong Faculty of Law Research Paper No. 2017/007, 2017) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2959925>.

institutions, given the former's already superior infrastructure for collecting, processing and storing data, and large existing troves of consumer data.[578]

By combining newly acquired financial transaction data with their existing troves of consumer data and well-trained ML models, TechFins can likely predict and exploit consumers' preferences and misperceptions with even greater precision than other data-driven lenders.[579] And, by integrating credit and other financial services into the everyday technology used by consumers—notably, smartphones and smartphone apps—these companies are especially well positioned to bring more consumers into their digital, datafied ecosystems, as well as lock in existing customers.[580] In turn, this feedback loop generates

578 Jon Frost et al, 'BigTech and the Changing Structure of Financial Intermediation' (BIS Working Papers no. 779, 2019) <https://www.bis.org/publ/work779.pdf>; Bank for International Settlements, 'Big Tech in Finance: Opportunities and Risks' <https://www.bis.org/publ/arpdf/ar2019e3.pdf>; Juan C Crisanto, Johannes Ehrentraud, and Marcos Fabian, 'Big Techs in Finance: Regulatory Approaches and Policy Options' (BIS Financial Stability Institute Briefs No. 12, 2021) <https://www.bis.org/fsi/fsibriefs12.pdf>. *See also* Leyshon and Thrift, *Lists Come Alive*, 436 (observing that the rise of credit-scoring systems shifted the 'nature of competitive advantage within the [British retail banking] industry which because of the imperatives of 'forensic' marketing is now tilted towards expertise in data handling, manipulation and analysis').

579 Harald Hau et al, 'How FinTech Enters China's Credit Market' (2019) 109 AEA Papers and Proceedings 60 <https://www.aeaweb.org/articles?id=10.1257/pandp.20191012> (finding more accurate creditworthiness assessment by Big Tech SME credit providers); Verma et al, 'Artificial Intelligence System With Hierarchical Machine Learning For Interaction Session Optimisation' (2021) US Patent no. US 10977711 B1 <https://patents.google.com/patent/US10977711B1/en?oq=US+Patent+no.+US+10977711+B1+> (patent assigned to Amazon, and at 9 referring to the development of models for creditworthiness assessment using various input variables).

580 Nikita Aggarwal, 'Fintech Credit and Consumer Financial Protection', in Iris Chiu and Gudula Deipenbrock (Eds) *Routledge Handbook of Financial Technology and Law* (Routledge & CRC Press 2021), 138. Note, many TechFins (such as Amazon and Apple) offer their services through bank partnerships, thereby avoiding bank start-up and regulatory compliance costs. *See e.g.* Amazon Money Store, Credit Cards <https://amzn.to/3Yowm9r> (describing four Amazon Mastercards offered by Amazon, as credit broker, in partnership with NewDay Ltd or Capital One, and using the Mastercard payment network); Apple, 'Apple Card Launches Today For All US Customers' <https://www.apple.com/newsroom/2019/08/apple-card-launches-today-for-all-us-customers/> (offering the Apple credit card in partnership with Goldman Sachs and Mastercard, although at the time of writing this is only available to US customers). *See further*: 'Big Tech Takes Aim at the Low-Profit Retail-Banking Industry' *Economist* (November 21 2019) <https://www.economist.com/finance-and-economics/2019/11/21/big-tech-takes-aim-at-the-low-profit-retail-banking-industry>; Board of Governors of the Federal Reserve System, 'Community Bank Access to Innovation Through Partnerships' (2021) <https://www.federalreserve.gov/publications/files/community-bank-access-to-innovation-through-partnerships-202109.pdf>.

more data, and enables further improvements in Techfins' data analytics capabilities, allowing them to increase market share.[581]

On the other hand, data, ML models, and digital software/hardware more broadly, are becoming cheaper and more accessible.[582] Among other things, public and private data portability initiatives, including Open Banking, and open source ML libraries and toolkits, offer to increase competition in historically oligopolistic, bank-dominated (consumer) financial markets—both by lowering the barriers to entry for firms, and reducing 'search and switch' costs for consumers.[583] Equally, consumer credit markets should eventually reach a point of diminishing marginal returns to additional data insights, such that access to data and digital technologies no longer gives lenders (or other firms) a significant competitive advantage. This being said, greater product differentiation and personalization due to the use of data-driven technology—and thus greater consumer ignorance—mean that even in a technically competitive market with many firms, individual firms can still enjoy a degree of market power and engage in anti-competitive pricing.[584]

---

581 Bank for International Settlements, n 578 (describing this as the 'data analytics, network externalities and interwoven activities' ('DNA') business model of big techs in finance).

582 Anja Lambrecht and Catherine Tucker, 'Can Big Data Protect a Firm from Competition?' (2015) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2705530>; Yan Carriere-Swallow and Vikram Haksar, 'The Economics and Implications of Data: An Integrated Perspective' (2019) <https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2019/09/20/The-Economics-and-Implications-of-Data-An-Integrated-Perspective-48596> (noting that data is non-rivalrous and only partially excludable). *See also* Bartlett et al, n 566 (finding an increase in competition and lower prices in US home mortgage credit markets due to fintech lending).

583 Armour et al, *Principles*, 60; Fracassi and Magnuson, n 174; Varian, n 61, 18 (observing that the Internet 'can lower the cost of search quite dramatically'). For an example of a popular ML model library, *see e.g.* TensorFlow <https://www.tensorflow.org/resources/libraries-extensions>. *See further* section 6.4 (examining digital consumer-helping solutions) and ch 7, section 7.2 (discussing data portability under the GDPR).

584 *Supra* and Posner and Hynes, n 313, 6; Ausubel, n 306; Akerlof and Shiller, n 336 (coining the term 'phishing equilibrium'); David Ulph and Nir Vulkan, 'Electronic Commerce and Competitive First-Degree Price Discrimination' (2000) cited in Varian, n 61, 13-14 (finding that the 'enhanced surplus extraction effect' of personalized pricing dominates the 'intensified competition effect' where consumer tastes are heterogeneous). *See further* section 6.4 (examining digital consumer-helping solutions).

Two further hypothetical effects, which are relevant to the distributional outcomes due to alternative credit scoring, bear mentioning. *First*, the greater automation of credit decision-making due to the use of digital, data-driven technology—including but not limited to alternative credit scoring—reduces transaction costs throughout the credit lifecycle. Among other things, this enables lenders to extend smaller value loans that were previously too costly to underwrite, as well as to reach consumers for whom access to credit was previously restricted by their remote location (e.g., a lack of bank branches) or the inconvenience of traditionally lengthy credit approval processes.[585] *Second*, automation due to alternative credit scoring also offers to reduce 'taste-based' discrimination in credit allocation and pricing decisions.[586] That is, to the extent that taste-based discrimination in credit decisions is 'irrational', in a profit-maximising sense—for example, lenders are leaving money on the table by not lending to profitable consumers due to personal animus—a 'rational' credit scoring algorithm optimized to maximise profit, and substituting for an 'irrational' human loan officer, could reduce taste-based discrimination.[587]

In this respect, Bartlett et al's study of alternative credit scoring in US house mortgage markets is instructive.[588] It found that the use of alternative credit scoring by

---

585 Petersen and Rajan, n 535; Julapa Jagtiani, Lauren Lambie-Hanson, Timothy Lambie-Hanson, 'Fintech Lending and Mortgage Credit Access' (2019) <https://doi.org/10.21799/frbp.wp.2019.47> (showing that fintech lenders have been effective in expanding mortgage access in nonmetropolitan areas in the US); Sahay et al, n 13; Hartfree and Collard, *Poverty, Debt and Credit*, 34 (citing research showing that the most appropriate form of credit for low-income households is small, short, fixed-term loans, but banks generally are unwilling to make these loans available because it is not commercially viable and that not-for-profit lenders and credit unions are better placed.). However, *see* Thomas Philippon, 'The FinTech Opportunity' (2016) <https://www.nber.org/papers/w22476>, 3-6 (hypothesising that firms may not pass on cost savings due to the use of new tech).

586 *See* n 305.

587 Of course, lenders' decision-making algorithms may still seek to discriminate based on race or gender, or proxies for them, if these variables are correlated with the target variables such as the borrower's probability of default and willingness to pay (although the scope for doing so is restricted by discrimination law). These effects are also dependent on the degree to which credit decisions are fully automated, i.e., the human lending officer is fully 'substituted'. *See further* section 6.3.1.1.

588 Bartlett et al, n 566 (*see further* section 6.3.2, below).

lenders both increased loan origination to minority groups as well as reduced their cost of credit, overall, relative to the status quo. The study's authors hypothesise that these effects are due not only to the more accurate triangulation of borrowers' characteristics with their probability of default (consistent with the studies discussed earlier),[589] but also the reduction of taste-based discrimination due to greater automation of credit decisions—as well as increased competition from fintech lenders in consumer credit markets.

6.3 Distributional effects of alternative credit scoring

The analysis thus far has hypothesised that the reduction of creditor ignorance and the exacerbation of consumer ignorance due to the use of alternative credit scoring (and related technologies) stands to increase the scope for lenders to profit by (i) price differentiating based on consumers' credit risk, and (ii) price discriminating based on consumer demand. Additionally, automation and digitisation enable lenders to profit from (i) extending smaller value loans and reaching borrowers in remote locations, and (ii) lending to borrowers that would otherwise have been denied credit due to the personal prejudices of loan officers.

What are the potential distributional effects of alternative credit scoring through these channels? The answer to this question depends, among other things, on: (i) how credit providers apply their data-driven insights in credit allocation and pricing decisions, and thus the cost and affordability of credit for borrowers, as well as the overall volume of lending and rate of credit growth (which in turn are influenced, among other things, by credit providers' compliance with, and the enforcement of, existing laws, particularly the requirement to assess credit affordability under the FCA's consumer credit regime);[590] and (ii) how changes in the cost, affordability, volume and speed of expansion of credit due to

---

589 *See* section 6.1.1.

590 *See* ch 5, section 5.3.4; ch 4, section 4.2.2.2.

alternative credit scoring affect the net and relative levels of consumption, income and wealth of low-income and high-income consumers, respectively, including different subsets of these consumer populations.[591]

By enabling lenders to estimate consumer creditworthiness and price credit more accurately, and more generally by reducing the costs of (small value) lending, alternative credit scoring enables improved access to credit for marginalized consumers. To the extent that this results in the expansion of access to *affordable* credit for *lower-income*, marginalized consumers, alternative credit scoring could mitigate existing, regressive distributional effects due to unaffordable borrowing by these consumers—as well as enable positive distributional outcomes due to more affordable borrowing, as discussed in Chapter 5.

These positive distributional outcomes are, however, contingent. First, due to the limits of consumer credit itself as a mechanism for improving distributive justice. As discussed, although access to affordable credit due to alternative credit scoring can increase consumer welfare through consumption smoothing, the conditions under which credit—especially unsecured, short-term, small value credit—will enable low-income consumers to increase their income and/or wealth are highly stringent. Second, due to the potential negative distributional effects of alternative credit scoring. Notably, by enabling the *over*-expansion of credit—including a too rapid expansion—and *un*affordable borrowing, particularly by low-income consumers, alternative credit scoring will tend to produce regressive distributional effects. Among other things, unaffordable borrowing could result from lenders intentionally exploiting consumer ignorance, the scope for which is exacerbated

---

[591] Section 6.4 and ch 7 will extend this distributional analysis by incorporating the effects of consumer-helping solutions and data protection regulation, respectively. Although beyond the present scope of analysis, as noted previously there are additional distributional effects due to the use of credit scores as screening mechanisms in non-credit contexts, such as housing and employment, inter alia (*see* n 480). Further distributional effects could emerge from a combination of the 'digital divide' (*see* Ofcom, n 155) and the role of (fintech) credit firms as providers of non-credit services. *See e.g.* Sahay et al, n 13 (observing that the digital divide exacerbated disparities in access to pandemic fiscal support, much of which was delivered through fintech platforms—for reasons of both speed and hygiene, given their contactless nature).

by the use of alternative credit scoring and related technologies, as discussed above. Importantly, lower income, less educated consumers typically have lower levels of technological and financial literacy, and thus are more susceptible to exploitation of their ignorance by unscrupulous lenders, with attendant regressive effects. At the same time, to the extent that lenders are subject to and complying with the FCA's rules on affordable credit (and alternative credit scoring improves the accuracy of affordability assessment),[592] we might not expect strong negative distributional effects from an increase in unaffordable lending due to alternative credit scoring.[593]

Additionally, in the absence of strong redistribution through markets or the state, the expansion of affordable credit to *higher-income* consumers due to alternative credit scoring could have regressive distributional effects.[594] Furthermore, more personalized credit pricing due to alternative credit scoring reduces the cross-subsidization of credit risk between higher and lower income consumers within credit scoring bins—which is expected to be distributionally regressive (if only to a limited extent).[595]

It should be noted that lenders can price discriminate within the boundaries of affordable lending—for example, by charging more and extracting more surplus from myopic, *low or high*-income consumers, based on a more exact estimation of their reservation price. Even though the terms of credit offered to these consumers may still be affordable, consumers who shop around would find a better offer. To the extent that low-income consumers are more likely to observe higher credit costs due to data-driven price discrimination in this way, the effect is likely to be distributionally regressive: lenders extract

---

592 *See* ch 5, section 5.3.4.

593 *See further* ch 8, section 8.1.

594 *See* ch 5, section 5.3.3.

595 *See* n 538 and associated text.

greater surplus from low-income consumers, and low-income consumers cross-subsidize the cost of credit for high-income consumers.

6.3.1 Three hypothetical borrowers

To help articulate the hypothetical distributional outcomes due to alternative credit scoring, let us imagine three hypothetical credit invisible consumers—Jacinda, Volodymyr, and Boris. Jacinda is a high-income credit invisible; Volodymyr and Boris are low-income credit invisibles.[596] Note, the scenarios developed below do not aim to illustrate all potential distributional effects due to consumer borrowing.[597] Moreover, as already emphasised, the distributional effects due to alternative credit scoring will not be determined by just three (credit invisible) borrowers. Sub-section 6.3.2 will discuss, and identify the key takeaways from, available empirical studies of alternative credit scoring and access to credit, as well as recent market developments in alternative credit scoring practices, which are relevant to understanding the potential distributional effects due to alternative credit scoring.

6.3.1.1 Jacinda (recent graduate, high-income credit invisible)

In January 2023, Jacinda started her first job as an investment analyst for an investment bank in London. She earns £100,000 a year, well above the median household disposable income and placing her in the 'high-income' bracket.[598] Until now, Jacinda has only ever used a debit

---

[596] As discussed in section 6.1, the marginal value to lenders of alternative credit scoring is likely to be greater in the credit invisible segment, due to higher levels of creditor ignorance. However, given that credit invisibles represent only 7% of the UK population, the potential distributional effects due to the use of alternative credit scoring in the credit invisible segment should not be overstated (*see* ch 3, section 3.1).

[597] As summarised in ch 5, Table 3.

[598] ONS, 'Average Household Income, UK: Financial Year Ending 2021' <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householddisposableincomeandinequality/financialyearending2021>.

card. She also has a student loan, but hasn't started repaying it.[599] Jacinda has a thin, albeit unblemished, credit file, and a low ('poor') credit score.

Jacinda wishes to apply for a credit card for the first time. She applies to Lender A, a high street bank, which offers her a 'credit builder' card with a representative variable APR of 30 percent per annum and a £1000 credit limit.[600] Lender A uses conventional credit data from Experian and conventional statistical credit scoring models. Although Jacinda does not have a credit history, she is on the electoral roll and has a good income and stable employment (as revealed by her credit card application).

Jacinda subsequently applies to Lender B, an online non-bank fintech lender that makes more extensive use of alternative credit scoring. Drawing additionally on Jacinda's rental payments and cash flow data (accessed through an Open Banking API), Lender B offers her a credit builder card with a lower representative APR of 25 percent per annum (variable) on a £1500 credit limit, reflecting a more favourable estimate of her credit and affordability risk.[601]

In this scenario, alternative credit scoring has improved Jacinda's access to credit by increasing the observability of positive characteristics that lenders consider relevant to her creditworthiness. From a distributional perspective, improving access to affordable credit for high-income consumers like Jacinda could have a number of different outcomes, depending on whether or not such access enables them to smooth consumption, or increase their income and/or wealth levels, relative to lower-income consumers.[602] Jacinda is more likely to

---

[599] Note, all student loan repayments in the UK are contingent on income. *See* <https://www.gov.uk/repaying-your-student-loan/what-you-pay>.

[600] For illustrative credit card interest rates charged by UK high street banks, *see* <https://www.hsbc.co.uk/credit-cards/credit-builder-credit-cards/> (<https://perma.cc/LX5H-EUBU>). Of course, assuming Jacinda pays her credit balance on time each month, she won't incur the 30% APR.

[601] *See* Appendix 3, n 869 et seq and associated text (illustrative APR on Zopa credit cards in February 2023).

[602] *See* ch 5, Table 3.

use her credit card to smooth consumption rather than invest, thereby limiting the potential for better credit access due to alternative credit scoring to increase her income and/or wealth, at least not directly.[603]

Alternatively, we can imagine a scenario in which alternative credit scoring instead *increases* Jacinda's cost of credit by unveiling hidden information about her *negative* characteristics. For example, Jacinda's rental payments data could reveal that she is in arrears to her landlord, and her cash flow data could show that she is spending heavily on expensive dinners and holidays. Using alternative credit scoring, Lender B might assess Jacinda to be less creditworthy (a higher credit and affordability risk) than Lender A had assessed—resulting in a lower credit limit and higher interest rate. Increasing the cost of credit for consumers like Jacinda could have positive distributional effects if it limits consumption smoothing (and income and wealth accretion) by higher-income consumers, more so than any corresponding changes experienced by lower-income consumers.[604]

6.3.1.2 Volodymyr (recent immigrant, low-income credit invisible)

Volodymyr has a low but steady income of £15,000 per annum, before deducting housing costs.[605] He also has a variable income from temporary 'gigs', such as on-demand food delivery jobs. To fill financial shortfalls, he often takes out high-cost, short-term loans from payday lenders, and sometimes from unauthorised loan sharks. As a recent immigrant, and due to his reliance on mostly non-CRA reporting credit products, he has not built up a credit history in the UK.

[603] *See* text to n 444.

[604] *See* ch 5, Table 3.

[605] *See* Appendix 1 (defining 'low income' and poverty).

Volodymyr applies to Lender A, the high-street bank, for a credit builder card. He is immediately rejected. Under conventional statistical credit scoring, Volodymyr's low income and lack of credit history is associated with a higher credit (and affordability) risk than Lender A is willing to accept. He learns of Lender B, the online non-bank fintech lender that makes use of alternative credit scoring. Drawing on Volodymyr's cash flow and other alternative payments data, Lender B assesses Volodymyr's creditworthiness to be better than his lack of credit history suggests. They offer him a credit builder card with a 30 percent variable APR, and a £500 credit limit.

Volodymyr's cost of borrowing with the credit builder card from Lender B is significantly lower relative to borrowing from payday lenders and loan sharks, especially if he does not maintain a balance and therefore does not pay interest. From a distributional perspective, this is a positive outcome insofar as it protects Volodymyr—and consumers like him—from the regressive effects of high-cost and often unaffordable borrowing (and associated predatory practices) and improves his ability to smooth consumption due to access to more affordable credit.[606]

Alternatively, we can imagine a scenario in which, rather than improving Volodymyr's perceived creditworthiness, alternative credit scoring worsens it due to the revelation of negative information, in turn perpetuating his exclusion from formal, lower cost credit markets. As with Jacinda, this could be deemed a fairer outcome in an interpersonal and actuarial sense to the extent that it is more commensurate with Volodymyr's 'true' creditworthiness.[607] However, to the extent that it perpetuates the

[606] *See* ch 5, section 5.3.2 and Table 3; text to n 444.

[607] Arrow, n 235.

dependence of low-income consumers like Volodymyr on high-cost, unaffordable, informal credit, it is likely to be regressive from a distributional perspective.[608]

6.3.1.3 Boris (unemployed, low-income credit invisible)

Boris is unemployed and has a criminal record. He cannot subsist on social welfare benefits alone. However, due to his criminal record, lack of income, and lack of credit history, both traditional and alternative lenders are unwilling to lend to him. He has no family to support him and cannot even access government-financed concessional financing (such as 'no-interest' loans).[609] In desperation, he borrows from an unauthorised loan shark that does not carry out a credit check. However, given Boris' lack of income, he is unable to service the debt. The debt quickly balloons. Although he has no legal obligation to repay, and nothing to lose by defaulting, he experiences distress due to the threatening and abusive behaviour of the loan shark.

Alternative credit scoring will not change the plight of consumers like Boris given that he lacks the income necessary to repay debt. Indeed, for the poorest members of society like Boris, credit—money conditional on repayment—is not an appropriate mechanism for meeting their financing needs.[610]

---

[608] *See also* Iversen and Rehm, n 57 (hypothesising that alternative credit scoring will increase interest rates for high-risk borrowers due to the more precise observation of credit risk, and this will have distributionally regressive effects: 'As interest payments come out of disposable income, and insofar as disposable income is negatively correlated with default risk, the distribution of discretionary income (which is disposable income net of debt service) becomes more unequal.').

[609] *See* HM Treasury, n 94, 15 (discussing the pilot 'no interest loan scheme' designed to 'help consumers in vulnerable circumstances who struggle to access affordable forms of credit'); Fair By Design, 'No Interest Loan Scheme' <https://fairbydesign.com/no-interest-loan-scheme/>; JP Morgan, 'JPMorgan Chase Commits £1.2 Million to Fair4All Finance to Expand No Interest Loan Scheme for People on Low Incomes' (2022) <https://www.jpmorganchase.com/news-stories/jpmc-commits-1-2-million-to-fair4all-finance-to-expand-no-interest-loan-scheme>.

[610] *See further* ch 8 and Appendix 1.

6.3.2 *Insights from empirical studies and recent market developments in alternative credit scoring*

Several recent empirical studies examine the effects of alternative credit scoring (alternative data and/or ML methods) on credit market access for marginalized borrowers, such as credit invisibles and ethnic minorities.[611] There are, however, limitations to the conclusions that we can draw from these studies about the *distributional* effects due to alternative credit scoring. In addition to the limitations identified earlier (inter alia, relating to geographical scope and variation in the subject of study),[612] most of these studies focus narrowly on the impact of alternative credit scoring on credit origination and pricing decisions by lenders, and thus short-term credit outcomes for borrowers. As such, they do not generally aim to measure the affordability of credit in the hands of borrowers, nor indeed the longer-term effects of credit access and pricing on the consumption, income, and wealth levels of low- and high-income consumer populations, respectively. As discussed, these are key determinants of the distributional effects due to alternative credit scoring and consumer credit.[613]

Further limitations arise from the failure of many of these studies to incorporate the effects of regulation, such as the requirement for lenders to assess credit affordability, as well as the heavy focus on measuring discrimination on the grounds of protected characteristics, particularly race. The focus on racial discrimination limits the conclusions that we can draw from these studies about the *distributional* effects of alternative credit scoring based on variations in access to and affordability of credit across income and wealth deciles. However,

---

[611] Note, several of these studies were examined in section 6.1.1. While the prior discussion focused on the effects of alternative credit scoring on predictive accuracy in credit risk analysis, this section focuses on hypothetical and observed outcomes due to alternative credit scoring in terms of access to credit (credit origination and price). As most of these studies are based on US consumer credit markets, ethnic minorities are generally defined as African Americans ('Blacks') and (non-white) Hispanics.

[612] *See* n 560 and associated text in section 6.1.1.

[613] Di Maggio, Ratnadiwakara, and Carmichael, n 125, 2 ('researchers interested in the impact of credit on household financial health would need to follow applicants over time, which would require not only cross-sectional data at the time of origination, but longitudinal information about the same set of applicants.').

to the extent that race, income, and wealth are (strongly) correlated, the distributional effects of alternative credit scoring could be inferred from its effects on different racial groups.[614]

With these caveats in mind, the key takeaways from available empirical studies of alternative credit scoring, which are relevant to understanding its distributional effects, are as follows:

a. *Credit origination*: there is evidence that alternative credit scoring has improved access to credit—measured as increased credit origination, or loan acceptance rates—for marginalized borrowers, including high-risk credit invisibles;[615]

b. *Credit pricing*: there is also evidence that alternative credit scoring has lowered the cost of credit for these borrowers relative to the status quo;[616] however, the reduction may be greater for *low risk* marginalized borrowers (so-called 'invisible primes', like our hypothetical borrower Jacinda) than for *high risk*

---

614 *See further* Appendix 1.

615 *See* Di Maggio, Ratnadiwakara, and Carmichael, n 125 (finding that the use of alternative data in credit underwriting by the US-based fintech lender Upstart increased loan origination to previously marginalized borrowers—including high-risk, low credit score, credit invisible borrowers who would have been rejected under conventional statistical credit scoring models); Jagtiani and Lemieux, n 547 (finding that the use of alternative data by Lending Club expanded access to credit and lowered the cost of credit for higher risk subprime borrowers). Note that, although these studies do not disaggregate borrowers by income level, given that income and credit risk are strongly correlated, we might infer income level from risk, i.e., a low risk/high credit score borrower is more likely to be high-income, and vice versa. *See also* Agarwal et al, n 185 (finding that the use of alternative data expanded access to credit for credit invisibles, without adversely affecting default outcomes); Fuster et al, n 557 (estimating that the use of ML in credit underwriting will increase loan origination to minority groups, specifically Hispanic and African American borrowers); Bartlett et al, n 566. A related set of studies finds that fintech lenders have increased access to credit in areas underserved by traditional banks. However, the mechanisms producing these outcomes extend beyond alternative credit scoring and include the greater ease of access to online lenders in banking 'deserts', the state of the local economy, and increased competition (et c.). *See e.g.* Julapa Jagtiani and Catherine Lemieux, 'Do Fintech Lenders Penetrate Areas That Are Underserved By Traditional Banks' (FRB of Philadelphia Working Paper No 18-13, 2018) <https://ssrn.com/abstract=3178459>; Jagtiani et al, n 585 (finding that fintech lenders have been effective in expanding mortgage access to borrowers with weaker credit scores, and in areas with higher mortgage denial rates from traditional bank lenders). However*, see* Huan Tang, 'Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?' (2019) 32(5) The Review of Financial Studies 1900 (finding that 'credit expansion resulting from P2p lending likely only occurs among borrowers who already have access to bank credit' i.e., p2p lending, here by Lending Club and using conventional credit scoring, primarily acts as a substitute for lending to infra-marginal bank borrowers, however, may complement bank lending by offering smaller loans).

616 *See e.g.* Jagtiani and Lemieux, n 547 (finding that the use of alternative data by Lending Club lowered the cost of credit for higher risk subprime borrowers). *See also* Bartlett et al, n 566 (but focusing on racial disparities and attributing the reduction in the cost of credit to increased competition from fintech lenders).

marginalized borrowers (like our hypothetical borrower Volodymyr),[617] and some high-risk borrowers may instead observe an *increase* in their cost of credit, or probability of credit denial, relative to the status quo.[618]

c. *Temporality and cyclicality*: there is some evidence to suggest that these effects are temporal and cyclical, i.e., lenders expand credit access to high-risk marginalized borrowers in the short term, but over the longer term (over the course of the business cycle), they evolve towards using their data-driven insights to 'cherry-pick' low-risk, marginalized borrowers (such as the invisible primes), rather than increasing access to credit for high-risk marginalized borrowers.[619]

The last finding, (c), appears to be supported by anecdotal evidence of the evolution of fintech lending in the UK in recent years. Fintech lenders, such as Zopa, that originated the distributional promise of alternative credit scoring have, in recent years, tightened their underwriting criteria and evolved towards lending to lower risk consumers with 'good' credit

---

[617] Di Maggio, Ratnadiwakara, and Carmichael, n 125.

[618] Fuster et al, n 557 (estimating that African American and Hispanic borrowers are more likely to be offered higher interest rates, and observe greater within-group dispersion of rates, relative to White and Asian borrowers due to the use of ML for credit underwriting, explained by the improved observation of borrowers' characteristics, including previously hidden negative characteristics, and greater price differentiation and discrimination based on consumers' credit risk and demand). *See also* Ben-David et al, n 14 (observing that, due to various institutional constraints, fintech lenders do *not* leverage alternative data to reduce the cost of lending to subprime borrowers, and credit pricing remains very sensitive to FICO score bins).

[619] Di Maggio, Ratnadiwakara, and Carmichael, n 125 (hypothesising that, over time, lenders will use their data-driven insights due to alternative credit scoring and fintech lending to 'cherry-pick' the best borrowers—such as the invisible primes—and 'skim the most creditworthy segment of the market for themselves'); Seth Freedman and Ginger Z Jin, 'Learning By Doing With Asymmetric Information: Evidence From Prosper.com' (2011) <http://www.nber.org/papers/w16855> (finding that over time, the US-based p2p lender, Prosper, excluded sub-prime borrowers and evolved towards the population served by traditional credit markets); Marco Di Maggio and Vincent Yao, 'Fintech Borrowers: Lax Screening or Cream-Skimming?' (2021) 34(10) The Review of Financial Studies 4656; Jess Cornaggia, Brian Wolfe and Woongsun Yoo, 'Crowding Out Banks: Credit Substitution by Peer-To-Peer Lending (2018) <http://dx.doi.org/10.2139/ssrn.3000593>; Calebe de Roure, Loriana Pelizzon, Anjan Thakor, 'P2P Lenders Versus Banks: Cream Skimming or Bottom Fishing?' (2022) 11(2) The Review of Corporate Finance Studies 213.

scores.[620] The cyclicality of fintech lending, and its distributional effects, may be explained by changes in macro-economic conditions and laws. That is, lenders—particularly less regulated, non-bank fintech lenders—were more willing and able to expand credit access to high-risk borrowers during periods of low interest rates and relatively light-touch regulation.[621] As prudential and consumer protection regulation tightened,[622] and, more recently, as macroeconomic conditions deteriorated, fintech lenders tightened their underwriting criteria. Indeed, it is arguable that macro-fundamentals and the relative pro- or counter-cyclicality of regulation—rather than technological advances per se—played the more significant role in shaping the development of alternative credit scoring and the associated distributional outcomes due to access to credit.[623]

Other factors that have shaped, and continue to shape, the trajectory of alternative credit scoring in the UK in recent years, and thus influence its potential distributional effects, include the development of the Open Banking platform, changes in social norms relating to the commodification of personal data, and tighter restrictions imposed by companies such as Facebook on data collection by third parties (as well as the effects of these developments on competition in consumer credit markets). As discussed in Chapter 3, these developments

[620] For example, Zopa announced a tightening of its lending policy in the wake of Covid-19. *See* Zopa, <https://www.zopa.com/coronavirus-and-my-investment>. *See further* Appendix 3 and n 130 (insolvency of Wonga).

[621] However, *see* Ben-David et al, n 14 (finding that fintech lenders did not lower the cost of credit, due to lower competition in the nonprime sector, disincentives to efficiently screen borrowers, and incentives to maximise lending volumes due to originate-to-distribute business models).

[622] *See* ch 4, section 4.2.2.

[623] Mian and Sufi, n 109 (discussing the 'fundamentals' view of household indebtedness). An alternative explanation is that fintech lenders are funding unprofitable loans in the short term to subsidize market share growth (*see* Ben-David et al, n 14). However, *see* Di Maggio et al, n 125, 6 (finding that loans granted by the fintech Upstart to borrowers deemed high risk under conventional statistical credit scoring models were *not* less profitable).

have collectively narrowed the focus of alternative credit scoring to the use of alternative *financial* data, and *positive* financial data more specifically.[624]

Positive-only alternative data sharing products, such as Experian Boost, could subsidize a borrower's perceived credit risk (by suppressing relevant negative data) and/or reduce the scope for price discrimination based on borrowers' misperceptions.[625] To the extent that this reduces the cost of credit for *lower-income* consumers, like Volodymyr, it could have positive distributional effects. In this sense, consumer credit markets are distributionally fairer with a degree of informational asymmetry, i.e., when the cost of lending to the proverbial 'lemons' is partly shared by the proverbial 'cherries'.[626] Alternatively, where positive-only data sharing reduces the cost of credit for *high-income* consumers, like Jacinda, it is more likely to be distributionally regressive.

At the same time, however, lenders are likely to adjust for the possibility of negative data suppression, particularly in credit market segments characterized by high levels of creditor ignorance. From a distributional perspective, this may be desirable if it means that lenders ration credit due to creditor ignorance,[627] and this mitigates the expansion of unaffordable credit (to both low and high-income consumers). It could also be distributionally desirable if it prevents lenders from cherry-picking and expanding affordable credit to high-income consumers, thereby improving the position of the already well-off.[628] It

---

[624] *See* ch 3, section 3.2.1.

[625] *See* section 6.2.

[626] *See also* Iversen and Rehm, n 57; Mark Jansen, Fabian Nagel, Constantine Yannelis, Anthony Zhang, 'Data and Welfare in Credit Markets*,* (2022), <https://ssrn.com/abstract=4015958> (finding that greater data availability increases lenders' surplus, and data suppression—in their case, of bankruptcy data—increases consumers' surplus). For a related discussion in the insurance context, *see* Guy Thomas, *Loss Coverage: Why Insurance Works Better With Some Adverse Selection* (CUP 2017).

[627] Stiglitz and Weiss, n 64; n 315 et seq and associated text.

[628] *See* ch 5, Table 3.

is distributionally *undesirable*, however, if it prevents lenders from expanding access to affordable credit to low-income consumers, on balance, or increases the cost of credit for these consumers. Indeed, studies have found that incorporating additional alternative data is more beneficial for low-income credit consumers in terms of improving market access, relative to suppressing negative data.[629]

***

To summarise, to the extent that available empirical data can be a reliable guide, it suggests that, at least in the short term, alternative credit scoring contributes to an increase in the *volume* of lending to higher risk, lower income borrowers. Evidence on the effects of alternative credit scoring on the *cost* of borrowing is, however, mixed. More particularly, available data does not tell us anything about the *affordability* of borrowing due to alternative credit scoring, nor the effects of borrowing on the consumption, income, and wealth levels of low and high-income populations respectively—information that is necessary to ascertain the overall distributional effects of alternative credit scoring.

Further empirical investigation is thus needed to evaluate the distributional promise of alternative credit scoring. Ideally, this would include a longitudinal study of credit and life outcomes due to alternative credit scoring for borrowers in different income and wealth

[629] *See e.g.* Michael A Turner, Patrick Walker, Kazumi Moore, 'Addition is Better than Subtraction' (*Policy and Economic Research Council*, 2020) <https://www.perc.net/wp-content/uploads/2020/06/credit-data-suppression-deletion-addition.pdf> (finding that 'suppression/deletion will greatly reduce access to affordable sources of credit, harming consumers, but particularly lower to moderate income persons, as well as the young and members of minority communities.'). There is a related literature studying the effects on employment outcomes of suppressing criminal history, particularly in the US context under so-called 'ban the box' laws. *See e.g.* Jennifer Doleac and Benjamin Hansen, 'The Unintended Consequences of "Ban the Box": Statistical Discrimination and Employment Outcomes When Criminal Histories Are Hidden' 38(2) 2020 Journal of Labour Economics 321.

deciles.[630] The concluding chapter will discuss directions for further research along these lines.[631]

6.4 Fintech adoption by consumers

The analysis thus far has focused on the distributional effects of the adoption of alternative credit scoring and its underlying technologies by *creditors,* and the supply and demand-side forces that drive these effects.[632] This section will deepen the analysis to incorporate the effects of *consumers* adopting the same technologies in the form of consumer-helping digital solutions. Building on the analysis of informational asymmetries in consumer credit markets in sections 6.1 and 6.2, there are two main ways in which the adoption of digital consumer-helping solutions by consumers could influence the distributional effects due to the use of alternative credit scoring, and related technologies, by creditors: first, by reducing consumer ignorance; and second, by increasing/preserving a degree of creditor ignorance.

6.4.1 Reducing consumer ignorance

Third-party, data-driven consumer-helping tools can help to make less financially sophisticated consumers more informed about the terms and performance of different credit

[630] Hartfree and Collard, *Poverty, Debt and Credit*, 29 ('We lack evidence about how the experience of credit use varies across low-income households e.g. between households in the bottom income quintile compared to households in the bottom 20 to 50 per cent'). For previous studies in this vein, *see e.g.* Richard Disney, Sarah Bridges, and John Gathergood, 'Drivers of Over-indebtedness: Report to the Department of Business, Enterprise, and Regulatory Reform' (Jun 1, 2008) (mixed methods study of the drivers of overindebtedness in the UK since the 1990s); Chris Dearden, Jackie Goode, Grahame Whitfield, and Lynn Cox, 'Credit and Debt in Low-Income Families' (June 2010) <https://www.jrf.org.uk/sites/default/files/jrf/migrated/files/credit-debt-low-incomes-full.pdf> (both as cited in Hartfree and Collard, *Poverty, Debt and Credit* (reviewing literature on over-indebtedness among low-income households). *See also* Sullivan et al, n 41 (examining consumer bankruptcy data).

[631] *See* ch 8, section 8.2.

[632] *See also* FSB, 'Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications' (2017) <https://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/>, 9 (discussing the demand and supply side drivers of AI and ML adoption in financial markets).

products, thereby improving personal financial management by these consumers and their ability to shop around for the best price (lowering search/switch costs and increasing credit market competition).[633] In turn, these tools offer to mitigate unaffordable and/or higher cost borrowing, and the attendant regressive effects, due to both poor personal financial management by (low-income) consumers, and the exploitation of their ignorance by lenders.

For example, digital tools can help borrowers compare the terms of credit contracts more effectively, thereby reducing the effort and cost required for borrowers to inform themselves and shop around.[634] Although certain aspects of credit products (i.e., interest rates and fees) are often tailored to individual borrowers—and increasingly so with data-driven personalised pricing—for the most part they rely on standard form contracts. In theory, ML systems can be trained to focus on the key terms that are likely to vary. ML can also be used to link identified patterns in contractual terms with patterns in other, related data—such as data on the marketing behaviour of credit providers, reviews left by consumers, and even the past behaviour of consumers using these products—to evaluate their benefits and disadvantages. Importantly, these tools offer to complement and improve upon existing (analogue) personal financial management and education solutions, including government-provided services such as debt advisory and financial literacy programs, the FCA's consumer helpline, and the Financial Ombudsman Service.[635] They also offer to

[633] *See* section 6.2; Hartfree and Collard, *Poverty, Debt and Credit*, 11 (identifying 'poor money management and low financial awareness' as a reason that households get into financial difficulties and arrears); Ausubel, n 306, 68ff (attributing the failure of competition in credit card markets to high search/switch costs due partly to consumer myopia). On digital intermediaries, *see generally* Rory Van Loo, 'Rise of the Digital Regulator' (2017) 66 Duke Law Journal 1267.

[634] *See e.g.* Scott R Peppet, 'Freedom of Contract in an Augmented Reality: The Case of Consumer Contracts' (2012) 59 UCLA Law Review 676; Michal Gal and Niva Elkin-Koren, 'Algorithmic Consumers' (2017) 30(2) Harvard Journal of Law and Technology 309; FCA, 'Applying Behavioural Economics at the Financial Conduct Authority' at <https://bit.ly/33ghiit>.

[635] <https://www.financial-ombudsman.org.uk/>; <https://moneyandpensionsservice.org.uk>.

improve upon existing 'Web 1.0' digital consumer-helping solutions, such as the product comparison websites Which? and moneysupermarket.com.[636]

As discussed, however, greater personalisation and product differentiation in digital consumer credit markets, and the greater ability of firms (particularly 'TechFins') to capture consumers in digital ecosystems, could limit the scope even for digital consumer-helping tools to meaningfully improve consumers' ability to shop around for the best price, and in turn mitigate regressive distributional effects due to price discrimination and unaffordable borrowing, particularly by lower-income consumers.[637] The behavioural weaknesses of consumers could also prevent them from seeking out these tools in the first instance, or understanding and acting on the advice that they offer.[638] More particularly, tools that simply give consumers a greater volume, or more convenient access to, information about the terms of credit products will only solve one aspect of the consumer ignorance problem. Even if consumers were to read the information distilled by third-party digital helpers (and behavioural research indicates that they do not),[639] consumers do not always respond 'rationally' to potential risks, including risks due to the use of their personal data—such as higher cost and unaffordable credit resulting from data-driven exploitation of their misperceptions.[640]

---

636 <https://www.moneysupermarket.com>; <https://www.which.co.uk/money/credit-cards-and-loans>.

637 n 579 et seq and associated text.

638 *See* sections 4.2.1.2 and 6.2, and *further* HM Treasury, 'Review of the Money Advice Service' (2015) <https://www.gov.uk/government/publications/review-of-the-money-advice-service>; Dmitry Kingsford-Smith and Olivia Dixon, 'The Consumer Interest and the Financial Markets' in Niamh Moloney, Eilis Ferran and Jennifer Payne (eds) *The Oxford Handbook of Financial Regulation* (OUP 2015), 707–710.

639 *See* Ben-Shahar and Schneider, n 319.

640 Online privacy policies are notoriously vague, with catch-all clauses enabling service providers to collect, store and re-use customer data for broadly-defined related purposes. *See e.g.* Natwest, n 181; Google, 'Why Google Collects Data' <https://policies.google.com/privacy?hl=en-US#whycollect>; Katherine J Strandburg, 'Monitoring, Datafication, and Consent: Legal Approaches to Privacy in the Big Data Context' in Lane et al n 567; Solove, n 388 (discussing the challenges of privacy self-management).

ML and data-driven tools could, however, help consumers to overcome these behavioural biases by 'nudging' them into making better choices with respect to credit as well as the use of their personal data.[641] In recent years, several ML and data-driven third-party consumer finance apps have been developed to help consumers calculate the likely cost of credit, set up automatic savings and debt repayments, and issue alerts when they overspend or go into overdraft, among other things.[642] Many of these tools leverage Open Banking to access consumers' data. The same technologies are driving the growth of 'robo-advisors' and personalized virtual financial assistants, which could help to further de-bias consumers and improve personal financial decision-making by consumers.[643]

Of course, as before, the effectiveness of these tools depends on consumers adopting them to begin with. More behaviourally biased, less financially and/or technologically literate consumers—who are also more likely to be lower-income—are less likely to recognize the value of third-party de-biasing tools to adopt them or use them effectively. The effectiveness of these tools also depends on the extent to which they substitute for, or merely assist, the human borrower. Where a virtual assistant or comparison tool is only one factor in the consumer's decision-making process, the scope for biased decision-making remains—the consumer, driven by their irrationality, can simply ignore the prompt or advice. Indeed, to the extent that these tools are more likely to help *higher*-income consumers access affordable credit, and avoid unaffordable credit, their effect could be distributionally regressive.[644]

---

641 On nudging, *see generally* Richard H Thaler and Cass R Sunstein, *Nudge: Improving Decisions About Health, Wealth, and Happiness* (Yale University Press 2008).

642 *See e.g. Empower* <https://empower.me>. Lenders offer similar proprietary solutions. *See* Appendix 3 (describing personal financial management tools offered by the fintech lender Zopa via its mobile app). There are, however, principal-agent risks that could compromise the effectiveness of lender-provided solutions.

643 *See e.g.* Cleo <https://www.meetcleo.com/>.

644 Ch 5, Table 3.

Moreover, it is questionable whether third-party solutions that reduce consumer ignorance—including through de-biasing—could ever overcome the informational and behavioural advantage of lenders. As discussed in Chapter 4, lenders enjoy privileged access to data about product use patterns and performance, gleaned over time from multiple transactions with multiple borrowers.[645] Relatedly, the nature of feature-rich, networked personal data means that potential inferences from that data are technically unobservable at the point of consenting to data processing—whether to the average consumer or to an independent consumer-helping solutions, inhibiting their ability to anticipate potential harms due to data processing by lenders. For example, a person's mouse tracking data can reveal their propensity to develop conditions such as Alzheimer's disease, an inference that would generally be considered unintuitive.[646] Detailed yet unforeseeable behavioural inferences can also be obtained by aggregating personal data with seemingly unrelated and/or non-personal data, such as demographic or environmental data.[647]

There are also externalities to the processing of personal data.[648] A consumer's data can yield detailed, potentially harmful inferences about third parties, particularly their friends and associates, and members of similar social/affinity groups, which the latter are unable to control. As such, independent consumer-helping tools may be unable to effectively anticipate the inferences that a creditor could glean about a consumer from not only their personal data but also the data pertaining to *other* consumers, as well as non-personal data, nor least the distributional effects of these inferences. The informational and behavioural advantage of creditors in these ways is expected to be more pronounced in the case of

---

645 *See* n 322 et seq and associated text.

646 Adriana Seelye et al, 'Computer Mouse Movement Patterns: A Potential Marker of Mild Cognitive Impairment' (2015) 1(4) Alzheimers Dement (Amst) 472.

647 Mittelstadt, n 568.

648 *See* n 567 et seq and associated text.

TechFins.[649] TechFins could also more effectively leverage their market power to obstruct independent, third-party digital helpers.[650]

6.4.2 Preserving/increasing creditor ignorance

In addition to reducing consumer ignorance, and the scope for lenders to price discriminate by exploiting consumer ignorance, consumer-helping solutions could also function to increase (preserve a degree of) creditor ignorance, and thereby reduce creditors' informational and behavioural advantage over borrowers. For example, 'privacy-enhancing technologies' ('PETs'), such as ad and cookie blockers, and privacy-preserving browser settings, such as the Tor Browser and Apple's 'do not track' feature, reduce lenders' ability to (legally) collect data about borrowers without their consent.[651] As discussed in Chapter 3, these developments have partly forced the evolution of alternative credit scoring towards the greater use of alternative *financial* data, rather than social and behavioural data.[652]

Whereas PETs obfuscate and limit the processing of consumer data, other solutions allow consumers to selectively share their data with lenders. This includes, for example, Open Banking-based tools such as Experian Boost, discussed earlier.[653] Similarly, blockchain-based tools, such as the Bloom 'credit chain',[654] and decentralized 'data stores', such as the

---

649 *See* n 577 et seq and associated text.

650 *See* Rory Van Loo, 'Digital Market Perfection' (2019) 117 Michigan Law Review 815. A related consideration is the risk of deadweight efficiency losses due to a technological 'arms race' between lenders—seeking to extract and manipulate consumer data—and consumers—seeking to defend and control the use of their data. *See* Gal and Elkin-Koren, n 634, 329; Wagner and Eidenmüller, n 566, 588-589.

651 Ian Goldberg, 'Privacy Enhancing Technologies for the Internet III: Ten Years Later', in Alessandro Acquisti et al (eds) *Digital Privacy: Theory, Technologies and Practices* (New York 2007); Nick Statt, 'Apple Updates Safari's Anti-Tracking Tech with Full Third-party Cookie Blocking' *The Verge* (March 24, 2020) <https://bit.ly/2GXWTZ0>.

652 *See* ch 3, section 3.2.1.

653 Ibid.

654 <https://bloom.co/>.

Mydex Platform,[655] offer consumers greater control over the use of their personal data. More generally, technology-savvy consumers could game their data and credit scores, whether by obfuscating negative behaviour or falsifying positive ('creditworthy') behaviour. [656]

As before, however, the use of data obfuscation and selective data-sharing strategies by consumers, and their effectiveness in mitigating adverse distributional outcomes due to alternative credit scoring, is limited by informational and behavioural market failures in digital consumer credit markets. More behaviourally biased, less financially and/or technologically literate consumers—who are more likely to be lower-income—are less likely to recognize the value of these solutions to adopt them in the first instance. Furthermore, the inferences due to alternative credit scoring are less intuitive to consumers than those due to conventional statistical credit scoring. For example, it is relatively straightforward for consumers to understand that a good credit history is positively associated with creditworthiness. In contrast, the association between social media activity data—'likes' and posts, or the size and composition of one's social network—and creditworthiness is largely unintuitive.[657] More particularly, consumers cannot fully anticipate whether obfuscating or selectively sharing this data will mitigate potential negative outcomes, such as unaffordable borrowing, or pre-empt potential positive outcomes, such as affordable borrowing, nor the associated individual and distributional effects. Consumers, particularly low-income consumers, may also not have a real choice to obfuscate or selectively share their data.[658]

---

655 <https://mydex.org/>.

656 For example, a consumer could register a relative's fitness tracking device to their name in order to piggy-back off the latter's positive health data, without making any real-world improvements to their own health. It is evidently more difficult to game financial credit data, such as account transaction and credit history data, than certain categories of alternative social and behavioural data. *See* Berg et al, n 186, 34-35; Wei et al, n 182.

657 CFPB, n 157, 17-18.

658 Lenders' terms of use (including website terms) often prevent consumers from adopting tools such as cookie blockers. In this regard, access to (a certain amount of) personal data is a condition for access to credit.

Relatedly, adverse individual and distributional outcomes due to personal data processing (in the context of consumer credit allocation)—such as unaffordable debt—typically emerge over the longer-term and depend on the cumulative behaviour of multiple consumers, in ways that cannot be fully anticipated nor managed by individual consumers or individual consumer-helping tools. As a result, consumers, particularly those that are more present-biased, will tend to hand over more personal data to lenders, and reveal more personal information, than they are aware of or prefer, normatively.[659]

Furthermore, even if consumers successfully adopt these tools—such as PETs or cookie blockers—their effectiveness in mitigating adverse (distributional) outcomes due to alternative credit scoring may be limited. Among other things, these tools can only limit lenders' future access to data: they cannot prevent lenders from processing data that has already been collected, aggregated, commingled, and embedded in ML models, and the inferences due to those models.[660] As discussed earlier, they also cannot limit the inferences that lenders derive from processing data pertaining to other consumers (i.e., those who do not obfuscate), and non-personal data. And, as discussed earlier, lenders would be expected to adjust for increased ignorance by charging more or lending less.[661]

Due to these market failures, firms are also unlikely to implement extensive privacy-preserving features and techniques—such as anonymisation, differential privacy, and encryption—in the absence of a legal obligation to do so.[662] The market alone does not

[659] Ignacio N Cofone, 'Nothing to Hide, But Something to Lose' (2020) 70(1) University of Toronto Law Journal 64.

[660] Carl Öhman and Nikita Aggarwal, 'What if Facebook Goes Down? Ethical and Legal Considerations for the Demise of Big Tech' 9(3) Internet Policy Review, 8. *See further* ch 7, section 7.2.

[661] *See* n 627 et seq and associated text.

[662] Although there is evidence that some consumer credit and other financial services firms are using anonymisation and synthetic data techniques, these practices remain nascent. *See e.g.* Hazy, <https://hazy.com/industries>.

create strong enough incentives for firms to optimise for privacy over profit—for example, by favouring the use of de-identified data over personally identifiable data—if the latter offers greater predictive, and therefore commercial, value. Indeed, to the extent that firms are adopting 'privacy-preserving' features, it seems that they may be using privacy as a pretext to consolidate their market share.[663] For example, while features such as Apple's 'ask app not to track' limit the processing of personal data by *third-party* apps, they do not stop Apple itself from processing personal data. The pretext of privacy could thus further expand the TechFin advantage, by giving them preferential access to personal data and embedding consumers even deeper in their 'walled garden' digital ecosystems.[664]

To summarize, under conditions of large and persisting asymmetry of knowledge and power between lenders and borrowers (which favour lenders), behavioural weaknesses of borrowers, and negative externalities to data processing, individualised, market-based consumer-helping solutions may be unlikely to effectively mitigate regressive distributional effects due to alternative credit scoring, nor harness progressive distributional effects—whether by increasing creditor ignorance or reducing consumer ignorance. Indeed, these tools could encourage regressive distributional effects to the extent that they are more likely to be adopted by high-income, technologically and financially sophisticated consumers, who as a result increase their chances of mitigating unaffordable debt and accessing more affordable credit. Similar considerations afflict individualised, market- and rights-based remedies under consumer credit and information laws—as examined in the next chapter.[665]

663 Rory Van Loo, 'Privacy Pretexts', Cornell Law Review (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4048919>

664 Jonathan Zittrain, *The Future of the Internet—And How to Stop it* (Yale University Press, 2008); Van Loo, ibid.

665 Katherine J Strandburg, 'Free Fall: The Online Market's Consumer Preference Disconnect' (2013) University of Chicago Legal Forum 95.

7 INFORMATION LAW AS A SITE OF DISTRIBUTIVE JUSTICE

This chapter extends the distributional analysis of alternative credit scoring to include the effects of data protection regulation, pursuant to the DPA 2018/GDPR.[666] The analysis thus far has examined consumer credit regulation as a 'site' or locus of distributive justice in consumer credit markets.[667] As consumer credit markets become increasingly data-driven, data protection regulation will be an increasingly salient site of distributive justice in these markets. In recent years, developments in EU data protection law pursuant to the GDPR have introduced major changes to the UK's data protection regime.[668] More particularly, the GDPR sought to strengthen the rights of data subjects to control their data, as well as the obligations of firms to mitigate the harms due to data processing.

The chapter examines how the legal obligations of credit providers and credit-related firms *qua data controllers and processors*, as well as the rights of borrowers *qua data subjects*, pursuant to the DPA 2018/GDPR, could additionally influence the distributional effects due

---

[666] The prior literature has focused on the impact of information privacy laws on allocative efficiency in consumer credit markets due to restrictions on credit information sharing between lenders, rather than distributional outcomes *per se*. *See e.g.* Bertola, Disney, and Grant, n 396, also at 22 ('information sharing arrangements are more pervasively shaped by official regulatory frameworks in the case of household borrowing because an individual's privacy is more likely than a corporation's to be protected by regulators'); Tullio Jappelli and Marco Pagano, 'The Role and Effects of Credit Information Sharing', in Bertola, Disney, and Grant (eds), n 396, 347ff ('However, one should not necessarily take a negative view of the effect of privacy laws on credit information systems…a moderate concern for privacy may also indirectly serve economic efficiency').

[667] *See* ch 5, section 5.3.4. On the terminology of a 'site' of distributive justice, *see* Cohen, n 3.

[668] n 384 and associated text.

to alternative credit scoring and datafied consumer credit markets more broadly.[669] The working hypothesis will be that, whereas permissive information laws enabled the growth of alternative credit scoring,[670] more stringent information law pursuant to the DPA 2018/GDPR could constrain it, and thus limit the distributional effects (positive as well as negative) due to alternative credit scoring.

The chapter finds that, in practice, the distributional effects due to the DPA 2018/GDPR are likely to be limited. Despite its greater emphasis on the protection of fundamental rights, and much early commentary to the contrary, the DPA 2018/GDPR regime remains relatively permissive. As such, it is unlikely to significantly influence the distributional effects due to alternative credit scoring—whether by amelioration or exacerbation. This is partly a function of the design of this regime, especially its emphasis on private, contractual mechanisms such as user consent to manage personal data processing. It is partly a function of the political economy and private interests—notably, the outsize role that data and data-rich tech firms play in the modern economy, and consequently the powerful commercial interests that inhibit strict enforcement of this regime.[671] It is also a function of a lack of interpretative guidance and weak enforcement of data protection regulation in consumer financial markets.

The chapter proceeds as follows. Section 7.1 begins by examining, at a high-level, the normative goals of the DPA 2018/GDPR regime, which motivate the working hypothesis stated above. Sections 7.2 and 7.3 examine the scope, and limits, of the DPA 2018/GDPR regime as a site of distributive justice in consumer credit markets, focusing on two key

---

[669] The enforcement of the consumer credit and data protection regulatory regimes is coordinated between the FCA and ICO. *See* ICO and FCA, 'Memorandum of Understanding Between the Financial Conduct Authority and the Information Commissioner' (Feb 18, 2019) <https://ico.org.uk/media/about-the-ico/documents/2614342/financial-conduct-authority-ico-mou.pdf>.

[670] *See* ch 4.

[671] Bank, n 398; n 242 (discussing private interest theories of regulation).

aspects of this regime: individual rights to control the processing of personal data (section 7.2); and data protection obligations of firms (section 7.3).

7.1 The DPA 2018/GDPR and the normative goals of data protection regulation

As with the DPD 1995/DPA 1998 data protection regime, examined in Chapter 4, the DPA 2018/GDPR regime is characterised by a duality between efficiency and non-efficiency goals. It seeks to both enable the aggregate economic benefits due to data processing, as well as prevent harm to individuals arising from the misuse of their data.[672] This duality is evident in the title of the GDPR, which refers to both the 'protection of individuals with regard to the processing of their data' as well as the 'free movement of personal data'.[673] Relative to the previous data protection regime, however, the GDPR/DPA 2018 regime increases the valence of non-efficiency concerns, at least on a literal and teleological reading. More specifically, it elevates the protection of fundamental rights under EU law, in particular the right to the protection of personal data (the 'right to data protection').[674] It also emphasises the protection of the fundamental right to non-discrimination. Indeed, the GDPR, and associated regulatory guidance, specifically highlight discrimination in credit scoring as a data processing harm and a motivation for strengthening data protection regulation.[675]

[672] Lynskey n 273, 76ff (discussing the twin 'economic and social' goals of EU data protection law). On the normative goals of the DPD 1995/DPA 1998 and previous data protection regimes, *see* ch 4, sections 4.1.2.2 and 4.2.3.

[673] Fuster, n 290, 125-126 (describing these as the 'fundamental rights dimension' and the 'internal market facet', respectively), at 130 (referring to 'dual' objectives)

[674] GDPR, recital 2 (stating that 'The principles of, and rules on the protection of natural persons with regard to the processing of their personal data should, whatever their nationality or residence, *respect their fundamental rights and freedoms, in particular their right to the protection of personal data*'. Emphasis added).

[675] GDPR, recital 75 (discussing the risk of discrimination due to the processing of personal data), recital 71 (discussing automatic credit decision-making and behavioural profiling), recital 91. *See also* Article 29 Data Protection Working Party, 'Guidelines on Data Protection Impact Assessment (DPIA) and Determining Whether Processing is "Likely to Result in High Risk" for the Purposes of Regulation 2016/679'

The greater emphasis on fundamental rights under the GDPR, particularly the right to data protection, is due to developments in both EU fundamental rights law as well as the political economy. The EU Charter and, latterly, the Treaty of Lisbon elevated the status of fundamental rights in EU law.[676] Notably, the Treaty of Lisbon gave binding status to the right to data protection.[677] The GDPR is explicitly based on this newly recognized right.[678] The right to data protection is, in turn, rooted in the right to (information) privacy, i.e., it grants individuals enhanced control over more types of personal data, in more contexts.[679]

Regarding changes in the political economy, advances in technology and the increase in cross-border data flows since the passage of the DPD 1995/DPA 1998 amplified public concern about privacy and other risks to individuals due to the processing of personal data—in many ways echoing the socio-technical changes that first spurred the growth of data protection regulation in the early 1970s.[680] The Snowden revelations in 2013 triggered a crisis of public trust in the handling of personal data by large institutions, particularly

---

<https://ec.europa.eu/newsroom/article29/item-detail.cfm?item_id=611236>, 8-12 (setting out the types of data processing that are likely to result in a high risk to fundamental rights and freedoms, which includes credit scoring). Note that the designation of AI credit scoring systems as de facto 'high risk' under the proposed EU AI Act is also shaped by the risk of discrimination in access to financial resources or essential services. *See* European Commission, 'Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts COM/2021/206 final' <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206>, recital 37. On the right to non-discrimination under EU law, *see* EU Charter, arts 21, 33, 34, 35.

676 The EU Charter recognizes an independent right to data protection (Article 8), in addition to the right to privacy (Article 7).

677 Treaty on the Functioning of the European Union ([2012] OJ C326/47 [Treaty of Lisbon Amending the Treaty on European Union and the Treaty establishing the European Community [2007] OJ C306/1]), art 16(1).

678 GDPR, Introductory text and recital 1. *See generally* Lynskey, n 273, 46-88; Fuster, n 290, 2, 163-212. In contrast, the DPD 1995 (which predates the adoption of the EU Charter) was based on the EU's internal market competence under Article 114 TFEU (Article 100a TEC). *See* DPD 1995, introductory text.

679 GDPR, recitals 7, 68, 75, and 85 (referring to data control); Lynskey, n 273 90. Privacy scholars, at least in the West, have long considered individual control over personal data to be a key facet of information privacy. *See e.g.* Alan F Westin, *Privacy and Freedom* (Athenaeum 1967); Anita L Allen, 'Privacy as Data Control: Conceptual, Practical and Moral Limits of the Paradigm' (2000) 32 Connecticut Law Review 861.

680 *See* ch 4, section 4.1.2.

government institutions. As Laurer and others have argued, this 'salience shock' strengthened the rationale for data protection law and diluted the effectiveness of lobbying by powerful interest groups (including the US and UK governments), who under a different political climate may have been more successful in watering down the GDPR.[681]

7.2 Individual rights to control personal data

Data protection regulation has long given consumers the right to access and control the processing of their personal data.[682] The DPA 2018/GDPR sought to strengthen and extend these rights. Inter alia, it raises the threshold of consumer consent as a lawful basis for processing personal data. Consumer consent can now only provide a lawful basis for data processing if it is affirmative (often referred to as 'opt-in' rather than 'opt-out' consent).[683] The DPA 2018/GDPR also gives consumers new and/or broader rights to: have their personal data erased (the so-called 'right to be forgotten');[684] to be given more information about data held about them pursuant to the right to data access (known as a 'subject access request');[685] and to receive their personal data in a 'structured, commonly used and machine readable format' and 'transmit those data to another controller' (the so-called 'right to data

681 Laurer and Seidl, n 170.

682 *See* ch 4, section 4.1.2. As discussed therein, consumers' rights under data protection law were both pre-empted, and reinforced, by consumer credit law—notably, the right for consumers to access and correct errors in their credit files.

683 GDPR, Art 4(11) ('"consent" of the data subject means any freely given, specific, informed and unambiguous indication of the data subject's wishes by which he or she, by a statement or by a clear affirmative action, signifies agreement to the processing of personal data relating to him or her;'). *See also* GDPR, recital 32. This should be contrasted with the thinner definition of consent under the DPD 1995, Art 2(h) (' 'the data subject's consent' shall mean any freely given specific and informed indication of his wishes by which the data subject signifies his agreement to personal data relating to him being processed').

684 GDPR, Art 17. The right to data erasure under the previous data protection regime was much more limited. *See* DPD 1995, Art 12(b); DPA 1998, s 14.

685 GDPR, Art 15.

portability').[686] Of course, these rights are not unqualified. The right to be forgotten is subject to the data no longer being necessary for the purposes for which it was collected, among other exemptions.[687] Likewise, there is a presumption that any subject access request addressed to a CRA is limited to data relevant to the consumer's 'financial standing', unless the consumer specifically requests access to additional personal data.[688]

Additionally, the DPA 2018/GDPR strengthens consumers' rights to object to a decision taken solely on the basis of 'automated processing', and to obtain human intervention in the decision.[689] Consumers also have a more general right to receive information about the existence and 'logic involved' in automated individual decision-making.[690] This includes the use of (alternative) credit scoring models for assessing creditworthiness and making credit decisions.[691] Although this so-called 'right to an

---

686 GDPR, Art 20. In contrast, the DPD 1995 regime only gave data subjects access to information *about* data relating to them, not the data itself. Open Banking, examined in Chapter 3, may be understood as a sector-specific form of data portability pursuant to payment services law, limited to financial account data. *See* Oscar Borgogno and Cristina Poncibò, 'The Day After Tomorrow of Banking: On FinTech, Data Control and Consumer Empowerment' in Nikita Aggarwal et al (eds) *Autonomous Systems and the Law* (Beck 2019).

687 GDPR, Article 17(1)(a) and (3). *See* ICO, 'Guide to Data Protection—Exemptions' <https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/exemptions/> (setting out exemptions for financial services organizations from data deletion, inter alia).

688 DPA 2018, s 13(2). *See also* n 405 and associated text.

689 GDPR, Arts 21 and 22.

690 GDPR, Arts 13(2)(f), 14(2)(g), 15(1)(h).

691 GDPR, recital 71.

explanation'[692] existed under the previous data protection regime, the greater automation of (credit) decision-making since then has made it much more relevant.[693]

In theory, stronger consumer data rights, and the higher standard of consent for data processing, could help to mitigate regressive distributional effects (enable progressive effects) due to alternative credit scoring and credit allocation. For example, consumers can withhold consent to processing, 'port', or request the deletion, of personal data that a credit firm would otherwise have used to price differentiate and discriminate.[694] This could help to mitigate the regressive distributional effects due to high(er) cost and unaffordable credit, and the loss of cross subsidisation between higher and lower risk borrowers within a given credit scoring range due to more personalised credit pricing.[695] The exercise of these rights could, however, instead have negative distributional effects to the extent that lenders adjust for creditor ignorance due to consumers withholding or deleting data (inter alia) by charging more to lend, or by rationing credit, as discussed earlier.[696]

Separately, the exercise of the right to an explanation could improve consumers' understanding of the reasons for their credit scores and credit decisions, thereby enabling them to take measures to improve their creditworthiness and potentially access credit on

---

692 Goodman and Flaxman, n 230; Sandra Wachter, Brent Mittelstadt and Luciano Floridi, 'Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation' (2017) 7(2) International Data Privacy Law 76; Margot E Kaminski, 'The Right to Explanation, Explained' 3 (2019) 4(1) Berkeley Law and Technology Journal; Lilian Edwards and Michael Veale, 'Slave to the Algorithm? Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking For' (2017) 16 Duke Law & Technology Review 18.

693 DPA 1995, Art 12(a). For a discussion of this point, *see* Lee A Bygrave, 'Minding the Machine v 2.0: The EU General Data Protection Regulation and Automated Decision-Making' in Karen Yeung and Martin Lodge (eds), *Algorithmic Regulation* (OUP 2019), 248–262.

694 The category of data processing harms addressed by the GDPR/DPA 2018 is broad and includes both 'material' (tangible) as well as 'non-material' (intangible) harms. *See* GDPR, recitals 75, 83 and 85 (referring to 'physical, material and non-material harms') and Art 82(1) (referring to 'material and non-material harms').

695 *See* ch 5 and 6.

696 *See* n 627 et seq and associated text; n 661 et seq and associated text.

more favourable terms. And, to the extent that the obligation of data controllers to provide explanations encourages the use of more 'interpretable' credit scoring models,[697] it could help to mitigate (distributionally) unfair price discrimination—both by improving detection by regulators, as well as via a transparency/social shaming mechanism, particularly where lenders are exploiting consumers' misperceptions.

In practice, however, the scope for these rights to influence the distributional effects due to alternative credit scoring and credit allocation may be limited. To begin with, greater transparency about automated decisions, and informational remedies more generally, cannot directly force data controllers to change their decisions. For example, the rights to object to, obtain human intervention in, and receive an explanation for, an automated credit decision, do not per se give consumers legal grounds to receive a different or better decision from the credit provider—such as a reversal of a denial of credit, or lower price of credit—although these grounds may arise under other laws, such as consumer credit and discrimination law.[698] A related consideration is that the rights to object to, and obtain human intervention in, automated decisions (such as alternative credit scoring) are limited to decisions based 'solely' on automated processing.[699] If interpreted literally, and strictly, this would *not* allow

[697] n 232 et seq and associated text (discussing ML 'explainability'); Philip Bracke et al, 'Machine Learning Explainability in Finance: An Application to Default Risk Analysis' (Bank of England Staff Working Paper No. 816, 2019) <https://bit.ly/2TyIk0d>; Chaofan Chen et al., 'A Holistic Approach to Interpretability in Financial Lending: Models, Visualizations, and Summary-Explanations' (2021) <https://arxiv.org/abs/2106.02605>.

[698] *See also* Talia Gillis and Josh Simons, 'Explanation < Justification: GDPR and the Perils of Privacy' (2019) 2(1) Pennsylvania Journal of Innovation 71 (arguing that the focus of the GDPR and explainable AI research on technical, individual-level explanations is myopic, and that the focus should be on system-level justification and accountability); Edwards and Veale, n 692; Berk Ustun, Alexander Spangher and Yang Liu, 'Actionable Recourse in Linear Classification' (Proceedings of the Conference on Fairness Accountability and Transparency, Atlanta, January 2019), <https://arxiv.org/abs/1809.06514> (arguing that individuals should have the right to change the decision of a model by altering actionable input variables).

[699] Note, the proposed revision to the EU Consumer Credit Directive (CCD 2021) would implement a broader right for borrowers to contest and receive explanations for automated credit decisions that is not limited to decisions that are 'solely' automated. As noted in ch 4, post-Brexit, these changes do not directly affect UK consumer credit regulation, however they could still impact credit market consumers in the UK. *See* n 516 and associated text.

consumers to object to or obtain human intervention in credit decisions that are only partly automated (i.e., still involve humans).[700]

There are also limitations to the rights to access, delete, and port data. Notably, once data is aggregated, commingled, and embedded in ML models, it is technically impossible to identify (all of) an individual consumer's personal data for the purposes of exercising their rights of access, deletion, and portability.[701] Consumers' data rights under the GDPR also do not generally extend to the inferences and predictions that data processors and controllers derive from personal data processing, nor how they use those inferences and predictions.[702] Thus, even if consumers exercise their rights to port or delete personal data held by a lender, and thereby limit the scope for harm due to the processing of that data, they cannot delete the inferences that lenders may have already derived from the data—nor potential future inferences. As discussed in previous chapters, there are also externalities due to data processing, such that individuals cannot, through the exercise of their data protection rights, control inferences about them that are derived from the processing of other consumers' data.[703]

Likewise, the distributional impact of the raised threshold of consent under the DPA 2018/GDPR is constrained by the fact that CRAs and credit providers both rely heavily on *non-consent* bases to justify the processing of personal data. As discussed earlier, CRAs rely

[700] As confirmed by the recent decisions of the Dutch high court adjudicating claims against the ride-hailing companies Uber and Ola (*see* <https://ekker.legal/2021/03/13/dutch-court-rules-on-data-transparency-for-uber-and-ola-drivers/>). At the EU level, this question will also be considered by the European Court of Justice in a request for a preliminary ruling from the Administrative Court of Wiesbaden (Germany) relating to the credit scoring practices of Schufa, the German credit scoring agency. *See* Request for a Preliminary Ruling from the Verwaltungsgericht Wiesbaden (Germany) lodged on 15 October 2021 – OQ v Land Hesse, Case C-634/21-1.

[701] Öhman and Aggarwal, n 660.

[702] Sandra Wachter and Brent Mittelstadt, 'A Right to Reasonable Inferences: Re-Thinking Data Protection Law in the Age of Big Data and AI' (2019) 2 Columbia Business Law Review.

[703] n 567 and associated text; n 648 and associated text.

primarily on the 'legitimate interest', and to a lesser extent, 'legal obligation' grounds to justify the processing of personal data for credit referencing.[704] Similarly, credit providers rely heavily on the legitimate interest and legal obligation, as well as contractual necessity, grounds. In practice, neither CRAs nor credit providers map individual categories of data to the interests and purposes served by their processing. Rather, they make a broad appeal to their 'legitimate interests' and 'legal obligations' to justify the processing of a vast range of personal data. And, to the extent that credit providers do rely on consumer consent, the relevant contractual clauses are still being drafted broadly, thereby giving credit providers wide discretion over the sources of information they can rely on, and for which purposes.[705]

The lack of specific consent and the extensive, broad-brushed reliance on non-consent grounds for personal data processing by CRAs and credit providers raises questions about the appropriate limits of these grounds.[706] With respect to the legitimate interest ground, this is partly a question of the scope of a lender's or CRA's legitimate interests. For example, do/should lenders have a legitimate (business) interest in marketing, and if so, how far should this interest extend? In part, it is a question of the scope and scale of personal data processing necessary for CRAs and credit providers to satisfy their marketing and other interests. For example, (to what extent) do CRAs and credit providers need to share customer data with social media platforms, and vice versa, in order to acquire and retain customers through marketing?[707]

---

704 n 389 et seq and associated text.

705 *See e.g.* Natwest, n 181, 11-12.

706 ICO, 'How Do We Apply Legitimate Interests in Practice?' <https://bit.ly/32a8gEt>. German law has long restricted reliance on the legitimate interests ground to only the sharing of negative data, whilst the sharing of positive data requires consumers' consent. *See* Jentzsch, n 289, 8.

707 Natwest, n 181.

More generally, and as argued in the previous chapter, consumers' cognitive and behavioural biases prevent them from effectively exercising their data rights to begin with. Less advantaged, lower-income consumers, who are likely to have lower levels of financial and technological literacy and may be more present biased, are even less likely to recognize the value of their data rights. Relatedly, the private, individualized nature of consent and data rights constrains their scope for effectively policing the aggregate and longer-term distributional effects due to data processing, including but not only in the context of alternative credit scoring.[708] Whilst certain consumers may gain from the processing of their personal data—for example, where alternative credit scoring unlocks access to credit on more favourable terms—other consumers may be harmed, particularly in the longer term—for example, due to high-cost, unaffordable credit. However, consumers cannot easily anticipate whether they will be winners or losers, nor anticipate the system-level distributional effects due to the processing of their personal data.[709] It follows that stronger individual, procedural or informational remedies—for example, more detailed disclosure of 'alternative data' in consumer credit files, or more detailed explanation of the logic involved in an algorithmic credit decision—are likely to have only limited effect in mitigating adverse distributional outcomes (enabling positive outcomes) due to alternative credit scoring.[710]

---

708 *See* ch 4, section 4.2.1.2 (describing behavioural and cognitive biases that impede rational decision-making by consumers) and ch 6, section 6.4 (discussing how behavioural and cognitive biases undermine the effectiveness of third-party consumer self-help remedies.).

709 Consent and rights-based data protection approaches, and the compliance costs of data protection/privacy regulation more generally, could also produce negative distributional (and welfare) effects by favouring large firms and reducing competition in datafied (credit) markets. *See* Michal S Gal and Oshrit Aviv, 'The Competitive Effects of the GDPR' (2020) 16 Journal of Competition Law and Economics 349; James Campbell, Avi Goldfarb, and Catherine Tucker, 'Privacy Regulation and Market Structure' (2015) 24 Journal of Economics and Management Strategy 47.

710 Edwards and Veale, n 692, 67 (discussing the 'transparency fallacy'); Nikita Aggarwal, 'Big Data and the Obsolescence of Consumer Credit Reports' (*Oxford Business Law Blog*, July 2019) <https://www.law.ox.ac.uk/business-law-blog/blog/2019/07/big-data-and-obsolescence-consumer-credit-reports> (observing that, although the recent move to include limited categories of alternative data in UK statutory credit reports—such as utility and mobile phone payment data—is certainly helpful, it does not overcome the fundamental limits of informational remedies in mitigating the harms due to alternative credit scoring).

7.3 Data protection obligations of firms

Individual data rights, and the corresponding obligations of data processors and controllers, are not the only mechanisms by which data protection regulation influences the distributional effects due to alternative credit scoring. Data protection regulation also establishes various independent obligations for data processors and controllers. There are two sets of obligation that offer the greatest promise in mitigating regressive distributional outcomes (enabling positive outcomes) due to alternative credit scoring: (i) the data protection principles, particularly the principles of 'data minimisation' and 'purpose limitation', and the meta-principle requiring the data protection principles to be implemented 'by design and by default'; and (ii) data protection risk or 'impact' assessments. They are examined next.

7.3.1 Data Protection Principles

The data protection principles were a key feature of the DPA 1984, the UK's first data protection regime.[711] The DPA 2018/GDPR strengthens and extends these principles.[712] There are seven principles, of which the following are especially pertinent to the present inquiry (emphasis added):

1. Personal data shall be:

*processed lawfully, fairly and in a transparent manner in relation to the data subject (**'lawfulness, fairness and transparency'**);*

[711] *See* ch 4, section 4.1.2.

[712] GDPR, art 5(1).

*collected for specified, explicit and legitimate purposes and not further processed in a manner that is incompatible with those purposes; further processing for archiving purposes in the public interest, scientific or historical research purposes or statistical purposes shall, in accordance with Article 89(1), not be considered to be incompatible with the initial purposes (**'purpose limitation'**);*

*adequate, relevant and limited to what is necessary in relation to the purposes for which they are processed (**'data minimisation'**);*

The other data protection principles are *accuracy* (ensure erasure or rectification of inaccurate personal data); *storage limitation* (personal data should only be kept in a form in which data subjects are identifiable for as long as necessary to meet the purposes of data processing); *integrity and confidentiality* (process personal data in a way that ensures appropriate data security); and *accountability* (for compliance with the other principles).[713]

Additionally, the DPA 2018/GDPR introduced a new meta-principle of 'data protection by design and by default'.[714] This requires data controllers and processors to 'implement appropriate technical and organisational measures for ensuring that, *by default*, only personal data which are *necessary* for each specific purpose of the processing are processed' (emphasis added).[715] This reinforces the principle of data minimisation, set out above. Firms are also required to implement 'appropriate technical and organizational measures, such as pseudonymisation, which are *designed* to implement data-protection

[713] Of these, the principles of 'transparency', 'accountability' and 'integrity and confidentiality' were introduced by the GDPR, or at least made more explicit relative to the previous regime.

[714] GDPR, recitals 78 and 108, art 25 (and article 28(1), extending the obligation to data processors, where different from the data controller). This implements the well-established data protection principle of 'privacy-by-design'. *See* Ann Cavoukian, 'Privacy by Design – The Seven Foundational Principles' <https://privacysecurityacademy.com/wp-content/uploads/2020/08/PbD-Principles-and-Mapping.pdf>.

[715] GDPR, art 25(2).

principles, such as data minimisation, in an effective manner and to integrate the necessary safeguards into the processing in order to meet the requirements of this Regulation and protect the rights of data subjects' (emphasis added). In complying with this obligation, firms should take '[i]nto account the state of the art, the cost of implementation and the nature, scope, context and purposes of processing as well as the risks of varying likelihood and severity for rights and freedoms of natural persons posed by the processing'.[716] Although the GDPR specifically mentions pseudonymisation as a technique for implementing data protection by design, it does not preclude the use of other techniques, such as federated or transfer learning (and other 'privacy-preserving' ML techniques), nor data obfuscation techniques such as encryption, anonymisation, and synthetic data.[717]

To the extent that they are applied and enforced prudently, the principles of data minimisation and purpose limitation—reinforced by the meta-principle of data protection by design and default—offer to reduce the scope and scale of personal data processing in consumer credit markets.[718] As before, by limiting the insights that lenders and CRAs can glean about consumers' credit risk, preferences and misperceptions through the processing of their personal data for alternative credit scoring, these principles could help to mitigate the regressive distributional effects due to data-driven price differentiation and discrimination that results in high(er) cost and unaffordable credit—particularly for low-

[716] GDPR, Article 25(1).

[717] GDPR, recital 28. Note, the DPA 2018/GDPR regime does not apply to personal data that is anonymised; that is, 'personal data rendered anonymous in such a manner that the data subject is not or no longer identifiable' (GDPR, recital 26; art 4(1)). Anonymised data is subject to a lighter regulatory regime governing the processing of 'non-personal' data. *See* Regulation (EU) 2018/1807 of the European Parliament and of the Council of 14 November 2018 on a Framework for the Free Flow of Non-Personal Data in the European Union [2018] OJ L303/59.

[718] There is limited guidance, from both regulators and the courts, on the meaning and scope of the fairness principle. On a literal reading, at least, it appears to be more focused on procedural fairness rather than substantive, outcome-based fairness. *See e.g.* Damian Clifford and Jef Ausloos, 'Data Protection and the Role of Fairness' (2018) 37 Yearbook of European Law 130; Gianclaudio Maglieri, 'The Concept of Fairness in the GDPR: A Linguistic and Contextual Interpretation' (2020) Proceedings of FAT* ACM 154.

income consumers—as well as due to 'cherry picking' of high-income borrowers (the 'invisible primes'). At the same time, however, creditor ignorance due to more limited data processing could limit the expansion of access to affordable credit for low-income (credit invisible) consumers, and the associated positive distributional effects.[719]

Alternatively, the distributional effects due to the application of the data protection principles in consumer credit markets may be muted by the fact that lenders still enjoy considerable discretion in implementing these principles—for example, in determining when personal data is 'adequate, relevant and necessary', what are 'legitimate' purposes of data processing, and in balancing competing interests such as the protection of fundamental rights and the cost of implementing technical and organisational measures.[720] Another limitation is that privacy-by-design techniques, such as anonymisation and pseudonymisation, are increasingly ineffective in a world of AI/ML. ML techniques can easily re-identify the data subject and construct detailed relationships in data by relying on proxies for anonymised/pseudonymised variables, or through group-level profiling.[721]

7.3.2 Data Protection Impact Assessments

The DPA 2018/GDPR also introduced obligations for data processors and controllers to prospectively assess and mitigate risks due to the processing of personal data. This includes, notably, the obligation for data processors and controllers to carry out a 'data protection

---

719 *See* ch 6, section 6.3; ch 5, Table 3.

720 A related question is how these principles interact with related obligations under the FCA's creditworthiness assessment regime, which inter alia require lenders to base their assessment on 'sufficient' information (*see* ch 4, section 4.2.2.2; Aggarwal, n 98).

721 *See e.g.* Paul Ohm, 'Broken Promises of Privacy: Responding to the Surprising Failure of Anonymization' (2010) 57 UCLA Law Review 1701; Fuster et al, n 557; Gillis, n 224; Tal Zarsky, 'Incompatible: GDPR in the Age of Big Data' (2017) 47(4) Seton Hall Law Review (arguing that the GDPR was drafted for a pre-AI world). As discussed in ch 6, the implementation by credit and financial firms of 'data protection by design' techniques (such as data anonymisation and synthetic data) remains nascent. *See* n 662 and associated text.

impact assessment', or DPIA.[722] Pursuant to a DPIA, data controllers are required to 'carry out an assessment of the impact of the envisaged processing operations on the protection of personal data' when 'a type of processing in particular using new technologies, and taking into account the nature, scope, context and purposes of the processing, is likely to result in a high risk to the rights and freedoms of natural persons'. The GDPR and associated guidance suggest that a DPIA is likely to be required for (alternative) credit scoring on the basis that it involves 'a systematic and extensive evaluation of personal aspects relating to natural persons which is based on automated processing, including profiling, and on which decisions are based that produce legal effects concerning the natural person or similarly significantly affect the natural person'.[723]

The DPIA must contain the following, at a minimum (emphasis added):

…

(a) a systematic description of the envisaged processing operations and the purposes of the processing, including, where applicable, the legitimate interest pursued by the controller;

(b) ***an assessment of the necessity and proportionality of the processing operations in relation to the purposes;***

(c) ***an assessment of the risks to the rights and freedoms of data subjects*** *referred to in paragraph 1; and*

[722] GDPR, art 35. Additionally, where personal data is processed on the 'legitimate interests' basis, the recommended best practice is for the controller to carry out a 'legitimate interests assessment' (LIA). *See* GDPR, art 6(1)(f) and recital 47; ICO, n 706.

[723] GDPR, Art 35(3) (setting out cases in which a DPIA is required), GDPR recital 91; Article 29 Data Protection Working Party, n 675. *See also* ICO, 'Data Protection Impact Assessments' <https://bit.ly/3nJlPUH>.

(d) ***the measures envisaged to address the risks,*** *including safeguards, security measures and mechanisms to ensure the protection of personal data and to demonstrate compliance with this Regulation taking into account the rights and legitimate interests of data subjects and other persons concerned.*

Importantly, this assessment must be carried out *prior* to processing. Where the assessment reveals a high risk (in the absence of mitigating measures), the data controller is required to consult the ICO, which can, amongst other things, limit or ban the processing or order the controller to bring the processing into compliance.[724]

The DPIA obligation reinforces the obligations of firms to implement the data protection principles, as well as introducing an additional principle of 'proportionality'. As with the data protection principles and meta-principle, the DPIA obligation also reinforces the importance of mitigating risks to individual rights and freedoms due to the processing of personal data. From a distributional perspective, however, the likely impact of DPIAs is subject to many of the same limitations discussed above. Notably, firms are given considerable discretion in implementing DPIAs—including in determining whether data processing is 'necessary and proportionate' in relation to the purposes (and what those purposes are to begin with), and whether there is a 'high risk to rights and freedoms' that would merit mitigating measures and prior consultation with the data protection authority. Furthermore, the individual, case-by-case, approach to risk assessment under the DPIA cannot effectively account for the externalities due to data processing, nor the longer-term, cumulative, system-level distributional effects due to alternative credit scoring and credit allocation (or other data-driven practices), as articulated previously.[725]

---

[724] GDPR, art 36 (prior consultation) and art 58 (powers).

[725] *See* n 703 et seq and associated text; generally, ch 6, section 6.4. *See also* Andrew Selbst, 'An Institutional View of Algorithmic Impact Assessments' (2021) 35(1) Harvard Journal of Law and Technology 1.

More generally, the impact of DPIAs—and data protection regulation more broadly—in consumer credit markets is limited by a lack of sector-specific regulatory guidance. To be effective in holding firms accountable, discretionary, process-oriented and principles-based regulatory approaches generally need to be accompanied by close regulatory oversight of, and engagement with, regulated firms.[726] Whilst the Article 29 Working Party and ICO have issued guidance on DPIAs, including a generic DPIA template and data protection guidance for the use of AI, there is no specific template or guidance for DPIAs in the consumer credit context, nor the financial sector more generally.[727]

Sector-specific DPIA guidance and templates have, for example, been developed for RFID applications, smart grids and surveillance camera systems—the latter jointly developed by the ICO and Surveillance Camera Commissioner.[728] Likewise, there is no sector-specific guidance from the ICO on the implementation of the data protection principles and meta-principles in financial markets—in contrast to the approach taken in other contexts, such as employment.[729] Although the financial industry has various industry codes of conduct,[730] they do not offer detailed guidance on the implementation of data protection regulation.[731]

---

726 Julia Black, 'Forms and Paradoxes of Principles-Based Regulation' (2008) 3(4) Capital Markets Law Journal 425; Bygrave, n 693, 257 (discussing weaknesses in regulatory design and enforcement of the GDPR). This could be partially compensated for by the fact that the penalties for breach of data protection rules are significantly higher under the GDPR/DPA 2018 regime. *See* n 397.

727 n 723.

728 <https://bit.ly/2SNQeTk>.

729 Aislinn Kelly-Lyth, Halefom Abraha, and Jeremias Adams-Prassl, 'From 'Code' to 'Guidance': Revising the Instrument on Data and Employment' (2022) 51 Industrial Law Journal 744 (arguing, however, that the ICO's proposed changes to its guidance are inadequate, in particular due to the 'quasi-legislative' status of ICO guidance, and citing anecdotal evidence that in the employment context ICO guidance is already being ignored).

730 *See e.g.* Standards of Lending Practice (formerly known as the Lending Code) <https://bit.ly/2STkgW8>.

731 Pursuant to the DPA 2018/GDPR, trade associations can adopt 'codes of conduct' as a way of demonstrating compliance with the regime. *See* GDPR art 40; Kelly-Lyth et al, n 729, 751.

Whilst there is anecdotal evidence that lenders are carrying out DPIAs, given that these are not made public it is unclear how they are assessing and mitigating the risks due to alternative credit scoring in practice, if at all. It is also unclear whether lenders are consulting the ICO, as required when a DPIA reveals a high risk to the fundamental rights of data subjects that cannot adequately be mitigated—and, if so, whether the ICO has taken any regulatory action in response.[732] Credit providers may be treating the DPIA as a tick-box compliance exercise,[733] assessing an absence of 'high risks' due to alternative credit scoring and/or deeming these risks to be sufficiently well-mitigated and documented, and outweighed by the necessity and proportionality of processing.

[732] This problem is not limited to credit/financial markets. *See* Kelly-Lyth et al, n 729, 746 (reporting, based on a freedom of information request, that as of December 2021 'the UK data protection authority has been approached just 17 times by data controllers proposing high-risk processing;').

[733] Edwards and Veale, n 692, 80; Selbst, n 725.

8 CONCLUSION

This thesis set out to understand how recent advances in predictive technology could influence the distributional outcomes due to consumer credit markets. To examine this question, the thesis used a case study of alternative credit scoring, as a paradigmatic example of advances in predictive technology in consumer credit markets. Alternative credit scoring has emerged from a confluence of socio-technical, economic, political, and legal changes over the course of the last half a century, spurred in recent years by the 2008 GFC. It has been heralded—by the credit industry and policymakers—with the implicitly distributional promise of improving access to credit for marginalized consumers, particularly lower-income, higher-risk credit invisible consumers.

However, the history of consumer credit policy and innovation in consumer credit markets gives us good reason to be sceptical of this promise. Will this time be different?[734] Leveraging theoretical and empirical insights, the thesis argued that the distributional promise of alternative credit scoring is credible, yet strictly bounded. Crucially, by enabling lenders to estimate consumer creditworthiness and price credit more accurately, alternative credit scoring enables the expansion of credit to consumers who were previously marginalized from credit markets, particularly credit invisibles. To the extent that this entails

[734] Carmen M Reinhart and Kenneth S Rogoff, *This Time is Different: Eight Centuries of Financial Folly* (Princeton 2009).

the expansion, on balance, of *affordable* credit to marginalized, lower-income consumers, alternative credit scoring offers to mitigate existing regressive distributional effects due to unaffordable borrowing by these consumers, as well as enable positive distributional effects due to more affordable borrowing and consumption smoothing.

The thesis emphasised, however, that the potential positive distributional effects due to alternative credit scoring are contingent. First, due to the limits of consumer credit itself as a mechanism for increasing distributive justice. Although access to affordable credit due to alternative credit scoring can increase the lifetime utility of a low-income consumer by enabling consumption smoothing, the conditions under which consumer credit—especially unsecured, short-term, small value credit—can enable low-income consumers to increase their income and/or wealth, through investment, are highly stringent.

Second, there are potential negative distributional effects due to alternative credit scoring. Notably, by enabling greater extraction of consumer surplus by lenders and *un*affordable borrowing, particularly by low-income consumers, and/or by increasing the speed of credit expansions, developments in credit scoring technology will tend to produce regressive distributional effects.[735] Additionally, in the absence of strong redistribution through the state (tax and transfer) or markets (wages), the expansion of credit to *higher-income* consumers due to alternative credit scoring will likely have regressive effects, due to the increase in consumption smoothing and income and wealth accretion by these consumers.

Importantly, given their lower consumption needs, the conditions under which higher-income consumers can grow their income and wealth through borrowing and

[735] As noted previously, although beyond the scope of this thesis, there are further distributional effects due to the use of credit scores as screening mechanisms in non-credit contexts.

investment are less stringent than for lower-income consumers.[736] Higher-income consumers are also more likely to participate through investment in the profits generated by lending firms, including profits from lending to lower-income consumers. More personalized credit pricing due to alternative credit scoring also reduces the cross-subsidization of credit risk between higher and lower income consumers within credit scoring bins, which is expected to be distributionally regressive.

The distributional promise of alternative credit scoring is thus contingent on how lenders apply their data-driven insights due to alternative credit scoring, the resulting cost and affordability of credit for consumers and rate of credit growth, and in turn the relative effects of credit access on the levels of consumption, income, and wealth of high and low-income consumers, respectively. These conditions are, in turn, shaped by various individual and firm-specific factors—including the relative informedness (myopia) of borrowers and lenders' business models—as well as structural factors. The latter include the competitiveness of the market, and macroeconomic and regulatory conditions. Under conditions of easy money and light-touch regulation, lenders may be more inclined to expand credit to higher-risk, lower-income borrowers.

8.1 Policy implications

Clearly, there is a need for further empirical research to corroborate the hypothesised distributional effects due to alternative credit scoring, particularly in the UK.[737] To the extent that alternative credit scoring exacerbates poverty and/or inequality (of consumption, income, and/or wealth), and policymakers are concerned to reduce current high levels of

[736] Albeit acknowledging that the credit-investment channel is more limited in the case of short-term, small sum, unsecured consumer credit.

[737] *See* section 8.2 *infra*.

poverty and inequality,[738] the appropriate legal and policy reforms needed to help mitigate these regressive outcomes necessarily depend on the mechanisms through which they are generated. That is, whether regressive outcomes are generated primarily through the expansion of unaffordable credit, particularly to low-income consumers; the expansion of affordable credit to higher-income borrowers; and/or overheating of the economy due to too rapid credit expansion (et c.).[739] Moreover, the efficacy of any of these interventions needs to be justified relative to the non-efficacy of alternative credit data and ML in achieving distributional goals.[740] That is, market failure needs to be weighed against the possibility of regulatory failure, not only in terms of welfare (allocative efficiency) but also distribution.[741]

The rest of this section sketches—in broad strokes—the contours of policy reforms that could help to mitigate regressive outcomes and encourage more progressive outcomes due to alternative credit scoring in two specific scenarios: (i) the expansion of unaffordable credit to lower-income consumers; and (ii) the expansion of affordable credit to higher-income consumers.[742] Section 8.2 concludes by setting out a research agenda building on the main themes and contributions of this thesis.

---

738 Assuming a distribution-minded social planner. *See* n 3 and n 15.

739 As examined in chs 5 and 6. As noted previously (*see* n 15), questions of whether policymakers ought to pursue distributional goals, particularly through the reforms proposed, and whether these reforms would be politically feasible if pursued, are beyond the scope of this thesis.

740 In the hands of both lenders and borrowers. *See* ch 6, section 6.4.

741 *See generally* Joseph Stiglitz, 'Regulation and Failure' in David A Moss and John Cisternino (eds), *New Perspectives on Regulation* (Cambridge MA 2009), 17-19; Baldwin et al, n 239, 68-82; Sunstein, n 251, 74-111; Armour et al, *Principles*, 80-98.

742 Other scenarios may call for different or additional policy interventions, e.g., more countercyclical macro-prudential regulation to curb the increased (speed) of credit expansion. *See* n 355 and associated text.

8.1.1 *Expansion of unaffordable credit, particularly to low-income borrowers*

As this thesis has demonstrated, affordability—defined as the ability of individual borrowers to not only repay credit, but to do so in a sustainable manner without experiencing financial or non-financial distress—is a useful criterion for regulatory intervention in consumer credit markets aimed at mitigating regressive (and welfare-diminishing) outcomes, including but not only due to the affordances of alternative credit scoring.[743] However, the FCA's affordability rules still leaves considerable room for unaffordable borrowing. As discussed in Chapter 5, lenders have considerable discretion in how they carry out an affordability assessment. Not all lenders are within the perimeter of the affordability assessment regime.[744] And, there is no legal requirement for credit to be affordable to any specified degree of probability, nor a specific duty for lenders to deny credit that is assessed to be unaffordable.[745]

If regressive outcomes due to alternative credit scoring are generated primarily through the expansion of unaffordable credit (to lower-income borrowers), recourse may be found in strengthening interventions under consumer credit regulation to limit unaffordable credit. On the supply-side, this could include broadening the scope of application of, and strengthening, the affordability rules—for example, by requiring lenders to demonstrate that credit is affordable to a high degree of probability, stress-tested under a wide range of adverse scenarios. Broadening and strengthening the duty of affordable lending is not, however, a panacea. On the one hand, it could do too little. Credit risk and affordability are inherently probabilistic. Even with ample data about borrowers, and sophisticated data-analytic tools, lenders (and borrowers themselves) cannot predict with certainty, ex ante, whether or not borrowing will be affordable. Among other things, debt can rapidly become

---

[743] *See further* Rowlingson, n 128, 199.

[744] Including, pending reform, short-term 'interest-free' credit such as BNPL. *See* n 506.

[745] *See* n 513.

unaffordable ex post due to unexpected income shocks—particularly for low-income borrowers who have thinner financial safety nets, are typically in more precarious jobs, and have less predictable income streams and life trajectories.[746]

Thus, credit deemed to be 'affordable with high probability' ex ante, could still become unaffordable—although a stricter affordability criterion could reduce unaffordable borrowing, particularly by low-income consumers, to a level that is more aligned with a distribution-minded consumer credit market policy. Relatedly, the open-endedness of the affordability criterion still gives profit-maximising lenders room to abuse their discretion.[747] As discussed, lenders can still profit from lending that is unaffordable for borrowers, provided they can compensate themselves for the overall level of credit risk on a portfolio basis.[748]

Affordability rules may thus need to be supplemented with more substantive restrictions, such as a stricter interest rate cap.[749] They also need to be supplemented with *demand*-side interventions that reduce the demand for unaffordable credit and the probability that debt becomes unaffordable, particularly in the hands of lower-income borrowers.[750] This

---

[746] n 219 and associated text; ch 5, section 5.4.3.1.

[747] n 514 et seq and associated text.

[748] *See* ch 4, section 4.2.2.2.

[749] *See* ch 5, section 5.3.4.1 (discussing price regulation in the high-cost-short-term credit market and observing that it still leaves room for relatively high-cost lending). *See also* Starks et al, n 307, 9 (describing price regulation interventions to curb harmful price discrimination, including absolute or relative price caps, and limits on the number of prices that sellers can offer on similar products); FCA, n 334 (credit card market study); FCA, n 328, 28ff (setting out demand and supply-side remedies for unfair price discrimination). It is important to also acknowledge trade-offs, e.g., stricter price/product regulation could limit competition (*see* FCA, n 525, para 3.57). Stricter price caps and affordability rules could also cut off some low-income borrowers from credit that is potentially affordable, as well as increase substitution to higher-cost, informal consumer credit markets, while continuing to allow higher income, lower risk borrowers to access credit—with regressive distributional effects. *See* n 523 and associated text, and *infra* section 8.1.2.

[750] *See e.g.* Starks et al, n 307, 8 ('[w]here price discrimination is based on differences in consumers' understanding of products, there may be opportunities to help consumers with their decision-making process by improving information disclosure or the provision of advice.'). Although beyond the scope of this thesis, reforms to ex post debt restructuring, bankruptcy, and discrimination laws are also highly salient to efforts to mitigate the regressive distributional effects due to unaffordable consumer borrowing (*see infra* section 8.2.2 discussing areas for future research). For recent examples of ad hoc debt forbearance, *see e.g.* the FCA's Payment Deferral Guidance and Tailored Support Guidance initiatives

includes interventions to improve financial literacy and personal financial management by less advantaged, less financially sophisticated consumers—including with the help of digital technology.[751] It also involves strengthening the social safety net by both increasing social provision as well as improving uptake and delivery of existing social benefits.[752] More fundamentally, it involves investment in skills, to increase productivity, job stability, and wage earnings, and in turn to reduce poverty and inequality—collectively mitigating key drivers of unaffordable borrowing by lower-income consumers.[753]

The role of data-driven technology in generating regressive distributional outcomes opens an additional locus for regulatory intervention: data and technology. That is, to the extent that data-driven price differentiation and discrimination due to alternative credit scoring has regressive distributional effects, distribution-minded policymakers might be

(<https://www.fca.org.uk/publication/finalised-guidance/consumer-credit-coronavirus-tailored-support-guidance-jan-2021.pdf>; <https://www.fca.org.uk/publications/finalised-guidance/consumer-credit-and-coronavirus-updated-guidance-firms>). In the US, *see* the recent proposal to cancel a portion of student debt ex post (<https://www.whitehouse.gov/briefing-room/statements-releases/2022/08/24/fact-sheet-president-biden-announces-student-loan-relief-for-borrowers-who-need-it-most/>). *See also* Mian and Sufi, n 109, and Andreas Wiedemann, *Indebted Societies* (Princeton University Press 2021), 234-250 (hereinafter, 'Wiedemann, *Indebted Societies*') (both proposing 'contingent convertible' consumer credit contracts).

751 FCA, n 328, 29ff (setting out demand-side interventions to mitigate inertia pricing, including: disclosure (raising consumers' awareness of firms' pricing practices); reducing search and switch costs; behavioural interventions such as nudges and empowering digital intermediaries); FCA, 'Borrowers in Financial Difficulty Following the Coronavirus Pandemic—Key Findings' (2022) <https://www.fca.org.uk/publication/research/borrowers-in-financial-difficulty-following-coronavirus-pandemic-key-findings.pdf>. However, *see* ch 6, section 6.4 (discussing the limitations of demand-side interventions in the presence of behavioural and cognitive impediments to consumer decision-making); FCA, n 525, para 3.54 (acknowledging the behavioural limitations of demand-side interventions, particularly for the most vulnerable consumers).

752 Joseph Rowntree Foundation, n 327 (calling on the Government to reinstate the Universal Credit lifeline and provide grant funding for targeted debt relief). Addressing legacy debt burdens is a necessary part of any policy response. *See generally* Gardner, Gray, and Moser, *Debt and Austerity*.

753 Gardner, n 522; Rowlingson, n 128, 215 ('Successive governments have failed to tackle the root cause of the problem here which is that people lack sufficient incomes to afford necessities. If incomes are not raised then the chances of credit being a millstone rather than a lifeline become much greater.'); Cutler and Katz, n 436, 551 (arguing that 'it no longer appears true that macro-economic growth alone will boost the fortunes of low-income families. It appears that more activist anti-poverty policy will be necessary to overcome secular trends in labor demand.'); Ahmed and Henehan, n 327, 6 ('[p]olicymakers may want to consider the link between expensive borrowing and core living standards challenges, including insecure working arrangements, pay volatility and, increasingly, delays and difficulties with benefits payments. They should also broaden their focus on debt to include the growing role of council tax and utilities in pushing households into arrears.').

inclined to restrict technological development itself, including the data and statistical techniques that enable alternative credit scoring.[754] Regulatory reforms under this head might entail prohibiting the use of, or forgiving, a consumer's negative credit data, and more generally limiting lenders' access to personal data, as well as the use of that data and ML models to predict consumers' behaviour—in order to limit the scope for regressive pricing based on consumers' preferences, misperceptions, and/or actual risk.[755] The greater salience of data-driven technology to consumer credit markets, and financial markets more broadly, also opens new possibilities and challenges for coordination between consumer financial law and non-financial information and technology law (including data privacy and intellectual property law, among others), as well as the regulatory agencies that oversee these regimes.[756]

As before, the suitability of data- and technology-based interventions depends on the overall distributional effects due to alternative credit scoring, and the precise mechanisms producing these effects. Due to the duality of potential distributional effects resulting from alternative credit scoring (and technological development more generally),[757] regulatory interventions targeted at specific types of credit data, the granularity of data, or certain credit scoring techniques, also risk curbing desirable outcomes—such as improved access to affordable credit for lower-income consumers.[758] Among other things, there is a

---

[754] *See e.g.* Starks et al, n 307, 8 ('[o]ther interventions could be targeted at a firm's ability to identify such variations. This may include constraints on the way certain types of data are collected or used, such as the restricted use of individual protected characteristics under the Equality Act.').

[755] *See* ch 3, section 3.2.1 (discussing positive-only alternative data sharing policies).

[756] *See* n 669 (memorandum of understanding between the FCA and ICO).

[757] *See generally* Gary E Marchant, Braden R Allenby, and Joseph R Herkert (eds), *The Growing Gap Between Emerging Technologies and Legal-Ethical Oversight: The Pacing Problem* (Springer 2011) (discussing the 'pacing problem', the 'Collingridge dilemma', the precautionary principle, and generally the regulatory challenge of balancing the risks due to innovation with the risks of chilling beneficial innovation due to premature regulation); Christopher G Bradley, 'FinTech's Double Edges' (2018) 93 Chicago Kent Law Review 61; Yesha Yadav and Chris Brummer, 'Fintech and the Innovation Trilemma' (2019) 107 Georgetown Law Journal 235; Nikita Aggarwal and Luciano Floridi, 'Towards the Ethical Publication of Country of Origin (COI) Information in the Asylum Process' (2020) 30 Minds and Machines 247, 250ff (discussing 'dual-use' risk).

[758] *See also* section 8.2.1 *infra* (discussing the 'technology-credit cycle').

demonstrated risk that lenders will adjust for the suppression of negative data by rationing credit to groups that are likely to be higher risk, such as lower-income borrowers, who are also more likely to be from ethnic minority backgrounds.[759] Rather than restricting the information available to lenders, interventions based on affordability and credit risk management focus on the ways in which lenders use available information, inter alia to support distributional goals.[760]

8.1.2 Expansion of affordable credit to high-income borrowers

If alternative credit scoring primarily generates regressive outcomes through the expansion of affordable credit to *higher-income* borrowers, traditional consumer credit law interventions—such as limits on high-cost, unaffordable borrowing—are less directly relevant.[761] The regressive effects of an expansion of affordable credit to high income borrowers could, however, strengthen the justification for more progressive redistribution, including but not only through consumer credit markets. As this thesis has demonstrated, the distributional effects due to borrowing and consumption smoothing by low-income households could be more favourable if these households are able to access credit on more favourable terms (even if the conditions under which these households can grow income or wealth through unsecured, short-term, small value borrowing are highly stringent).[762]

---

759 *See* n 627 et seq and associated text in ch 6; *see also* ch 7.

760 Without prejudice to non-distributional reasons for intervening in the use of data and data-driven technology, e.g. to protect individual privacy. *See infra* section 8.2.3 (outlining directions for further research on the different dimensions of consumer financial privacy).

761 Although beyond the scope of this thesis, discrimination law could offer a partial solution, to the extent that lower income borrowers with protected characteristics are being excluded from affordable borrowing due to direct or indirect discrimination, i.e., they are being placed at a 'particular disadvantage' relative to non-protected borrowers.

762 *See* ch 5, Table 3.

The enduring policy challenge is determining the appropriate mechanism for redistribution. Possible avenues for reform include scaling up, and reducing the barriers for access to, existing social lending schemes, as well as strengthening the social lending obligations of for-profit lenders.[763] At present, concessional lending in the UK is largely confined to specialist, not-for-profit financial institutions—specifically, 'social lenders', 'Community Development Finance Institutions' (or, 'CDFIs'), and to a lesser extent, credit unions.[764] These lenders typically take less consumer surplus, and in some cases subsidize the cost of credit for low-income, high-risk consumers, i.e., charge them below cost. This subsidy may be passed on to other (higher income, lower risk) consumers, through higher credit costs, or absorbed by lenders, through lower profits, thereby redistributing between consumers or between firms and consumers, respectively. However, the cost of borrowing from these lenders can still be relatively high.[765]

Clearly, in designing the social obligations of lenders, an important normative consideration is the extent to which private firms should be required to subsidize the cost of lending to less well-off, higher risk borrowers. This entails curbing lenders' contractual freedom to compensate themselves ex ante for the risk of lending to higher risk consumers; to profit from lending to these consumers; and to encourage consumers to enter into credit

---

[763] UK Cabinet Office, n 128; n 609 (discussing the UK government's pilot no interest loan scheme); Rowlingson, n 128, 214; FCA, 'Alternatives to High-Cost Credit Report' (2019) <https://www.fca.org.uk/publications/research/alternatives-high-cost-credit> (observing that demand for high-cost credit is partly behavioural/reflects misperceptions: consumers aren't aware of lower cost options, and they fall prey to loan sharks); Hartfree and Collard, *Poverty, Debt and Credit*, 34ff (examining existing initiatives to deliver affordable small-sum loans as an alternative to high-cost credit, but noting that 'there is a lack of robust evidence as to their impact on low-income households and their experience of poverty.').

[764] HM Treasury, n 94, 6 (recognizing 'the vital role which credit unions play in tackling financial exclusion' and discussing government proposals to 'enable credit unions to offer a wider range of products and services.'); Davies and Finney, n 336, 187 (noting that coverage and take-up of credit products offered by credit unions and CDFIs remains low); Hartfree and Collard, *Poverty, Debt and Credit*, 25 (noting the low use of credit unions relative to other types of credit, particularly among low-income consumers).

[765] If only reflecting the high costs of lending to their target market. *See e.g.* Adage Credit <https://adagecredit.co.uk/about-us/> (offering a £200 loan repayable over 6 months at a representative APR of > 450%).

contracts where the consumer surplus appears positive but is actually negative once 'true' costs are taken into account (which may be unknowable to the lender at the point of credit marketing or origination). A related consideration is the extent to which other (lower risk, higher income) consumers should be required to share the cost of lending to low-income, higher-risk consumers.

Although these considerations demand careful deliberation, I suggest that, under conditions of restricted redistribution by the state and markets, the 'Matthew effect' due to technological development (i.e., the rich get richer, poor get poorer)—including but not only in consumer credit markets—and where credit is increasingly used to supplement welfare income for low-income households, there is a stronger normative justification for strengthening the positive social obligations of lenders to, inter alia, make credit available to lower-income consumers on terms that are affordable, and which replicate the redistributive and insurance functions of social welfare through the cross-subsidization and pooling of credit risk.[766]

The normative justification for strengthening the social obligations of lenders in this way is supported by the fact that many lenders, specifically banks, building societies, and credit unions, benefit from an explicit state guarantee in the form of deposit insurance, and state-provided benefits in the form of access to central bank liquidity.[767] Additionally, many low-income consumers cannot easily influence the reasons for their low perceived creditworthiness, and thus high cost of credit—thereby strengthening the moral justification

[766] *See also* Feibelman, n 463.

[767] <https://www.fscs.org.uk>. *See further* Hockett and Omarova, n 462; Rowlingson, n 128, 217 ('[m]ainstream banks should also be required to play a positive part given that the state effectively insures them for free.'). In the US context, *see* the literature on the Community Reinvestment Act of 1977, Pub. L. No. 95-128 §§ 2901-2908, 91 Stat. 1147 (1977), e.g., Anthony D. Taibi, 'Banking, Finance, and Community Economic Empowerment: Structural Economic Theory, Procedural Civil Rights, and Substantive Racial Justice' (1994) 107 Harvard Law Review 1463, 1496 ('[f]ederal bank charters confer upon these institutions certain economic benefits, including deposit insurance; in return for these benefits depository institutions have an obligation to the taxpayer and the community.'). Other (non-bank) financial institutions often also benefit from an implicit state guarantee (*see*: 2008).

for social lending obligations.[768] To the extent that advances in predictive technology in consumer credit markets—epitomized by alternative credit scoring—stand to *worsen* the terms of credit for lower-income consumers, technological change thus *strengthens* the case for a positive legal obligation incumbent on lenders to subsidize the cost of credit for these consumers.

At the same time, however, there are clear limits to redistribution through even highly concessional consumer credit. As this thesis has highlighted, the conditions under which affordable consumer credit—particularly unsecured, short-term, small value credit—can enable income and wealth growth, particularly by low-income consumers, are highly stringent, even if the cost of credit is highly subsidized. More fundamentally, credit is money that needs to be repaid—in contrast to, for example, grant financing, social insurance, or welfare in kind. As a result, there will be a set of high-risk (low-income) borrowers for whom credit, even at zero interest, will never be affordable with high probability, due to their sheer lack of income.[769]

Policymakers thus need to acknowledge the floor on consumer credit as a mechanism for supporting distributive justice and invest in other mechanisms to achieve distributional goals.[770] This includes strengthening the social safety net, including by improving uptake and delivery of existing social benefits, as discussed earlier. It also includes efforts to increase household savings and investment, including through improved access to

---

[768] *See* references in n 431; Lamont, n 99.

[769] Atkinson, n 441, 1104 (noting that under conditions of intergenerational poverty for low-income Americans, 'even credit that is extended at a low, or even zero, rate of interest is unlikely to be a meaningful form of social provision.') As a recent Citizens Advice survey of BNPL users notes, 'if you're using it out of desperation, you probably have no way to repay' (*see* n 829 in Appendix 1). *See* ch 6, section 6.3.1.3 (discussion of the hypothetical borrower Boris) and *infra* Appendix 1.

[770] Various scholars have emphasised this point. *See e.g.* Atkinson, n 441; Abbye Atkinson, 'Borrowing Equality' (2020) 120 Columbia Law Review 1403; Wiedemann, *Social Policy Theory*; Wiedemann, *Indebted Societies*; Macey, *Fair Credit Markets*.

‘productive’ credit such as small business loans, and more generally to increase skills, productivity, job stability, and wage earnings.

8.2 Further research

There are several directions for further research that flow from the analysis and findings of this thesis. This section outlines four such directions. Above all, the thesis has highlighted the pressing need for further empirical research into the distributional (and welfare) effects of technological development in consumer credit markets, particularly in the UK, and the mechanisms producing these effects. This includes further research on the effects of alternative credit scoring on longer-term outcomes for borrowers in different income and wealth deciles, and the demand and supply-side drivers of these effects.[771] As discussed, many of the available empirical studies of alternative credit scoring are based on US credit markets. Moreover, they focus on the immediate loan decision, i.e., whether credit is granted, and at what price.[772] As such, the results of these studies are insufficient to estimate the distributional (and welfare) effects of alternative credit scoring due to changes in consumption utility, income, and wealth of consumers in different income and wealth deciles. Further empirical research will also need to identify the precise mechanisms producing these effects—for example, an increase in unaffordable credit (to low-income consumers), price discrimination within the bounds of affordable lending, an increase in the speed of credit expansion and overheating, or the expansion of (affordable) credit to high-income borrowers (inter alia).

The rest of this section articulates three further avenues for research. These are: (i) the relationship between technological development in credit markets and the

[771] n 630 and associated text.

[772] n 612 et seq and associated text.

macroeconomy, including the mechanics of technology-credit cycles; (ii) the interaction between different sites of distribution, both within and outside the duration of consumer credit agreements; and (iii) the consumer privacy implications of fintech credit.

8.2.1 Fintech credit and the macroeconomy

Future research will examine more closely how technological development shapes the credit cycle, as well as the effect of credit cycles in driving technological development, including but not only in credit markets (collectively, the 'technology-credit cycle', and more broadly 'the fintech cycle');[773] the overall welfare and distributional effects of technology-credit and fintech cycles; the relationship between successive technology-credit and fintech cycles; and the implications for law and policy.

The analysis of alternative credit scoring in this thesis suggests that technological development plays two overlapping roles in goading the expansionary and contractionary gyrations of the credit cycle: *enabling* and *encouraging*. Advances in credit scoring technology (along with advances in digital technology more broadly) *enable* lenders to expand their loan portfolios, and more rapidly—whether by increasing credit allocation to higher-risk (lower income) borrowers and/or lower-risk (higher income) borrowers. There is some empirical evidence to suggest that the expansion of credit to higher-risk, lower-income borrowers due to alternative credit scoring is limited to the short term.[774] In these ways, advances in credit scoring and digital technology could accelerate the credit cycle by increasing the speed of credit expansions and exacerbating the risk of overheating and asset price bubbles—adding

[773] *See* n 90 et seq and associated text.

[774] *See* n 619 and associated text.

to the broader macroeconomic risks due to unaffordable borrowing and systemic non-performing loans,[775] as well as financial speculation in new technologies more generally.[776]

Relatedly, the hype accompanying credit scoring innovation—and innovation in AI/ML, alternative data, and fintech more broadly—could *encourage* lenders to take on more risk than is prudent, due to 'scientism' and 'techno-optimism' (excessive trust in data, machines, and new innovation).[777] Techno-optimism could also encourage *policymakers* to exercise greater regulatory restraint—both due to the fear of cutting-off productive innovation, as well as due to the outsize influence of powerful tech and financial actors over the political process (regulatory capture).[778]

These mechanisms resonate with the anatomy of other technology-credit and fintech cycles. For example, securitization and 'innovation' in credit risk management in the years leading up to the GFC enabled and encouraged greater risk-taking by lenders, culminating in a deep recession that was both welfare-diminishing and distributionally regressive.[779] More recently, innovation in, and the hype surrounding, blockchain technology and cryptocurrency enabled and encouraged greater risk taking in retail investment markets, resulting in a 'crypto

---

[775] *See* ch 5, section 5.2.2.

[776] Varian, n 61, 7-8 (attributing the faster speed of the Internet revolution, and generally accelerating pace of innovation, to the lower cost and greater speed of combining intangible information components, particularly due to open source software); 9 (noting that new captivating technologies inevitably lead to financial speculation and an investment boom, resulting in an asset price bubble); Sahay et al, n 13 (noting that automation of credit decisions makes credit extension more frequent and faster, and further that 'automation could also lead to procyclicality—to the extent that algorithms do not substitute for long-term relationship with clients, more automated credit decisions could also lead to faster contraction during a downturn (Carstens 2018).')

[777] *See* Perez, n 91, 782 (describing how 'faith in the miracle of technology' contributes to irrational exuberance); 786 (observing that excess confidence in the paper economy is much stronger when it involves new technology); Shiller, n 127. Arguably, the profit motive is sufficient to encourage lenders to take on excess risk, and technology hype is better characterized as an epiphenomenon. On 'techno-optimism' and 'techno-solutionism' *see generally* Evgeny Morozov, *To Save Everything, Click Here: The Folly of Technological Solutionism* (Public Affairs 2014).

[778] *See e.g.* n 398 and associated text.

[779] n 110 and n 345 et seq and associated text.

bubble'—as demonstrated by the spectacular collapse of the crypto exchange, FTX.[780] In this sense, the distributional promise of alternative credit scoring—as sold by lenders and embraced by policymakers—is partly a function of the techno-optimism and hype that accompanies most new innovation in fintech, and technology more generally.

Of course, technology is not the only driver of credit cycles and their distributional effects. Among other things, changes in financial and information law, as well as monetary policy, enabled the growth of alternative credit scoring.[781] Future research will examine how technological development interacts with other supply and demand-side drivers of credit and business cycles, and, among other things, whether it justifies a more countercyclical and cross-sectoral approach to financial market policy.

A related, less examined area for future research is the directionally opposite role of the credit cycle in driving technological development—including but not limited to credit or financial markets. More particularly, I am interested in the extent to which the credit cycle drives innovation and investment that is, on balance, socially beneficial over the longer term (as in the 'dot com' boom of the late 90s)—rather than socially wasteful rent-seeking and financial speculation, the returns to which are only shared by a small, wealthy elite (as in the 2008 subprime housing boom).[782] The examination of the rise of alternative credit scoring in Part One found that a significant portion of the progress in AI during the latter part of the twentieth century was due to developments in credit scoring technology and the demand

---

780 David Yaffe-Bellany, 'How Sam Bankman-Fried's Crypto Empire Collapsed' *New York Times* (Nov 14 2022) <https://www.nytimes.com/2022/11/14/technology/ftx-sam-bankman-fried-crypto-bankruptcy.html>.

781 *See* ch 4.

782 Whereas the 'dot com' bubble in the late 90s produced useful social innovation such as the consumer Internet, the 2008 subprime bubble produced no useful social innovation: financial 'innovation' in the form of MBSs and CDOs was socially wasteful rent-seeking. *See* Shiller, n 127; Varian, n 61, 2 ('[t]he social gain from Internet technology ended up being passed along to consumers, leaving little surplus in the hands of investors.'); 9-10 (discussing investment booms due to technological innovation, some of which—such as investment in human capital—has long-lasting social value).

from lenders to more accurately predict the behaviour of (credit) consumers.[783] An additional, related area for future research concerns the relationship between *successive* technology-credit, and fintech, cycles.

8.2.2 Locating distribution

This thesis has focused on the distributional effects due to credit scoring, credit allocation and credit pricing, and consumer credit and data protection regulation. Although beyond the scope of this thesis, future research will examine more comprehensively the relationship between these and other institutions for pursuing distributional goals.[784] This includes other institutions within the duration of the credit agreement—such as regulatory obligations for lenders to exercise forbearance for consumers experiencing financial difficulties, ex post judicial review of unfair and unconscionable contract terms, bankruptcy, and anti-discrimination protections. It also includes institutions outside the duration of the credit agreement, such as tax, welfare, and monetary policy. Among other things, future research will investigate whether it is distributionally fairer to redistribute through bankruptcy or social welfare than through the terms of credit contracts.[785] Relatedly, future research will examine the distributional effects of credit scores as screening mechanisms for access to *non*-credit goods and services, such as employment, housing, and insurance.

Another important area for future research relates to the factors that constrain access to existing social welfare and subsidized credit schemes. As discussed, low-income households increasingly depend on credit to finance essential needs, and thus ostensibly as a

---

[783] *See* n 90 and associated text.

[784] *See* section 5.3.1, ch 5.

[785] *Cf.* Kaplow and Shavell, n 465.

substitute for welfare.[786] One of the troubling features of this trend is that some consumers turn to high-cost credit options out of a lack of awareness of lower-cost options, and/or the stigma of seeking welfare support. Future research should use quantitative as well as qualitative tools to better understand the social, economic, and legal constraints to consumers accessing social welfare—and how digital technology could be part of the solution. Similarly, future research should examine the social, economic, and legal constraints to existing social lending programs, why they have struggled to scale up, and why low-income consumers are not able to access or discover them easily (given evidence of supply).

8.2.3 Consumer privacy

Finally, there is a need for deeper study of the privacy implications of alternative credit scoring, and data-driven fintech practices more generally. This thesis has analysed consumer privacy primarily through the lens of distributive justice: or, *privacy as fairness*. As such, it has focused on the instrumental dimensions of privacy—the consequential, material and non-material harms due to personal data processing for credit allocation and pricing, and the resulting distributional implications due to access to credit.[787] It has also examined the ways in which information law—data protection regulation, specifically—influences the distributional effects due to consumer credit allocation and pricing.

The thesis has not examined the intrinsic dimensions of privacy—the non-material, deontological harms to individual dignity and autonomy due to the loss of control over one's data, and data-driven behavioural profiling, through practices such as alternative credit

[786] *See* Appendix 1.

[787] Lynskey, n 273; Nikita Aggarwal, 'AI, Fintech, and the Evolving Regulation of Consumer Financial Privacy' in Justin Bullock et al (eds) *The Oxford Handbook of AI Governance* (OUP 2023) (distinguishing the intrinsic and instrumental dimensions of consumer (financial) privacy).

scoring.[788] As discussed in Chapter 3, the use of more exotic types of alternative data for consumer credit scoring has abated in recent years in favour of limited categories of positive, financial data, shared by consumers with lenders.[789] These developments arguably mitigate some of the autonomy and dignity-based privacy harms due to alternative credit scoring. Indeed, if Open Banking gives consumers greater control over their data, they may have *more* informational autonomy as a result, not less.[790]

Future research also needs to examine inter- and intra-normative conflicts between different dimensions of privacy, and between privacy and (distributive) fairness—or, between different dimensions of autonomy. As we have seen, access to low-cost, affordable credit due to alternative credit scoring can increase the welfare and support the financial autonomy of marginalized consumers, whether by increasing their income and wealth or simply increasing their consumption utility. However, the processing of personal, potentially intimate data to enable access to credit in this way could also be viewed as harmful to their dignity and *informational* autonomy, particularly to the extent that they did not have control over the use of that data. We could also view this tension as a contest between the political and economic dimensions of consumer financial privacy.

In addition to the normative questions outlined above, there are important questions that need to be addressed relating to coordination between different regulatory frameworks in datafied consumer credit markets. As Chapter 4 highlighted, consumer credit and data

---

[788] *See e.g.* Lynskey, n 273, 196-210 (discussing tangible and intangible data processing harms); GDPR, recitals 75, 83 and 85 (referring to 'physical, material and non-material harms') and Art 82(1) (referring to 'material and non-material harms'); *Lloyd v Google Inc* [2021] UKSC 50, [92] (Leggatt LJ); Aggarwal, n 98; Aggarwal, ibid. *See further* Antoinette Rouvroy and Yves Poullet, 'The Right to Informational Self-determination and the Value of Self-development: Reassessing the Importance of Privacy for Democracy' in Serge Gutwirth et al (eds) *Reinventing Data Protection?* (Dordrecht; London 2009); Julie E Cohen, 'What is Privacy For' (2013) 126 Harvard Law Review 1904; Nizan G Packin and Yafit Lev Aretz, 'On Social Credit and the Right to Be Unnetworked' (2016) Columbia Business Law Review 339.

[789] *See* ch 3, section 3.2.1.

[790] Fracassi and Magnuson, n 174; Aggarwal, n 787.

protection regulation in the UK have a shared developmental history, co-evolving in response to the same technological and socio-economic changes, and—more surprisingly—in response to one another. Likewise, consumer credit regulation has historically reflected concerns about privacy and data protection—for instance, by giving consumers the right to receive information about personal data processed by credit providers and CRAs.

Yet, despite their shared history, and despite the critical role that these frameworks play in governing digital consumer credit markets and new digital practices such as alternative credit scoring, there is a remarkable lack of coordination between them. It is as if they are trains running on a shared track that rarely communicate or coordinate with each other. At the very least, this lack of communication is a missed opportunity for strengthening digital credit markets, including but not only from the perspective of distributive justice.[791]

Thus, future research into, and regulation of, consumer financial privacy will, at a minimum, need to address the following questions:[792]

1) *First*, what relative value should be placed on intrinsic consumer (financial) privacy, i.e., individual control over the use of personal data as an end in itself?

2) *Second*, are the (tangible) harms of data processing, such as the data-driven exploitation of vulnerable consumers, best mitigated by strengthening individual rights over personal data, and/or by strengthening the obligations of data processors, and the latter's enforcement thereof?

[791] Aggarwal, n 98.

[792] Aggarwal, n 787.

3) *Third*, could 'resurrecting' and strengthening the duty of bank confidentiality (and relatedly, the duties of care of financial institutions) offer a suitable avenue for reform?

4) *Fourth*, should these questions be addressed under omnibus data protection regulation or sectoral, financial regulation, or both? In this regard, should existing provisions that govern consumer financial privacy under sectoral regulation—such as consumer credit and payment services laws—be construed as *lex specialis*, and therefore given precedence over cross-sectoral data protection regulation in the case of conflict?

Appendix 1 – Poverty, Inequality, and Credit

The UK has some of the highest levels of inequality (of income and wealth) among advanced economies.[793] Although these levels have remained relatively steady over the last couple of decades, they have increased over the last fifty years—and are not projected to decline (see **Figures 1, 2,** and **3**).[794] The US has followed a similar trajectory, with even higher levels of income and wealth inequality than in the UK.[795]

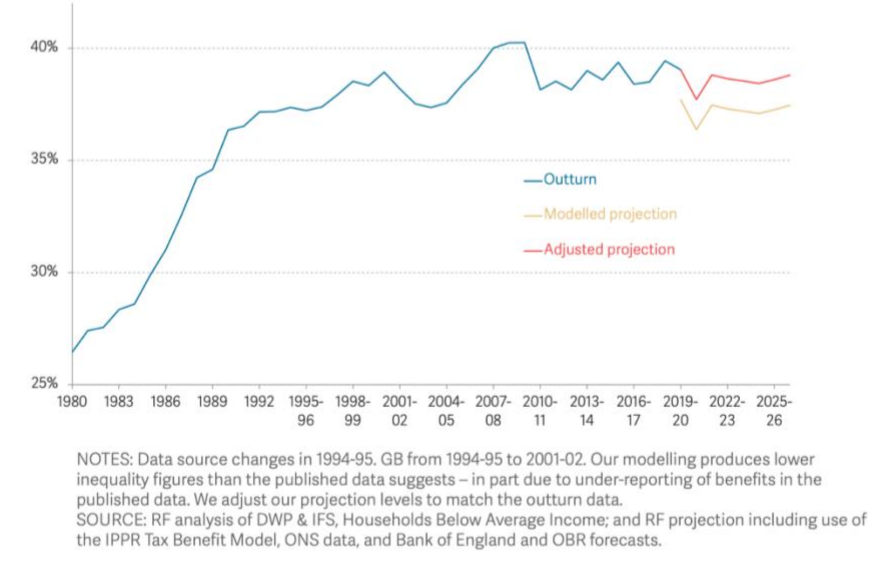
---

[793] Organization for Economic Cooperation and Development (OECD), 'Income Inequality' <https://data.oecd.org/inequality/income-inequality.htm> (showing that the UK ranks 8th among 38 nations in income inequality, as measured by the Gini coefficient, immediately after the US). The Gini coefficient, which is the main measure of (income) inequality in the UK, compares income in each percentile, and measures how much the income distribution deviates from equal distribution. This is expressed on a scale of 0 (complete equality) to 1 (complete inequality), or 0 to 100%. The more even the distribution, the lower the degree of inequality, and the lower the coefficient. According to official statistics, the UK's Gini coefficient in FY 2021 for the distribution of *disposable income* was 34%: *see* <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householdincomeinequalityfinancial/financialyearending2021> (measuring the Gini coefficient based on three measures of income: 'original income', which includes all sources of income from employment, private pensions, investments and other non-government sources; 'gross income', which adds the receipt of cash benefits to original income; and 'disposable income', which subtracts direct taxes and housing costs from gross income).

[794] Department for Work and Pensions, 'Households Below Average Income: An Analysis of the Income Distribution FYE 1995 to FYE 2021' (8 April 2022) <https://www.gov.uk/government/statistics/households-below-average-income-for-financial-years-ending-1995-to-2021/households-below-average-income-an-analysis-of-the-income-distribution-fye-1995-to-fye-2021>; Adam Cortlett and Lalitha Try, 'Resolution Foundation—The Living Standards Outlook 2022' (March 2022) <https://www.resolutionfoundation.org/app/uploads/2022/03/Living-Standards-Outlook-2022.pdf>, 52. On wealth inequality, *see* Krishnan Shah, 'Wealth on the Eve of a Crisis' (Resolution Foundation, 7 January 2022), 3 <https://www.resolutionfoundation.org/app/uploads/2022/01/Wealth-on-the-eve-of-a-crisis.pdf >; Bourquin et al, *IFS Deaton Review*. On rising levels of inequality internationally, *see* United Nations, 'Sustainable Development Goals, 10. Reduce Inequality Within and Among Countries' <https://unstats.un.org/sdgs/report/2020/goal-10/>.

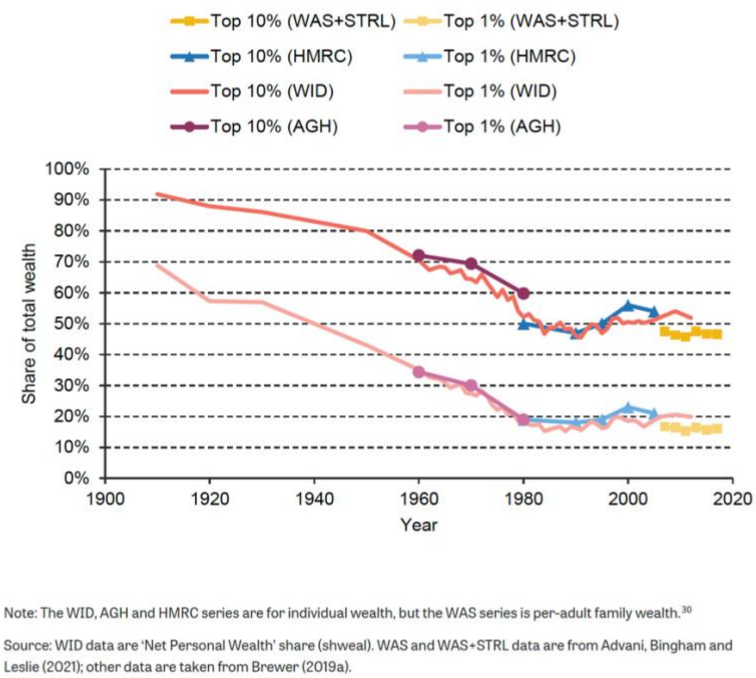
[795] OECD, n 793 (showing that the US has the 7th highest rate of income inequality among OECD nations). On the rise of inequality in the US since the 1970s, *see generally* Piketty and Saez, n 487; Piketty, n 431; Saez and Zucman, n 438 (demonstrating exponential growth in wealth inequality in the US since the 1970s).

Figure 1. Income Inequality in the UK (Gini Coefficient for Equivalised Household Disposable Income After Housing Costs, 1980-2026)



Source: Cortlett and Try (Resolution Foundation), 2022[796]

Figure 2. Wealth Inequality in the UK (Top Wealth Shares in the UK Since 1910)

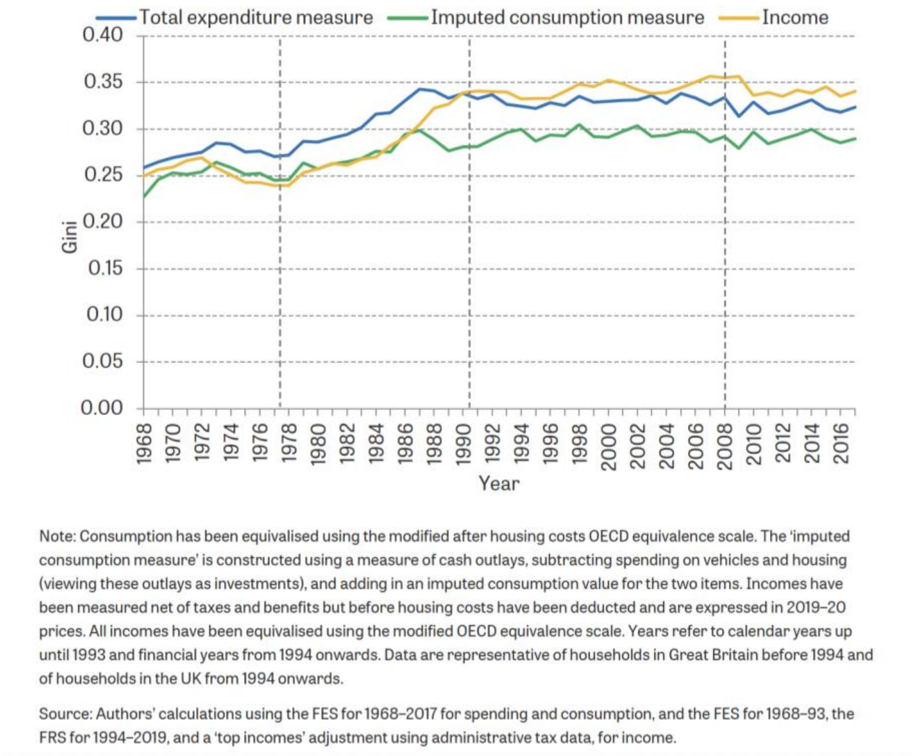


Source: Bourquin et al, *IFS Deaton Review* (2022)[797]

[796] *See* n 794.

[797] *See* n 436, 17.

Figure 3. Consumption Inequality in the UK (Gini Coefficient for Measures of Consumption and Household Net Income, 1968-2017)



Source: Bourquin et al, *IFS Deaton Review* (2022)[798]

The UK also has high rates of (relative) poverty relative to other developed economies,[799] and the second highest among G7 nations (after the US).[800] In the FY ending

[798] *See* n 436, 119; 16 (for discussion).

[799] *Relative* poverty is defined as living below a specified fraction of the median household income in the latest fiscal year, with the UK implementation being 60%. *Absolute* poverty is defined as living below a specified fraction of the median household income in an earlier base year (adjusted for inflation). In the UK, this is currently implemented as households living on less than 60% of the median household income in 2010/11. Absolute poverty is a less useful statistic than relative poverty as it does not account for increases in living standards and costs since the base year. *See* UK Parliament House of Commons Library, n 140; Department for Work and Pensions, n 794.

[800] OECD (2022), 'Poverty Rate' <https://data.oecd.org/inequality/poverty-rate.htm.> (showing that the UK has the 21st highest rate of relative poverty among 38 OECD nations, with the US at 12th place); Bourquin et al, *IFS Deaton Review*, 13 ('Figure 3 – Gini coefficient of income inequality across selected developed countries'). *See also* Philip Alston, 'Statement on Visit to the United Kingdom, by Professor Philip Alston, Special Rapporteur on Extreme Poverty and Human Rights' (2018) <https://www.ohchr.org/sites/default/files/Documents/Issues/Poverty/EOM_GB_16Nov2018.pdf> ('For almost one in every two children to be poor in twenty-first century Britain is not just a disgrace, but a social calamity and an economic disaster, all rolled into one.').

2021 (the latest year for which census data is available), a UK household was defined as 'low-income' (i.e., living in relative poverty) if it received an income of less than £283 per week, or £14,716 per annum (the poverty line).[801]According to official poverty statistics, 13.4 million people in the UK—20 percent of the population—were living in relative poverty in FY 2020/21, based on disposable income after accounting for housing costs.[802]

The relative poverty rate in the UK has remained relatively steady over the last two decades (see **Figure 4**). However, as with inequality, it has increased significantly since the 1970s.[803] Moreover, it is projected to increase over the medium to long term. The greatest increase in relative poverty is projected to be for households with children (see **Figure 5**).[804]

---

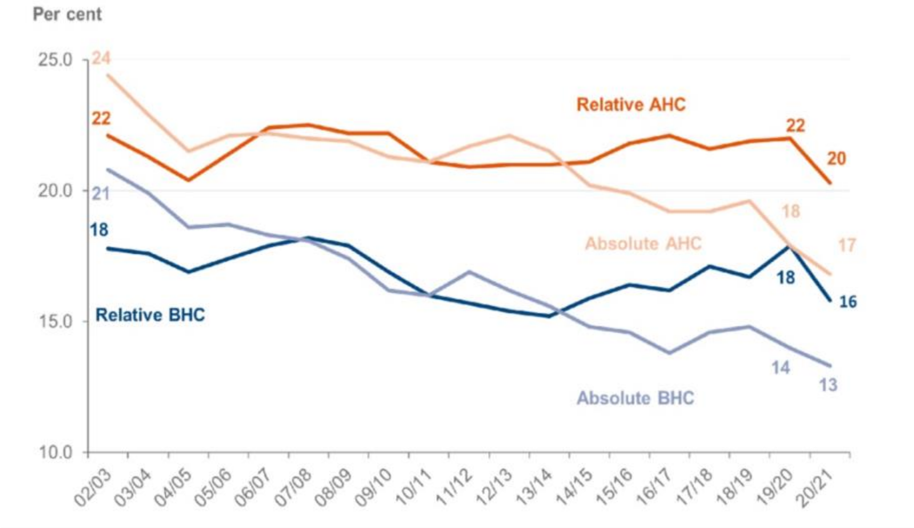
801 Calculated as 60% of £472, the latter being the median weekly household income in the UK in FY 2021, after deducting housing costs. *See* ONS, n 598.

802 Department for Work and Pensions, n 794. The proportion of people living in absolute poverty is expectedly lower (c. 11.1 million or 17% of the population, after accounting for housing costs).

803 There was a small drop in this figure in 2020/21. However, this was not statistically significant and moreover may be unreliable due to Covid-19 (due to errors in data collection, and the effects of both lower median incomes and greater state support, particularly emergency financing, on household income). *See* ibid.

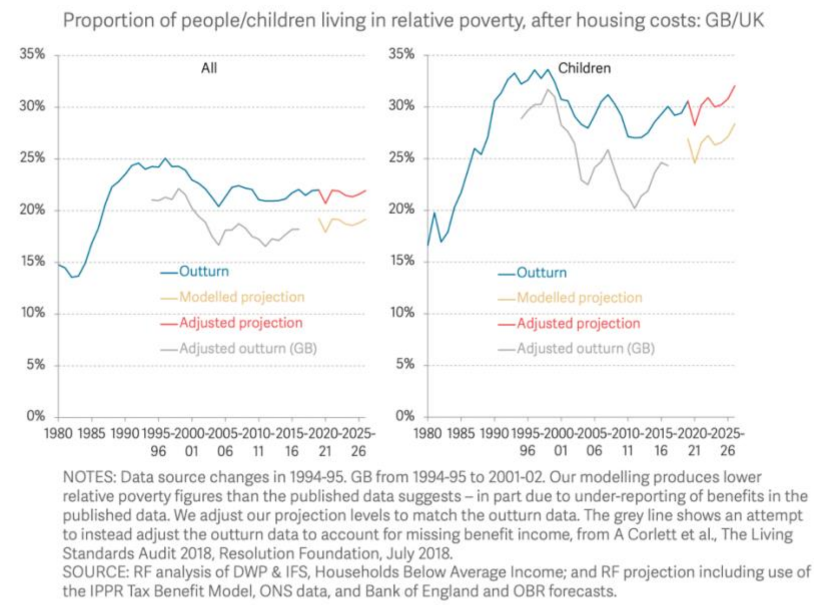
804 *See further* UK Parliament House of Commons Library, n 140, 30-31; Torsten Bell et al, 'Resolution Foundation—Inflation Nation: Putting Spring Statement 2022 Into Context' (March 2022) <https://www.resolutionfoundation.org/app/uploads/2022/03/Inflation-nation.pdf>; Cortlett and Try, n 794, 52.

Figure 4. Low-Income Households in the UK 2003-2021



Source: Department for Work and Pensions (2022)[805]

Figure 5. Poverty Trends in the UK



Source: Cortlett and Try (Resolution Foundation) (2022)[806]

[805] n 794.

[806] n 794.

There is significant correlation between poverty and ethnicity. Official data for 2008 to 2020 indicate that 'people in White British households were consistently the least likely to live in low-income households'. Whereas the proportion of low-income White (and White mixed) households was below the UK average (16 percent), the proportion of low-income Pakistani and Bangladeshi households was significantly above the UK average, at 41 percent and 35 percent respectively.[807] These figures are based on disposable income before accounting for housing costs. After accounting for housing costs, a staggering 55 percent of Bangladeshi households—a majority—are low-income and living in poverty, as defined.[808]

Rising inequality and poverty in the UK, as well as in the US, is the result of a confluence of political, legal, technological, and structural changes that have increased returns to capital, stagnated returns to labour, and contracted social welfare provision.[809] In turn, the expansion of consumer credit markets to substitute for greater income volatility and social welfare retrenchment (discussed further below)—particularly the expansion of high-cost lending to, and overindebtedness among, low-income households—has likely exacerbated inequality and poverty.[810]

---

[807] UK Government, 'People in Low-Income Households' <https://www.ethnicity-facts-figures.service.gov.uk/work-pay-and-benefits/pay-and-income/people-in-low-income-households/latest> (based on a poverty line of £17,000 before accounting for housing costs and £14,800 after accounting for housing costs, for a household comprised of a couple with no children).

[808] For an older study, *see* Omar Khan, 'Financial Exclusion and Ethnicity—An Agenda for Research and Policy Action' (2008) <https://bit.ly/31aJofv>.

[809] *See generally* Stephen Mackay, Karen Rowlingson, and Adele Atkinson, 'Financial Inclusion: Annual Monitoring Report 2022' (2022) <https://www.birmingham.ac.uk/documents/college-social-sciences/social-policy/publications/financial-inclusion-monitoring-report-2022.pdf> (detailing the rise in job precarity, fall in real wages, and diminution of the social safety net between 2012 and 2022, latterly exacerbated by the Covid-19 pandemic and the 'cost of living crisis'). *See also* ch 2 and 5, section 5.1.

[810] n 108 and associated text.

Social welfare retrenchment and credit usage by low-income households

Although social welfare spending as a share of GDP has increased over the course of the last century, the rate of increase has levelled off in recent years, particularly since the 1970s (see **Figure 6**).[811] More particularly, social welfare spending has not increased fast enough to meet the growing financing needs of low-income households. Among other things, the introduction of stricter 'means-testing' requirements has restricted access to social benefits.[812] There are other pathologies in the social welfare system: a large share of social welfare spending (13 percent) is lost to benefits fraud; and, for a variety of reasons, those eligible for welfare do not fully take up available benefits.[813]

In addition to ideological preferences for lower taxes and a smaller (welfare) state, social welfare retrenchment is a result of demographic changes, such as an ageing population, that have reduced tax revenues whilst increasing the state's pension liabilities.[814] International tax arbitrage has further reduced domestic tax revenues. Large companies (including financial institutions) increasingly locate their revenue-generating assets in low-tax

---

[811] *See also* ch 2, Figure 3, and *generally* Glennerster et al, n 58.

[812] Gray, Moser, and Gardner, n 95, 10 (discussing the UK's post 2008 welfare reform program, 'Universal Credit', and describing how 'the structure of Universal Credit has pushed many people on low incomes into debt.'); Office for Budget Responsibility (OBR), 'Welfare Trends Report 2018' (2018) <https://obr.uk/docs/dlm_uploads/WelfareTrends2018cm9562.pdf> (describing the changes introduced by Universal Credit); Glennerster et al, n 58, 103 ('Over much of the last 25 years, policies 'put the lid' on social spending, but did so at a cost of growing means testing, falling relative incomes for the poorest, and tight constriction of public services in relation to public demands for them.'); 105 ('The large increases in social security spending in the early 1980s and early 1990s took the form of means tested benefits.').

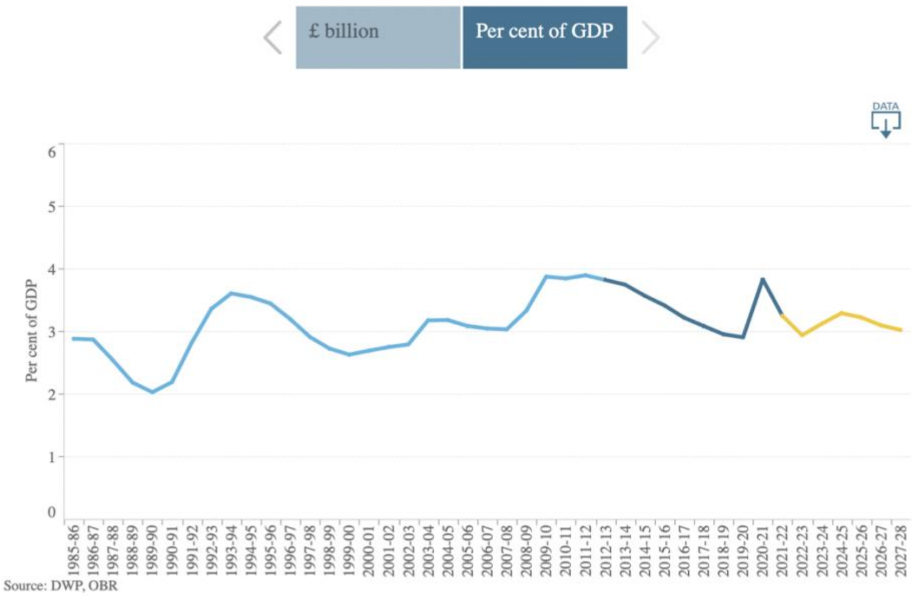
[813] A key motivation for the Universal Credit reforms was to increase take-up by combining multiple social benefits into a single payment that would be easier for eligible citizens to understand and access. *See* OBR, ibid.

[814] *See also* Wiedemann, *Social Policy Theory*, 3 ('In some countries, social insurance policies have come under pressure due to rising levels of unemployment, cost-cutting strategies of employers, and partisan politics. Policy responses range from outright retrenchment and tighter eligibility rules to policy drift where existing policies are not updated to meet changing realities (Hacker 2004).'); Jacob Hacker, 'Privatizing Risk Without Privatizing the Welfare State: The Hidden Politics of Social Welfare Retrenchment in the United States' (2004) 98 American Political Science Review 243, 244 (describing social welfare 'retrenchment': 'Spending cuts alone do not exhaust the definition; analysts need also to consider structural reforms that move the welfare state toward a more "residual" role, in which government does little to shift the distribution of income and services in a progressive direction').

jurisdictions.[815] Digitisation has exacerbated this trend: companies derive a greater share of their revenue from intangible assets—such as data and intellectual property—which can be located more easily in low-tax jurisdictions.

Meanwhile, the greater digitisation, automation, and globalization of the economy, particularly since the 1970s, has increased the returns to capital, whilst reducing (increasing the volatility of) returns to labour, and increasing unemployment, notably among unskilled and low-skilled workers.[816] These trends have gathered pace over the last two decades, with rapid advances in digital, data-driven technology and the increasing dominance of tech companies in the global economy. Rising costs of living, due inter alia to rising inflation, as well as, more recently, geo-political conflict and supply chain constraints, have put further downward pressure on real wages in recent years.[817]

Figure 6. Universal Credit and Legacy Benefits Spending in the UK as a Percentage of GDP, 1985 to 2027 (Projected)



[815] *See generally* OECD, 'International Taxation' <https://www.oecd.org/g20/topics/international-taxation/>.

[816] *See* n 487 and associated text.

[817] Bell et al, n 804; Mackay et al, n 809.

Source: OBR (2022)[818]

The retrenchment of social welfare and stagnation of real wages, beginning in the 1970s, has increased the unmet financing needs of lower-income households. As credit markets liberalized during the same period, low-income households in the UK have increasingly come to rely on credit as a partial substitute for income, including to fund essential consumption.[819] Cuts to social welfare spending under post-2008 'austerity' policies have cemented the dependence of low-income consumers on debt as a partial substitute for social welfare. Although the overall volume of household debt fell after the GFC, it has increased over the last decade—and at a much faster rate for low-income households, particularly due to an increase in unsecured, and often high-cost, borrowing.[820]

These trends are borne out in official data on income and credit usage by low-income households. **Figure 7** indicates that the poorest 20 percent of the population receive a majority of their income—more than 50 percent—from the state. However, as noted, this income is often insufficient to meet their financing needs. Official data show that c. 60 percent of households in the lowest wealth decile held consumer debt—almost double the share of households in the top wealth decile (see **Figure 8**).[821] Although the poorest households have low *total* debt compared to wealthier households (due to significantly less property/mortgage debt), intuitively, they have higher debt-to-wealth and debt-to-income

818 <https://obr.uk/forecasts-in-depth/tax-by-tax-spend-by-spend/welfare-spending-universal-credit/>.

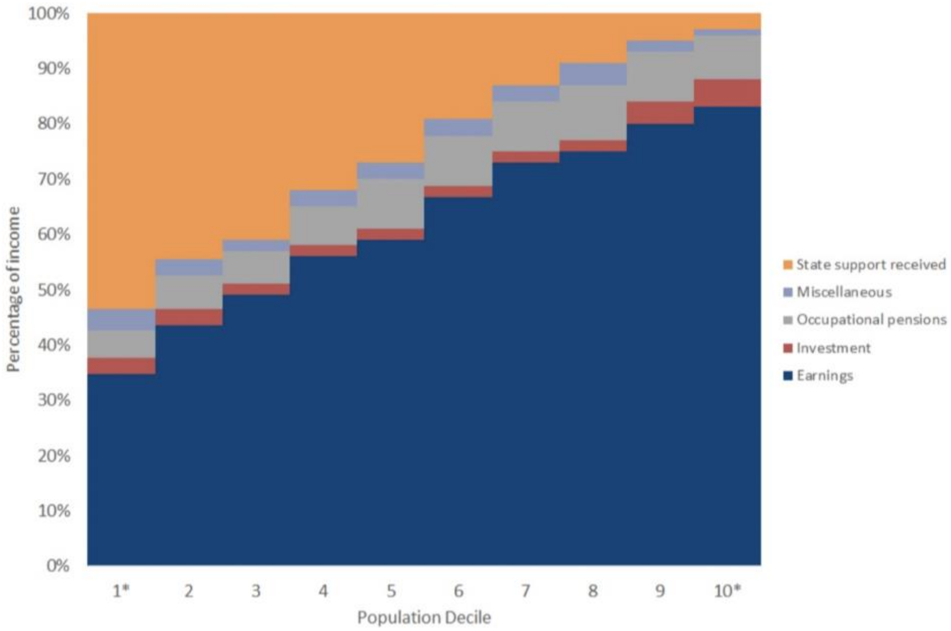
819 Wiedemann, *Social Policy Theory*.

820 Ahmed and Henehan, n 327.

821 ONS, 'Wealth and Assets Survey 2016-2018' (2019) <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householddebtingreatbritain/april2016tomarch2018>, figure 5. *See further* ONS, 'Household Debt: Wealth in Great Britain' (2022) <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/datasets/householddebtwealthingreatbritain> (dataset for 2010 to 2020).

ratios (see **Figure 9**).[822] Crucially, low-income households are more likely to have 'problem debt', or unaffordable debt (see **Figures 10** and **11**), pointing to the limits of credit as a substitute for welfare for low-income households.[823]

Figure 7. Income Source as a Percentage of Gross Income by Decile, FYE 2021



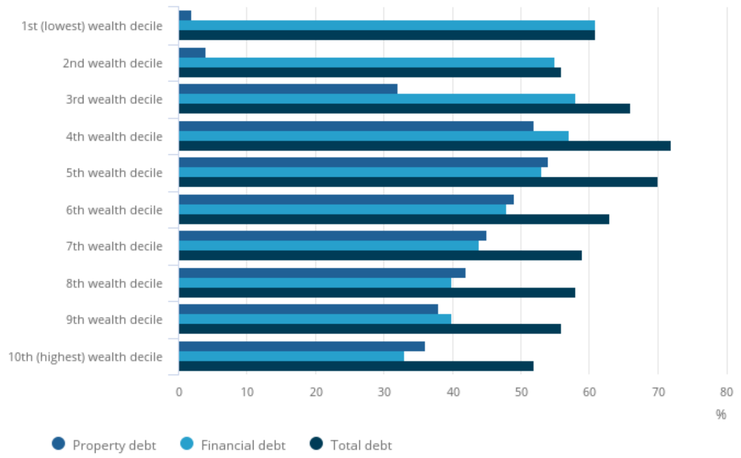
Source: Department for Work and Pensions (2022)[824]

[822] *See also* Hartfree and Collard, *Poverty, Debt and Credit*, 6 ('While households with higher incomes have higher levels of debt in absolute terms than lower income households, when measured as an unsecured debt repayment-to-income ratio (based on gross incomes) low-income households have higher levels of borrowing.'); Ahmed and Henehan n 327, 4 (observing that, in 2019, '[t]ypical consumer debt-to-income ratios remain more than three times higher for lower-income households as compared to their higher-income counterparts.'—whilst acknowledging that this estimate is likely to be affected by data reporting errors).

[823] *See* ch 5, section 5.3*;* Hartfree and Collard, *Poverty, Debt and Credit*, 5-6 ('there is clear and consistent evidence that problem debt is independently related to household income, whereby households on the lowest incomes are at greater risk of experiencing financial difficulties and problem debt'); Ahmed and Henehan, n 327, 4 (citing 'some indicative evidence to suggest a longer-term rise in distress at the tail: the proportion of households in the bottom income quintile with payments in excess of £500 (nominal) more than doubled, from 4 to 9 per cent, between 2006-08 and 2016-19.'). Note, the distress of low-income households is further compounded by unaffordable 'non-financial' debt, such as debts to energy suppliers and local councils. *See* Ahmed and Henehan, n 327, 5-6.

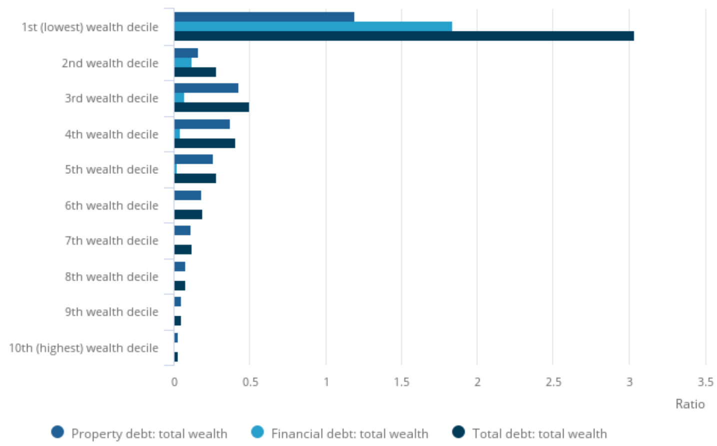
[824] n 794.

Figure 8. Percentage of Households in the UK With Household Debt by Type of Debt and Wealth Decile, Apr 2016 to March 2018



Source: ONS, Wealth and Assets Survey (2022)[825]

Figure 9. Total Debt to Total Wealth Ratio by Type of Debt, April 2016 to March 2018

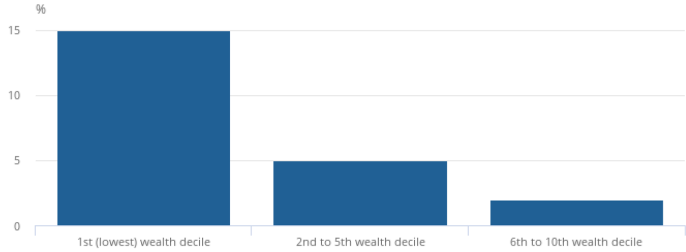


Source: ONS, Wealth and Assets Survey (2022)[826]

[825] n 821.

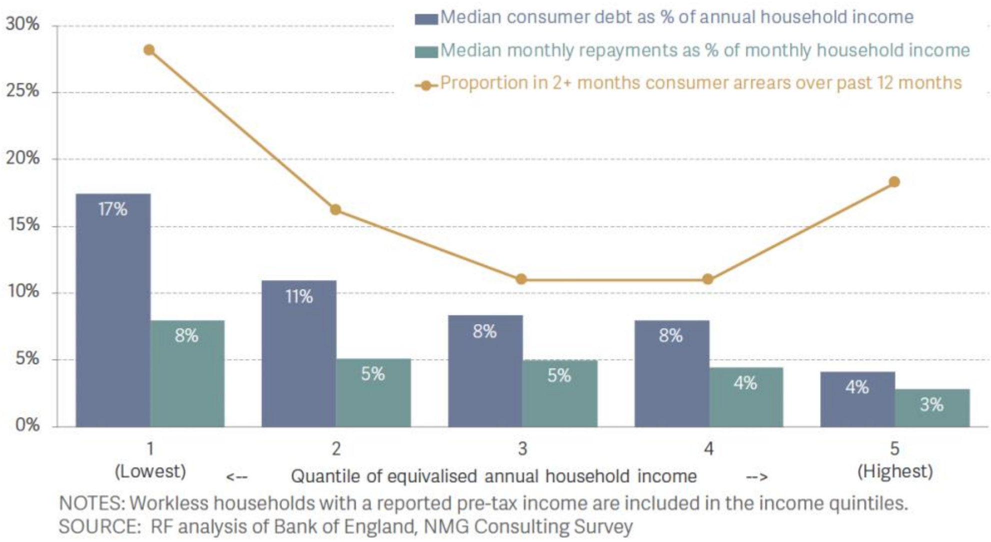
[826] n 821.

Figure 10. Percentage of Households with Problem Debt by Total Household Wealth Deciles in the UK, April 2016 to March 2018



Source: ONS, Wealth and Assets Survey (2022)[827]

Figure 11. Median Levels of Consumer Debt and Monthly Repayments as a Proportion of Pre-Tax Household Income, Proportion of Households in Arrears (2016-19)



Source: Ahmed and Henehan (Resolution Foundation, 2020)[828]

Partly corroborating these trends, recent survey data from Citizens Advice, a UK-based charity, indicates that consumers are increasingly using short-term 'interest-free' credit

[827] n 821.

[828] n 327, 23.

products, particularly BNPL, to purchase essential goods and services, such as food.[829] More particularly, those claiming Universal Credit were found to be twice as likely to use BNPL for essentials as compared to the general population. There are various drivers of this trend, including the withdrawal of pandemic era welfare benefits,[830] borrower myopia, and social norms and stigma relating to reliance on social welfare.[831]

[829] Citizens Advice, 'One in 12 Now Using Buy Now Pay Later to Cover Essentials' <https://www.citizensadvice.org.uk/about-us/about-us1/media/press-releases/one-in-12-now-using-buy-now-pay-later-to-cover-essentials/> (citing 'a parent using BNPL to buy baby clothes while waiting for a benefit payment and someone in debt using BNPL for the weekly food shop.' And another respondent stating that 'It was either use BNPL or starve, so I used it. I sort of knew I would struggle to make the repayments but I did not have any other way of getting food. I bought canned food as they are non-perishable and would last me longer.'). For discussion of similar trends in the US *see* CFPB, 'Buy Now, Pay Later: Market Trends and Consumer Impacts' (2022) <https://files.consumerfinance.gov/f/documents/cfpb_buy-now-pay-later-market-trends-consumer-impacts_report_2022-09.pdf>.

[830] Richard Milne, 'Klarna Boss Puts Brave Face on Buy Now, Pay Later Problems' *Financial Times* (May 27, 2022) <https://www.ft.com/content/8a184a14-230e-4a94-acf7-d919f1dc039b> ('James Wilkinson, head of lending and risk at the Fair for You Community Interest Company, says that the number of buy now, pay later transactions among applicants has nearly doubled since October, when the UK government ended a £20-a-week payment to those on welfare benefits, which was introduced at the start of the pandemic.').

[831] Citizens Advice, n 829 (observing that low-income, welfare-eligible consumers are often more attracted to digital credit products, such as BNPL, rather than welfare in the form of fuel vouchers and foodbanks, because 'if they use Buy Now Pay Later they're invisible. They don't need to speak to anybody, with a few clicks they can borrow instead.').

Appendix 2 – Primer on AI and ML

The definition of AI, and the scope, goals, and methods of AI research, vary according to the discipline from which one approaches them. The first documented use of the term AI is by John McCarthy, Claude Shannon, Marvin Minsky and Nathaniel Rochester, in their 1955 proposal for a study of AI at Dartmouth College.[832] But the foundations of AI as a field of research were laid some years earlier in the fields of cybernetics and mechanical computing, with notable contributions by Alan Turing, Charles Babbage, Ada Lovelace and Norbert Wiener.[833] Over time, AI has developed into a multi-disciplinary field of research, incorporating theories and methods from philosophy, mathematics, economics, biology, neuroscience, psychology, computer science, and linguistics, amongst others.[834]

For present purposes, it suffices to divide AI research into two broad, discipline-agnostic categories: 'artificial general intelligence' (AGI) and 'artificial specific intelligence' (ASI). The goal of AGI research is to develop computer systems that have 'general', or 'human-level' intelligence (itself a controversial and poorly defined construct). That is, AI systems that can learn, understand, and perform 'intellectual' tasks in a wide range of environments, similarly to humans.[835] In contrast, ASI research (also referred to as 'narrow' or 'applied' AI) focuses on the development of systems that can learn and perform specific

---

832 John McCarthy et al, 'A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence' (1955) <http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf>.

833 Alan M Turing, 'Computing Machinery and Intelligence' (1950) LIX (236) Mind 433; Norbert Wiener, *Cybernetics: Or Control and Communication in the Animal and the Machine* (MIT Press 1948). Of course, the idea of machine intelligence can be traced back to ancient times. *See e.g.* Ryan Abbott, *The Reasonable Robot* (CUP 2020), 18ff.

834 Russell and Norvig, n 204, 5-16.

835 *See generally* Ben Goertzel and Cassio Pennachin (Eds) *Artificial General Intelligence* (Springer 2005). A sub-category of AGI is artificial 'superintelligence', i.e., AI systems that have *super*-human intelligence. *See* Irving J Good, 'Speculations Concerning the First Ultraintelligent Machine' (1966) 6 Advances in Computers 31; Nick Bostrom, *Superintelligence: Paths, Dangers, Strategies* (OUP 2014).

intellectual tasks, such as predicting the weather, auto-completing and translating text—and assessing consumer creditworthiness.[836]

Whereas achieving AGI may be the ultimate ambition of many AI researchers, ASI is the reality today. Even the most advanced AI systems in existence today do not display 'general intelligence'.[837] This includes large language models, such as OpenAI's 'ChatGPT' (at least in this author's opinion).[838] This thesis is exclusively concerned with ASI, or applied AI; specifically, the development and use of ML systems for assessing consumer creditworthiness. As such, metaphysical questions about machine consciousness, and existential questions about the threat of a coming 'technological singularity'[839] or 'intelligence explosion',[840] are set aside.

This still leaves some foundational questions unanswered. Notably, what exactly is an AI system, and how does one build one? In their leading textbook on AI, computer scientists Stuart Russell and Peter Norvig define AI as the study and design of behaviour (action, as opposed to thought processes or reasoning) in artefacts that aims to be rational. Rationality is an idealized, abstract benchmark of performance, contrasted with actual human performance.[841] Applying their definition, an AI system could thus be conceptualised as a 'rational agent computer program running on an architecture', where the architecture is

---

[836] A partially overlapping, though not identical, distinction is made between 'weak AI' and 'strong AI', which distinguishes machines that simulate (aspects of) human intelligence from those that are actually intelligent and conscious. *See* Russell and Norvig, n 204, 1020-1033.

[837] Marcus and Davies, n 195.

[838] <https://openai.com/blog/chatgpt/>.

[839] The hypothesis that exponential technological growth (generally and in AI specifically) will eventually lead to machine intelligence greatly surpassing human intelligence, which would dramatically transform human civilisation. *See* Vernon S Vinge, 'The Coming Technological Singularity: How to Survive in the Post-Human Era' (1993) <https://edoras.sdsu.edu/~vinge/misc/singularity.html>.

[840] Good, n 835.

[841] Russell and Norvig, n 204, 34-61.

typically comprised of several computing devices and cloud servers. Consistent with the focus on ASI, this definition focuses on the *simulation* of intelligent behaviour in machines, as opposed to building machines that are *actually* intelligent.

In practice, the boundary between AI and ordinary computing is porous and dynamic. As a result, the definition of AI, and what is considered to be an artificially 'intelligent' system continually shifts: hence the adage, 'intelligence is whatever machines haven't done yet'.[842] The key characteristic that tends to be used to distinguish an 'intelligent' AI computer agent from an ordinary computer program is *autonomy*, defined by the ability to gather information (explore) and the ability to 'learn'. Thus, the rational *AI* agent, as an autonomous system, is dynamic and adaptive to its environment, able to compensate for partial or incorrect prior knowledge (imparted by its designer) through information gathering and learning.

There are two main approaches to designing AI systems.[843] These vary according to the type of information that is made explicit and used in the program design process. The first is the 'knowledge base' approach, in which programmers use rules-based programming (e.g., 'if-then' decision trees) to explicitly hand-code the knowledge that the system requires. This was the main approach to building AI systems from the 1950s to the 1990s. Hence, it is frequently referred to as 'GOFAI' ('Good Old-Fashioned AI')[844], 'classical AI', 'symbolic AI', or 'logical AI'.

The second main approach to AI is 'statistical AI', of which ML is a key method. ML involves building flexible systems that acquire 'knowledge' ('learn') by discovering patterns in data and using this experience to predict outcomes in previously unseen data, without being

---

842 Larry Tesler, 'Adages and Coinages' <https://www.nomodes.com/Larry_Tesler_Consulting/Adages_and_Coinages.html>.

843 Goodfellow et al, *Deep Learning*, 1-3; Marcus and Davies, n 195, 41-43.

844 John Haugeland, *Artificial Intelligence: The Very Idea* (MIT Press 1985).

explicitly programmed. Several different algorithms (instructions to perform a computational task) can be used under each approach, and there are various trade-offs in choosing between them—in terms of both technical performance (e.g., required speed, data, and memory) as well as societal 'performance' (e.g., fairness and privacy implications).[845]

It is important to note that either or both approaches—knowledge-based and statistical AI—can be, and often are, used to build an AI system if the environment permits. Thus, a knowledge/rules-based approach may be adequate if the agent's environment is closed, fully observable, certain, and deterministic at each point in time, such that the function mapping input to output can be precisely specified in formal programming language and does not need to be learnt. In reality, however, most environments are complex—involving stochasticity, partial observability, imperfect information, and uncertainty—such that a combination of rules-based and learning approaches is needed (so-called 'two-stage', 'ensemble', or 'hybrid' models).[846]

Machine learning and deep learning

ML has emerged as the most promising approach to building AI systems that can operate in complex, real-world environments.[847] As noted above, learning is necessary for an AI system to perform well under conditions of uncertainty and to carry out intuitive, non-linear tasks—such as recognizing a word or image—which are difficult to articulate in formal, mathematical rules. ML systems acquire this informal knowledge through *experience* and *data*.

[845] Michael Kearns and Aaron Roth, *The Ethical Algorithm* (OUP 2020), 13. For quantitative approaches to resolving value trade-offs in ML *see e.g.* Jon Kleinberg, Sendhil Mullainathan, Manish Raghavan, 'Inherent Trade-offs in the Fair Determination of Risk Scores' (2016) <https://arxiv.org/abs/1609.05807>; Esther Rolf et al, 'Balancing Competing Objectives with Noisy Data: Score-Based Classifiers for Welfare-Aware Machine Learning' (2020) <https://arxiv.org/abs/2003.06740>.

[846] n 206 and associated text.

[847] Goodfellow et al, *Deep Learning*, 8.

Artificial neural networks ('ANNs' or 'neural nets') are a specific approach to supervised ML,[848] comprised of networks of nodes or units, arranged in layers, and connected by links that simulate biological brain neural networks.[849] Labelled training data is presented to the neural net, which classifies the data into one of several categories (observed by the activation values of the nodes in the network's 'output layer'). During training, the strengths of the connections between nodes are progressively adjusted until the model produces sufficiently accurate classifications.

Multi-layer neural nets are referred to as 'deep' neural nets, and this approach to ML referred to as 'deep learning' (DL).[850] Deep, or multilayer, neural nets break down the function mapping input to output into a series of smaller steps, each comprising a different layer in the network. In between the input and output layers (which are visible), a series of hidden layers extract increasingly abstract features from the input data—the values of which are not given by the data but rather are determined by the system to be useful for explaining relationships in the observed data.[851]

Neural nets, particularly deep neural nets, have emerged as a powerful ML technique in recent years. That is, for exploring raw, unstructured (or semi-structured), high-dimensional datasets, and discovering which features are useful to perform the function (mapping input to output) for a new, previously unobserved dataset. This is most helpful in environments in which it is difficult to accurately interpret the data, i.e., articulate which features should be selected or extracted, particularly high-level abstract features. Deep neural nets have contributed to many of the recent, high-profile successes in AI performance, such

---

[848] *See* ch 3, section 3.3 (discussing supervised, unsupervised, and semi-supervised ML learning).

[849] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, 'Deep Learning' (2015) 251 Nature 436.

[850] *See generally* Goodfellow et al, *Deep Learning*.

[851] Goodfellow et al, *Deep Learning*, 5-10.

as Google DeepMind's AlphaGo and AlphaFold,[852] and large language models such as ChatGPT.[853]

Of course, developing effective and accurate ML models is not without challenges. Among other things, training and hosting a large, high performance ML model typically depends on having a lot of data to train the system (particularly for DL), vast amounts of computational power and storage, and in the case of supervised learning specifically, human labour to label the data.[854] This raises practical concerns about the cost of developing ML models, as well as broader ethical concerns about fair labour practices and the environmental costs of ML.[855]

---

[852] David Silver et al, 'Mastering the Game of Go with Deep Neural Networks and Tree Search' (2016) 529 Nature 484; Andrew W Senior et al, 'Improved Protein Structure Prediction Using Potentials from Deep Learning' (2020) 577 Nature 706.

[853] n 838.

[854] Li Yuan, 'How Cheap Labor Drives China's AI Ambitions' *New York Times* (25 November 2018) <https://www.nytimes.com/2018/11/25/business/china-artificial-intelligence-labeling.html>; Mary Gray and Siddharth Suri, *Ghost Work: How to Stop Silicon Valley from Building a New Underclass* (Houghton Mifflin Harcourt 2019). *See* ch 3, section 3.3.1 (describing supervised learning). The computational costs are ameliorated somewhat by the availability of 'off-the-shelf', pre-trained ML models and libraries.

[855] Emily Bender et al, 'On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?🦜' (2021) <https://doi.org/10.1145/3442188.3445922>; Zhi Ming Tan et al, 'The Ethical Debate About the Gig Economy' (2021) 65 Technology in Society. *See also* ch 3, section 3.3.2 (discussing sources of predictive inaccuracy in ML models).

Appendix 3 – Fintech Credit

To situate alternative credit scoring within the broader fintech (credit) paradigm, this Appendix examines how digital, data-driven technology, including alternative credit scoring, is used by Zopa, an archetypical fintech lender in the UK.[856] As discussed in Chapter 3, alternative credit scoring is also used by CRAs, and, increasingly, incumbent (bank) lenders, with a focus on alternative *financial* data.

Zopa is a digital, 'app-only' lender. It has no physical branches and is accessible only through the Zopa website and mobile app. It targets younger, so-called 'millennial' and 'Gen Z' consumers. Among other things, this target market is reflected in the bank's credit product range—which is limited to small, mostly unsecured loans and arranged overdrafts, credit cards and personal savings accounts—as well as its playful marketing and 'FeelGood Money' brand.[857]

Zopa's business model, and the regulatory framework governing it, have evolved since its inception in 2005.[858] Although it began as a p2p lender, it ended its p2p operations in 2021 and now operates only as a bank.[859] This is consistent with a broader trend in the

---

[856] For a recent review of the UK fintech market, *see* Ron Kalifa, 'The Kalifa Review of UK FinTech' (2021) <https://www.gov.uk/government/publications/the-kalifa-review-of-uk-fintech>. On the global fintech credit market, *see* CGFS and FSB, n 116; Stijn Claessens et al, 'Fintech Credit Markets Around the World: Size, Drivers and Policy Issues' (2018) <https://www.bis.org/publ/qtrpdf/r_qt1809e.htm>; Giulio Cornelli et al, 'Fintech and Big Tech Credit: A New Database' (2020) <https://www.bis.org/publ/work887.htm>.

[857] Zopa does not offer mortgages but does offer auto loans. *See* <https://www.zopa.com/>.

[858] Aggarwal, n 580.

[859] Jaidev Janardana, 'An Update on p2p at Zopa' (*Zopa Blog*, 6 December 2021) <https://www.zopa.com/blog/article/an-update-on-p2p-at-zopa>; Tamsin Fanning, 'Zopa Launches New Digital Bank, Offering Consumers a Compelling Alternative When They Need It Most' (*Zopa Blog*, 23 June 2020) <https://www.zopa.com/blog/article/zopa-launches-new-digital-bank-offering-consumers-a-compelling-alternative-when-they-need-it-most >.

p2p lending market, in both the UK and US.[860] In terms of its profit model, Zopa did not retain any risk on its balance sheet for p2p loans, profiting solely from commissions and fees. For its bank credit and savings products, it profits from interest rate spreads.[861] In terms of regulation, Zopa is authorised by the PRA and supervised by the PRA and FCA.[862] Deposits and savings products offered by Zopa Bank are protected by the Financial Services Compensation Scheme (FSCS), the UK government deposit insurance and investor compensation scheme (in contrast, its p2p loans and investments are *not* FSCS-protected).[863]

Along with the now-defunct Wonga,[864] Zopa was one of the early pioneers of alternative credit scoring in the UK, and advances in fintech more generally.[865] As articulated further below, Zopa continues to leverage digital technology to offer consumers more convenient, personalised, and lower-cost banking and credit products as compared to (less

---

860 Liam Proud, 'Peer-to-Peer Lending's Demise is Cautionary Tale' *Reuters* (13 December 2021) <https://www.reuters.com/markets/asia/peer-to-peer-lendings-demise-is-cautionary-tale-2021-12-13/>; Ryan Lawler, 'Why Fintechs Are Buying Up Legacy Financial Services Companies' *TechCrunch* (August 2021) <https://techcrunch.com/2021/08/16/why-fintechs-are-buying-up-legacy-financial-services-companies/>; Rupert Jones, 'Ratesetter Savers Claim Loans Being Sold Off "On the Cheap"' *Guardian* (6 February 2021) <https://www.theguardian.com/money/2021/feb/06/ratesetter-savers-investments-metro-bank>; 'Lending Club Closes Acquisition of Radius Bankcorp' (1 February 2021) <https://ir.lendingclub.com/news/news-details/2021/LendingClub-Closes-Acquisition-of-Radius-Bancorp/default.aspx>.

861 On different business models for platform lending, *see* CGFS and FSB, n 116, 11-17; Christopher K Odinet, 'Consumer Bitcredit and Fintech Lending' (2018) 69 Alabama Law Review 100, 108. Other digital lenders, like Monzo, also offer a marketplace, or 'financial hub', for non-credit consumer services—such as travel insurance and bill switching—as part of a broader trend towards 'platform banking', financial 'super apps', and newer forms of cross-selling by financial institutions. *See* Val Srinivas and Jan-Thomas Schoeps, 'Platform Banking as a New Business Model' (2019) <https://www2.deloitte.com/us/en/pages/financial-services/articles/platform-banking-as-a-new-business-model.html>; Lindsey Jayne, 'What We'll build in 2019' (*Monzo Blog*, 29 January 2019) <https://monzo.com/blog/2019/01/29/2019-features>; Croxson et al, n 576. In the US context, *see e.g.* CFPB, 'The Convergence of Payments and Commerce: Implications for Consumers', (Aug 4, 2022), <https://www.consumerfinance.gov/data-research/research-reports/the-convergence-of-payments-and-commerce-implications-for-consumers/>.

862 As Zopa Limited and Zopa Bank Limited (collectively, 'Zopa Group'). As discussed in ch 4, p2p platforms were originally lightly regulated; this regime was tightened in 2014, and subsequently in 2019.

863 n 767.

864 n 12; n 130.

865 Tamsin O'Neill, 'The Birth of Predictor—Machine Learning at Zopa' (*Zopa Blog*, 21 October 2016) <https://perma.cc/8EXJ-JETA>; Fanning, n 166.

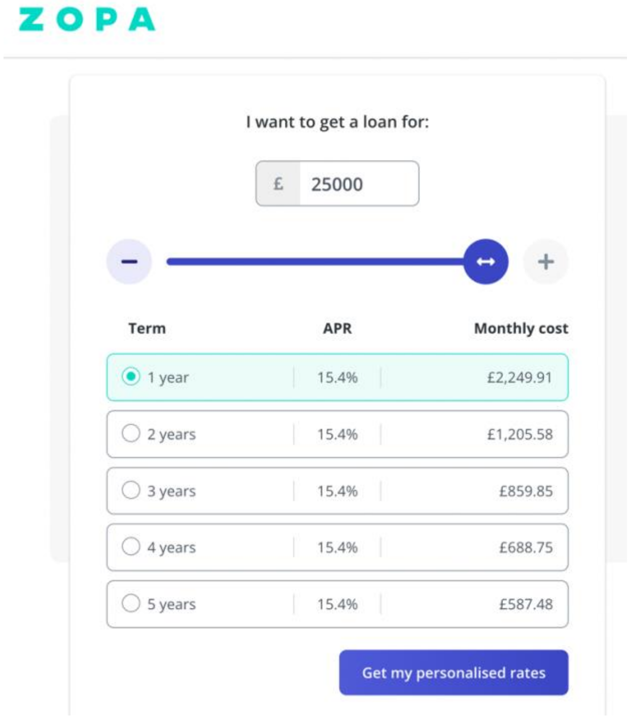
tech-savvy) traditional bank lenders. At the time of writing, to qualify for a Zopa personal loan applicants must be at least 20 years old, reside in the UK with at least 1 year of address history, be employed or self-employed, and have a pre-tax income of at least £12,000 or be retired with a pension. The Zopa website also stipulates that applicants must have a 'credit history that we [sic] can see, and a good track record of repaying debt, e.g. utility bills, credit cards' (emphasis added), as well as 'be able to afford the loan (in relation to your income and outgoings)'.[866] As such, it appears to now target a lower-risk, credit *visible* consumer market compared to when it was first launched.[867]

Figures 1 and **2** show Zopa's personal loan pre-approval portal, and changes in representative interest rates between 2022 and 2023:

[866] Zopa, 'Who Can Get a Zopa Loan?' <https://www.zopa.com/help/article/who-can-get-a-zopa-loan>.

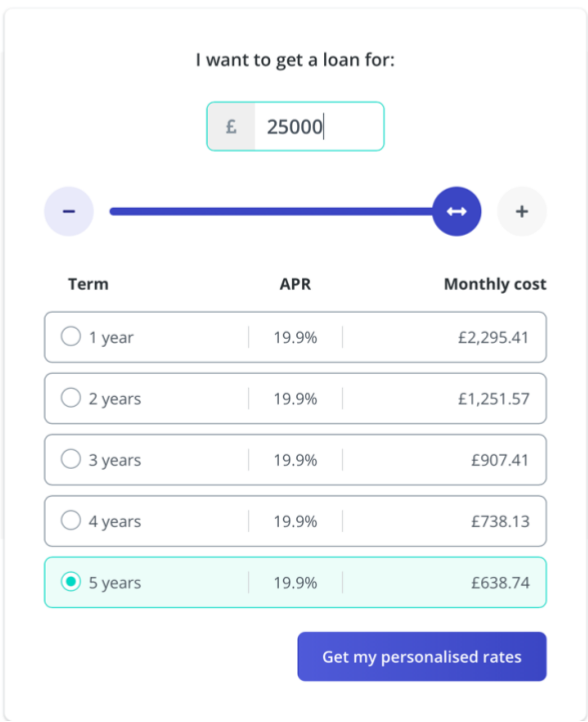
[867] In contrast, several lenders (banks and non-banks, often in partnership) offer 'credit builder' cards that are aimed at helping consumers with low/non-existent credit histories. *See e.g.* Amazon Money Store (credit cards), n 580.

Figure 1. Zopa's Personal Loan Pre-Approval Portal (April 2022)



Source: Zopa, https://www.zopa.com/loans

Figure 2. Zopa's Personal Loan Pre-Approval Portal (February 2023)



Source: Zopa, <https://perma.cc/JP4E-YDLV>

As **Figure 2** shows, consumers can borrow a maximum of £25,000 (the minimum is £1000), for a maximum of 5 years. The representative annual percentage rate (APR), in February 2023, is 19.9 percent, however the actual APR may be higher or lower depending on the applicant's individual circumstances. For the purpose of conducting a 'soft' credit search (one that does not leave a trace on the consumer's credit file), applicants must provide basic identification and contact information, as well as information about their income, employment status, postcode, and home-ownership status.

The eligibility criteria and information requirements for obtaining a Zopa credit card (which uses the Visa payment platform) are similar, albeit slightly lower, to those for Zopa personal loans. Applicants must be at least *18 years* old, have a UK address with at least 1 year history, a pre-tax income of at least *£10,000*, and at least two other lines of credit. As with personal loans, applicants must have a 'credit history that we [sic] can see, and a good track record of repaying debt, e.g. utility bills, credit cards' (emphasis added).[868] Unlike for personal loans, the Zopa website does not specifically mention credit affordability—although Zopa is nevertheless subject to the obligation to assess affordability pursuant to the FCA's consumer credit regime. Applicants must provide personal identification and contact information, as well as their address and period of residence, residential and employment status, pre-tax annual income, and monthly mortgage or rent contributions.[869]

The Zopa credit card offers a maximum initial credit limit of £1500 (minimum of £200), with a variable APR ranging from 24.9 percent to 34.9 percent (in February 2023), depending on individual circumstances.[870] It offers a 56-day interest-free period on non-cash

---

868 https://perma.cc/B4AR-9XAA; <https://www.zopa.com/credit-card>.

869 <https://credit-cards-signup.zopa.com/create-member?product=BUILDER&summaryboxid=e8ce5f75-baaf-45e3-a3cc-2f653351fd14 > (https://perma.cc/V2PB-7D3M)

870 <https://credit-card-origination-api.zopa.com/v1/products/summary-box/25dfcb67-8f9b-473f-83fa-91c9663b1664/pdf> (https://perma.cc/T8EE-Y33R) (compared to a range of 10% to 35% in April 2022: https://credit-card-origination-api.zopa.com/v1/products/summary-box/e8ce5f75-baaf-45e3-a3cc-2f653351fd14/pdf>).

transactions, provided that the cardholder pays any outstanding balance in full by the payment deadline. The customer is liable for late payment fees (at a rate of £12 per month, a comparable rate to traditional banks). There are no annual fees or over-limit charges.

In addition to credit underwriting, Zopa uses predictive data analytics and behavioural insights to improve personal financial management by consumers. This includes providing personalised prompts and notifications to help consumers save and/or avoid defaulting on their debts; in-app features that encourage saving, such as automated 'savings pots'[871] and the 'Credit Cushion' feature on the Zopa credit card; instant payment and bill-splitting functions; and 'Borrowing Power', a customised credit score and in-app tool that identifies bespoke actions to help consumers improve their loan eligibility and credit scores.[872]

More broadly, Zopa offers various digitally enabled services to consumers, including near-instant account opening; instant access to credit upon approval; online customer service through the use of virtual 'chatbots'; and enhanced security features, such as location-based security, automated identity verification, detection and mitigation of suspicious account activity. Among other things, a customer can freeze their account immediately and directly through their phone app as soon as they notice a suspicious transaction. This contrasts with the notoriously blunt and cumbersome fraud mitigation processes at traditional banks.

---

871 <https://www.zopa.com/smart-saver>

872 <https://www.zopa.com/borrowing-power>; Fanning, n 166.

BIBLIOGRAPHY

Abbott R, *The Reasonable Robot* (CUP 2020)

Abraham KS, 'Four Conceptions of Insurance' (2012) 161(3) University of Pennsylvania Law Review 653

Acemoglu D, 'Technical Change, Inequality, and the Labor Market' (2002) 40(1) Journal of Economic Literature 7

—— and Restrepo P, 'Automation and New Tasks: How Technology Displaces and Reinstates Labor' (2019) 33(2) Journal of Economic Perspectives 3

Acquisti A, 'The Economics of Personal Data and the Economics of Privacy' <https://bit.ly/32JAaX6>

Adams W, Einav L and Levin J, 'Liquidity Constraints and Imperfect Information in Subprime Lending' (2009) 99(1) American Economic Review 49

Agarwal S et al, 'Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech' (2019) <http://dx.doi.org/10.2139/ssrn.3507827>

Aggarwal N, 'Machine Learning, Big Data and the Regulation of Consumer Credit Markets: The Case of Algorithmic Credit Scoring', in Aggarwal N et al (eds) *Autonomous Systems and the Law* (Beck 2019)

—— 'Big Data and the Obsolescence of Consumer Credit Reports' (*Oxford Business Law Blog*, July 2019) <https://www.law.ox.ac.uk/business-law-blog/blog/2019/07/big-data-and-obsolescence-consumer-credit-reports>

—— 'Fintech Credit and Consumer Financial Protection', in Chiu I and Deipenbrock G (eds) *Routledge Handbook of Financial Technology and Law* (Routledge & CRC Press 2021)

—— 'The Norms of Algorithmic Credit Scoring' (2021) 80(1) Cambridge Law Journal 42

—— 'AI, Fintech, and the Evolving Regulation of Consumer Financial Privacy' in Bullock J et al (eds) *The Oxford Handbook of AI Governance* (OUP 2023)

—— and Floridi L, 'Towards the Ethical Publication of Country of Origin (COI) Information in the Asylum Process' (2020) 30 Minds and Machines 247

——, Valdovinos Kaye D B, and Odinet C K, '#Fintok and Financial Regulation' (2023) Arizona State Law Journal (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4216952>

Ahmed J and Henehan K, 'An Outstanding Balance? Inequalities in the Use—and Burden–of Consumer Credit in the UK' (2020) <https://www.resolutionfoundation.org/publications/an-outstanding-balance/>

Aikman D, Haldane AG, and Nelson BD, 'Curbing the Credit Cycle' (2015) 125(585) The Economic Journal 1072

Aire, 'An Introduction to First Party Data' (2020) <https://aire.io/wp-content/uploads/2020/10/Introducing-first-paty-data-from-Aire-US.pdf>

Aitken R, 'All Data is Credit Data: Constituting the Unbanked' (2017) 21(4) Competition and Change 274

Akerlof G, 'The Market for "Lemons": Quality Uncertainty and the Market Mechanism' (1970) 84(3) Quarterly Journal of Economics 488

— — and Shiller RJ, *Phishing for Phools: The Economics of Manipulation and Deception* (Princeton 2013)

Akin J, 'What are the Different Credit Scoring Ranges?' (*Experian Blog*, Jun 23 2020) <https://www.experian.com/blogs/ask-experian/infographic-what-are-the-different-scoring-ranges/>

Allen AL, 'Privacy as Data Control: Conceptual, Practical and Moral Limits of the Paradigm' (2000) 32 Connecticut Law Review 861

Anderson JP, Kidd J, Mocsary GA, 'Social Media, Securities Markets, and the Phenomenon of Expressive Trading' (2022) 25 Lewis & Clark Law Review 1223

Aplin T et al, *Gurry on Breach of Confidence: The Protection of Confidential Information* (2nd ed, OUP 2012)

Armour J et al, *Principles of Financial Regulation* (OUP 2016)

Arner DW, Barberis JN, and Buckley RP, 'The Evolution of Fintech: A New Post-Crisis Paradigm?' (2015) <https://doi.org/10.2139/ssrn.2676553>

Arrow K, 'Uncertainty and the Welfare Economics of Medical Care' (1963) 53 The American Economic Review 941

Article 29 Data Protection Working Party, 'Guidelines on Data Protection Impact Assessment (DPIA) and Determining Whether Processing is "Likely to Result in High Risk" for the Purposes of Regulation 2016/679' <https://ec.europa.eu/newsroom/article29/item-detail.cfm?item_id=611236>

Atkinson AB, *Inequality: What Can Be Done?* (HUP 2015)

Atkinson A, 'Rethinking Credit as Social Provision' (2019) 71(5) Stanford Law Review 1093

— — 'Borrowing Equality' (2020) 120 Columbia Law Review 1403

Ausubel LM, 'The Failure of Competition in the Credit Card Market' (1981) 81 The American Economic Review 50

Avery RB, Brevoort KP, Canner GB, 'Does Credit Scoring Produce a Disparate Impact?' (2012) 40(1) Real Estate Economics S65

Aveyard S, Corthorn P, and O'Connell S, *The Politics of Consumer Credit in the UK, 1938-1992* (OUP 2018)

Awrey D, 'Complexity, Innovation, and the Regulation of Modern Financial Markets' (2012) 2 Harvard Business Law Review 235

—— and Macey J, 'The Promise and Perils of Open Finance' (ECGI Working Paper, March 2022) <https://ecgi.global/sites/default/files/working_papers/documents/maceyawreyfinal.pdf>

Baldwin R, Cave M and Lodge M, *Understanding Regulation: Theory, Strategy, and Practice* (OUP 2012)

Bank for International Settlements, 'History of the Basel Committee' <https://www.bis.org/bcbs/history.htm>

—— 'International Convergence of Capital Measurement and Capital Standards' (1988) <https://www.bis.org/publ/bcbs04a.htm>

—— 'Countercyclical Capital Buffer Proposal' (2010) <https://www.bis.org/publ/bcbs172.htm>

—— 'Big Tech in Finance: opportunities and risks' (2019) <https://www.bis.org/publ/arpdf/ar2019e3.pdf>

—— 'The Basel Framework' (2023) <https://www.bis.org/basel_framework/index.htm>

Bank M et al, 'The Lobby Network: Big Tech's Web of Influence in the EU' (2021) <https://corporateeurope.org/en/2021/08/lobby-network-big-techs-web-influence-eu>

Bank of England, 'The Role of Macroprudential Policy – A Discussion Paper' (2009) <https://www.bankofengland.co.uk/-/media/boe/files/paper/2009/the-role-of-macroprudential-policy.pdf>

—— 'Model Risk Management Principles for Stress Testing' (Supervisory Statement 3/18, April 2018) <https://www.bankofengland.co.uk/prudential-regulation/publication/2018/model-risk-management-principles-for-stress-testing-ss>

—— and Financial Conduct Authority, 'Machine learning in UK financial services' (2019) <https://www.fca.org.uk/publications/research/research-note-machine-learning-uk-financial-services>

Bar-Gill O, 'The Behavioural Economics of Consumer Contracts' (2008) 92 Minnesota Law Review 749

——*Seduction by Contract* (OUP 2012)

— — 'Algorithmic Price Discrimination: When Demand Is a Function of Both Preferences and (Mis)Perceptions' (2019) 86(3) The University of Chicago Law Review 217

Baradaran M, *How the Other Half Banks: Exclusion, Exploitation, and the Threat to Democracy* (HUP 2018)

Barocas S and Nissenbaum H, 'Big Data's End Run Around Anonymity and Consent' in Lane J et al. (eds), *Privacy, Big Data, and the Public Good: Frameworks for Engagement* (CUP 2014)

— — and Selbst A, 'Big Data's Disparate Impact' (2016) 104 California Law Review 671

— —, Moritz Hardt, and Arvind Narayanan, *Fairness and Machine Learning: Limitations and Opportunities* <https://fairmlbook.org>

Bartlett R, Stanton A, Morse R and Wallace N, 'Consumer Lending Discrimination in the Fintech Era' (2022) 143(1) Journal of Financial Economics 30

Basel Committee on Banking Supervision, 'Banking Secrecy and International Cooperation in Banking Supervision' (1981) <https://www.bis.org/publ/bcbs00f.htm>

— — 'Information Flows Between Banking Supervisory Authorities' (1990) <https://www.bis.org/publ/bcbsc313.htm>

Bazarbash M, 'FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk' (IMF Working Paper, 2019) <https://bit.ly/2U2zckG>

Bebchuk LA, 'The Pursuit of a Bigger Pie: Can Everyone Expect a Bigger Slice?' (1980) 8 Hofstra Law Review 671

Ben-David I, Johnson MJ, Lee L, and Yao V, 'Fintech Lending with Lowtech Pricing' (2022) <https://cpb-us-w2.wpmucdn.com/u.osu.edu/dist/d/7877/files/2022/07/Ben_David__Johnson__Lee__Yao__FinTech.pdf>

Ben-Shahar O and Schneider CE, 'The Failure of Mandated Disclosure' (2011) 159 University of Pennsylvania Law Review 647

— — 'Data Pollution' (2019) 11 Journal of Legal Analysis 104

— — and Schneider CE, *More Than You Wanted to Know: The Failure of Mandated Disclosure* (Princeton 2014)

Bender E et al, 'On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?🦜' (2021) <https://doi.org/10.1145/3442188.3445922>

Benkler Y, *The Wealth of Networks: How Social Production Transforms Markets and Freedom* (Yale 2006)

Benmelech E and Moskowitz TJ, 'The Political Economy of Financial Regulation: Evidence from U.S. State Usury Laws in the 19th Century' (2010) LXV(3) Journal of Finance 1029

Bennett CJ, *The Privacy Advocates: Resisting the Spread of Surveillance* (MIT Press 2008)

Benöhr I and Micklitz H, 'Consumer Protection and Human Rights' in Howells G, Ramsay I and Wilhelmsson T (Eds) *Handbook of Research on International Consumer Law* (2nd Edition, Edward Elgar 2018)

Berg T et al, 'On the Rise of FinTechs — Credit Scoring using Digital Footprints' (2020) 33(7) The Review of Financial Studies 2845

Berger AN and Udell GF, 'Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure' (2002) 112(477) The Economic Journal

Bernanke BS, 'Credit in the Macroeconomy' (FRBNY Spring Quarterly Review, 1992-93) <https://www.newyorkfed.org/medialibrary/media/research/quarterly_review/1993v18/v18n1article6.pdf>

Bertola G, Disney R and Grant C, 'The Economics of Consumer Credit Supply and Demand' in Bertola G, Disney R, and Grant C (eds) *The Economics of Consumer Credit* (MIT Press 2006)

Bertrand M and Kamenica E, 'Coming Apart? Cultural Distances in the United States over Time' (NBER Working Paper No. 24771, 2018) <https://doi.org/10.3386/w24771>

Bholat D, Gharbawi M and Thew O, 'The Impact of Covid on Machine Learning and Data Science in UK Banking' (2020) <https://www.bankofengland.co.uk/quarterly-bulletin/2020/2020-q4/the-impact-of-covid-on-machine-learning-and-data-science-in-uk-banking>

Bijker WE, Hughes TP, and Pinch T (Eds.), *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology* (1st Edition, MIT Press 1987)

Binns R, 'Fairness in Machine Learning: Lessons from Political Philosophy' (2018) 81 Proceedings of Machine Learning Research 1 <https://arxiv.org/pdf/1712.03586.pdf>

— — and Gallo V, 'Data Minimization and Privacy Preserving Techniques in AI Systems' <https://ico.org.uk/about-the-ico/media-centre/ai-blog-data-minimisation-and-privacy-preserving-techniques-in-ai-systems/>

Björkegren D and Grissen D, 'Behaviour Revealed in Mobile Phone Usage Predicts Credit Repayment' (2020) 34(3) The World Bank Economic Review 618

Black J, 'Forms and Paradoxes of Principles-Based Regulation' (2008) 3(4) Capital Markets Law Journal 425

— — 'Financial Markets' in Kritzer H M and Cane P (eds) *Oxford Handbook of Empirical Legal Research* (OUP 2010)

Block-Lieb S and Janger E, 'The Myth of the Rational Borrower' (2006) 84(6) Texas Law Review 1481

Board of Governors of the Federal Reserve System, 'Community Bank Access to Innovation Through Partnerships' (2021)

<https://www.federalreserve.gov/publications/files/community-bank-access-to-innovation-through-partnerships-202109.pdf>

Bono T, Croxson L, Giles A, 'Algorithmic Fairness in Credit Scoring' (2021) 37(3) Oxford Review of Economic Policy 585

Borgogno O and Poncibò C, 'The Day After Tomorrow of Banking: On FinTech, Data Control and Consumer Empowerment' in Aggarwal N et al (eds) *Autonomous Systems and the Law* (Beck 2019)

Bostrom N, *Superintelligence: Paths, Dangers, Strategies* (OUP 2014)

Boulton D and Hammersley M, 'Analysis of Unstructured Data' in Sapsford R and Jupp V (Eds) *Data Collection and Analysis* (2nd Edition, Sage Publications 2006)

Bourquin P, Brewer M, and Wernham T, 'Trends in Income and Wealth Inequalities' (Institute for Fiscal Studies Deaton Review of Inequalities, 9 November 2022) <https://ifs.org.uk/sites/default/files/2022-11/Trends-in-income-and-wealth-inequalities-IFS-Deaton-Review-of-Inequality%20%286%29.pdf>

boyd d and Crawford K, 'Critical Questions for Big Data' (2012) 15(5) Information, Communication, and Society 662

Bracke P et al, 'Machine Learning Explainability in Finance: An Application to Default Risk Analysis' (Bank of England Staff Working Paper No. 816, 2019) <https://bit.ly/2TyIk0d>

Bradley CG, 'FinTech's Double Edges' (2018) 93 Chicago-Kent Law Review 61

Brevoort KP and Kambara M, 'CFPB Data Point: Medical Debt and Credit Scores' (2014) <https://files.consumerfinance.gov/f/201405_cfpb_report_data-point_medical-debt-credit-scores.pdf>

— —, Grimm P, and Kambara M, 'CFPB Data Point: Credit Invisibles' (2015) <https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf>

Brewer M, Etheridge B, O'Dea C, 'Why are Households that Report the Lowest Incomes So Well-Off?' (2017) 127 The Economic Journal F24

Brown Z and Mackay A, 'Competition in Pricing Algorithms' (2021) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3485024>

Browne R, 'Apple Buys UK Fintech Start-up Credit Kudos' *CNBC* (March 23 2022) <https://www.cnbc.com/2022/03/23/apple-buys-uk-fintech-start-up-credit-kudos.html>

Bruckner MA, 'The Promise and Perils of Algorithmic Lenders' Use of Big Data' (2018) 93(1) Chicago-Kent Law Review

Buchak G, Matvos G, Piskorski T, and Seru A, 'Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks' (2018) 130(3) Journal of Financial Economics 453

Bush GW, 'Remarks by the President at Signing of the American Dream Downpayment Act' *White House Archives* (Dec 16 2003) <https://georgewbush-whitehouse.archives.gov/news/releases/2003/12/20031216-9.html>

Bygrave LA, 'Minding the Machine v 2.0: The EU General Data Protection Regulation and Automated Decision-Making' in Yeung K and Lodge M (eds), *Algorithmic Regulation* (OUP 2019)

Calo R, 'Digital Market Manipulation' (2014) 82 George Washington Law Review 995

Calomiris CW, Longhofer SD, and Jaffee DM, 'Credit Rationing' in Durlauf SE and Blume LE (Eds) *The New Palgrave Dictionary of Economics* (2nd edition, Palgrave Macmillan 2008)

Campbell JY et al, 'Consumer Financial Protection' (2011) 25(1) Journal of Economic Perspectives 91

Campbell J, Goldfarb A, and Tucker C, 'Privacy Regulation and Market Structure' (2015) 24 Journal of Economics and Management Strategy 47

Caplovitz D, *The Poor Pay More: Consumer Practices of Low-Income Families* (Collier-MacMillan 1967)

Capon N, 'Credit Scoring Systems: A Critical Analysis' (1982) 46(2) Journal of Marketing 82

Carney M, 'The Grand Unifying Theory (and Practice) of Macroprudential Policy' (5 March 2020) <https://www.bankofengland.co.uk/-/media/boe/files/speech/2020/the-grand-unifying-theory-and-practice-of-macroprudential-policy-speech-by-mark-carney.pdf>

Carriere-Swallow Y and Haksar V, 'The Economics and Implications of Data: an Integrated Perspective' (2019) <https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2019/09/20/The-Economics-and-Implications-of-Data-An-Integrated-Perspective-48596>

Cassel et al (Klarna AB), 'Method for Using Supervised Model to Identify User' (US Patent application no. US 2018/0158037 A1, 2018) <https://patentimages.storage.googleapis.com/25/e0/a0/cfd88514addf2c/US20180158037A1.pdf>

Cavoukian A, 'Privacy by Design – The Seven Foundational Principles' <https://privacysecurityacademy.com/wp-content/uploads/2020/08/PbD-Principles-and-Mapping.pdf>

Chalton S, 'The Transposition into UK Law of EU Directive 95/46/EC (the Data Protection Directive)' (1997) 11(1) International Review of Law, Computers and Technology 25

Chancellor E, *The Price of Time: The Real Story of Interest* (Atlantic Monthly Press 2022)

Chatterjee S, 'Modelling Credit Risk' (Bank of England Centre for Central Banking Studies, 2015) <https://www.bankofengland.co.uk/ccbs/modelling-credit-risk>

Chen BX, 'To Be Tracked or Not? Apple is Now Giving us the Choice' *New York Times* (26 April 2021) <https://www.nytimes.com/2021/04/26/technology/personaltech/apple-app-tracking-transparency.html>

Chen C et al, 'A Holistic Approach to Interpretability in Financial Lending: Models, Visualizations, and Summary-Explanations' (2021) <https://arxiv.org/abs/2106.02605>

Chenven S and Shulte C, 'The Power of Rent Reporting Pilot—A Credit Building Strategy' (Credit Builder's Alliance, 2015) <https://www.creditbuildersalliance.org/wp-content/uploads/2019/06/CBA-Power-of-Rent-Reporting-Pilot-White-Paper.pdf>

Cherednychenko OO, 'Two Sides of the Same Coin: EU Financial Regulation and Private Law' (2021) 22 European Business Organization Law Review 147

Choi JH et al, 'Reducing the Black-White Homeownership Gap Through Underwriting Innovations—The Potential Impact of Alternative Data in Mortgage Underwriting' (Urban Institute, October 2022) <https://www.urban.org/sites/default/files/2022-10/Reducing%20the%20Black-White%20Homeownership%20Gap%20through%20Underwriting%20Innovations.pdf#page=38>

Chouldechova A and Roth A, 'The Frontiers of Fairness in Machine Learning' (2019) <https://arxiv.org/abs/1810.08810>

Ciocanel A et al, 'Algorithmic Risk Profiling in Housing: A Literature Review' (June 2022) <https://www.york.ac.uk/media/chp/documents/2022/Code%20Encounters%20Algorithmic%20risk%20profiling%20in%20housing%20a%20literature%20review.pdf>

Citron DK and Pasquale F, 'The Scored Society: Due Process for Automated Predictions' (2014) 89 Washington Law Review 1

Claessens S et al, 'Fintech Credit Markets Around the World: Size, Drivers and Policy Issues' (2018) <https://www.bis.org/publ/qtrpdf/r_qt1809e.htm>

Clifford D and Ausloos J, 'Data Protection and the Role of Fairness' (2018) 37 Yearbook of European Law 130

Coffee JC, 'The Political Economy of Dodd-Frank: Why Financial Reform Tends to be Frustrated and Systemic Risk Perpetuated' (2012) 97 Cornell Law Review 1019

Cofone IN, 'Nothing to Hide, but Something to Lose' (2020) 70(1) University of Toronto Law Journal 64

Cohen GA, 'Where the Action Is: On the Site of Distributive Justice', (1997) 26(1) Philosophy and Public Affairs 3

Cohen JE, 'What is Privacy For' (2013) 126 Harvard Law Review 1904

Collins H, 'Justification of Indirect Discrimination' in Collins H and Khaitan T (eds) *Foundations of Indirect Discrimination Law* (Hart 2018)

— — and Khaitan T, 'Indirect Discrimination Law: Controversies and Critical Questions', in Collins H and Khaitan T (eds) *Foundations of Indirect Discrimination Law* (Hart 2018)

Committee on the Global Financial System and Financial Stability Board, 'FinTech Credit: Market Structure, Business Models and Financial Stability Implications' (2017) <https://bit.ly/2W6yGF5>

Consumer Financial Protection Bureau, 'Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process' (2017) 82 FR 11183 <https://bit.ly/2IMH7NK>

— — 'Consumer Financial Protection Bureau Issues No Action Letter to Facilitate the Use of Artificial Intelligence For Pricing and Underwriting Loans' (Nov 30, 2020) <https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-issues-no-action-letter-facilitate-use-artificial-intelligence-pricing-and-underwriting-loans/>

— — 'Request for Information: Equal Credit Opportunity Act and Regulation B' (2020) <https://www.consumerfinance.gov/rules-policy/notice-opportunities-comment/archive-closed/request-information-equal-credit-opportunity-act-and-regulation-b-extension/>

— — 'CFPB Issues Order to Terminate Upstart No Action Letter' (Jun 08 2022) <https://www.consumerfinance.gov/about-us/newsroom/cfpb-issues-order-to-terminate-upstart-no-action-letter/>

— — 'CFPB Publishes Analysis of Potential Impacts of Medical Debt Credit Reporting Changes' (July 27 2022) <https://www.consumerfinance.gov/about-us/newsroom/cfpb-publishes-analysis-of-potential-impacts-of-medical-debt-credit-reporting-changes/>

— — 'The Convergence of Payments and Commerce: Implications for Consumers', (Aug 4, 2022), <https://www.consumerfinance.gov/data-research/research-reports/the-convergence-of-payments-and-commerce-implications-for-consumers/>

— — Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency, 'Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning' (2021) <https://www.federalregister.gov/documents/2021/03/31/2021-06607/request-for-information-and-comment-on-financial-institutions-use-of-artificial-intelligence>

Cordray R, 'Prepared Remarks of CFPB Director Richard Cordray at the Alternative Data Field Hearing' (Feb 16, 2017) <https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-alternative-data-field-hearing/>

Cornaggia J, Wolfe B and Yoo W, 'Crowding Out Banks: Credit Substitution by Peer-To-Peer Lending (2018) <http://dx.doi.org/10.2139/ssrn.3000593>

Cornelli G et al, 'Fintech and Big Tech Credit: A New Database' (2020) <https://www.bis.org/publ/work887.htm>

Cranston RS et al, *Principles of Banking Law* (OUP 2018)

Crisanto JC, Ehrentraud J, and Fabian M, 'Big Techs in Finance: Regulatory Approaches and Policy Options' (BIS Financial Stability Institute Briefs No. 12, 2021) <https://www.bis.org/fsi/fsibriefs12.pdf>

Crouch C, 'Privatized Keynesianism: An Unacknowledged Regime' (2009) 11(3) British Journal of Politics and International Relations 382

Crowther G, *Report of the Committee on Consumer Credit (Chairman: Lord Crowther)* (Cmnd 4596, 1971)

Croxson K et al, 'Platform-Based Business Models and Financial Inclusion' (BIS Working Paper No. 986, 2022) <https://www.bis.org/publ/work986.htm>

Cullerton N, 'Behavioral Credit Scoring' (2013) 101 Georgetown Law Journal 807

Cutler DM and Katz LF, 'Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980's' (1992) 82 American Economic Review 546

Danielsson J, Macrae R and Uthemann A, 'Artificial Intelligence and Systemic Risk' (2022) 140 Journal of Banking and Finance

Davies S and Finney A, 'The Poverty Premium and Debt' in Gardner J, Gray M, and Moser K (eds) *Debt and Austerity* (Edward Elgar 2021)

Davies S and Trend L, 'The Poverty Premium: A Customer Perspective' (2020) <https://fairbydesign.com/poverty-premium-research-turn2us/>

De Cnudde S et al, 'What does your Facebook Profile Reveal About Your Creditworthiness? Using Alternative Data for Microfinance' (2019) 70(3) Journal of the Operational Research Society 353

de Roure C, Pelizzon L, Thakor A, 'P2P Lenders versus Banks: Cream Skimming or Bottom Fishing?' (2022) 11(2) The Review of Corporate Finance Studies 213

Deakin S and Markou C, 'The Law-Technology Cycle and the Future of Work' (2018) 158 (2) Giornale di Diritto del Lavoro e di Relazioni Industriali 445

Dearden C, Goode J, Whitfield G, and Cox L, 'Credit and Debt in Low-Income Families' (June 2010) <https://www.jrf.org.uk/sites/default/files/jrf/migrated/files/credit-debt-low-incomes-full.pdf>

Debt Camel, 'Wonga—Administration Ended, Company Dissolved', <https://debtcamel.co.uk/wonga-has-stopped-issuing-loans/>

Deku SY, Kara A, Molyneux P, 'Exclusion and Discrimination in the Market for Consumer Credit' (Working Papers in Responsible Banking and Finance WP No. 13-006, 2013) <https://www.st-andrews.ac.uk/business/rbf/workingpapers/RBF13_006.pdf>

Demos T and Seetharam D, 'Facebook Isn't So Good at Judging Your Credit After All' *Wall Street Journal* (February 24 2016) <https://www.wsj.com/articles/lenders-drop-plans-to-judge-you-by-your-facebook-friends-1456309801>

DeNicola L, 'What Does Subprime Mean?' (*Experian Blog*, July 9 2022) <https://www.experian.com/blogs/ask-experian/what-is-subprime/>

Department for Education, 'A New Approach to Child Poverty: Tackling the Causes of Disadvantage and Transforming Families' Lives' (2011) <https://www.gov.uk/government/publications/a-new-approach-to-child-poverty-tackling-the-causes-of-disadvantage-and-transforming-families-lives>

Department for Levelling Up, Housing and Communities (2022), 'Levelling up the United Kingdom' <https://www.gov.uk/government/publications/levelling-up-the-united-kingdom>

Desai V, Crook J, and Overstreet G, 'A Comparison of Neural Networks and Linear Scoring Models in the Credit Union Environment' (1996) 95(1) European Journal of Operations Research 24

Deville J and van der Velden L, 'Seeing the Invisible Algorithm: The Practical Politics of Tracking the Credit Trackers' in Amoore L and Piotukh V (eds), *Algorithmic Life: Calculative Devices in the Age of Big Data* (Routledge 2016)

Di Maggio M and Yao V, 'Fintech Borrowers: Lax Screening or Cream-Skimming?' (2021) 34(10) The Review of Financial Studies 4656

— —, Ratnadiwakara D, and Carmichael D, 'Invisible Primes: Fintech Lending with Alternative Data' (2021) <https://ssrn.com/abstract=3937438>

di Martino P, 'The Historical Evolution of Bankruptcy Law in England, the US and Italy up to 1939: Determinants of Institutional Change and Structural Differences' in Gratzer K and Stiefe D (eds) *History of Insolvency and Bankruptcy: from an International Perspective* (Huddinge: Södertörns högskola, 2008)

Disney R, Bridges S, and Gathergood J, 'Drivers of Over-indebtedness: Report to the Department of Business, Enterprise, and Regulatory Reform' (Jun 1, 2008)

Djeundje VB et al, 'Enhancing Credit Scoring with Alternative Data' (2021) 163 Expert Systems with Applications 1

Dobbie W and Skiba PM, 'Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending' (2013) 5(4) American Economic Journal: Applied Economics 256

Dobbie W et al, 'Measuring Bias in Consumer Lending' (2021) 88 Review of Economic Studies 2799

Doleac J and Hansen B, 'The Unintended Consequences of "Ban the Box": Statistical Discrimination and Employment Outcomes When Criminal Histories Are Hidden' 38(2) 2020 Journal of Labour Economics 321

Duffy IPH, *Bankruptcy and Insolvency in London during the Industrial Revolution* (Routledge 1985)

Durand D, 'Credit-Rating Formulae' in Durand (ed) *Risk Elements in Consumer Instalment Financing* (NBER 1941) <https://www.nber.org/system/files/chapters/c9265/c9265.pdf>

Dworkin RM, 'Is Wealth a Value?' (1980) 9 Journal of Legal Studies 191

Economist, 'Big Tech Takes Aim at the Low-Profit Retail-Banking Industry' *Economist* (November 21 2019) <https://www.economist.com/finance-and-economics/2019/11/21/big-tech-takes-aim-at-the-low-profit-retail-banking-industry>

Edmonds T, 'Consumer Credit Regulation' (Briefing Paper No. 06842, March 2014) <https://commonslibrary.parliament.uk/research-briefings/sn06842/>

Edwards L and Veale M, 'Slave to the Algorithm? Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking For' (2017) 16 Duke Law & Technology Review 18

Einav L, Jenkins M, and Levin J, 'The Impact of Credit Scoring on Consumer Lending' (2013) 44(2) RAND Journal of Economics 249

Engel KC and McCoy PA, 'A Tale of Three Markets: The Law and Economics of Predatory Lending' (2002) 80 Texas Law Review 1255

—— *The Subprime Virus: Reckless Credit, Regulatory Failure, and Next Steps*, (OUP 2016)

Equifax, 'How are Credit Scores Calculated?' (2019) <https://bit.ly/2I7ppm6>

—— 'Credit Reference Agency Information Notice' (Version 1.1, March 26 2020) <https://www.equifax.co.uk/crain/>

—— 'Equifax Partners with Rent Reporting Innovator CreditLadder to Improve Tenants' Access to Credit', <https://www.equifax.co.uk/about-equifax/press-releases/en_gb/-/blog/equifax-partners-with-rent-reporting-innovator-creditladder-to-improve-tenants-access-to-credit/>

—— 'Expand Access to Credit with Alternative Data from Equifax' <https://www.equifax.com/resource/-/asset/video/expand-access-to-credit-with-alternative-data-from-equifax/>

European Commission, 'Communication to the Council on a Community Data-Processing Policy' SEC (73) 4300 final (1973)

—— 'Report from the Commission to the European Parliament and the Council on the Implementation of Directive 2008/48/EC on Credit Agreements for Consumers' (2020) <https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/1844-Evaluation-of-the-Consumer-Credit-Directive>

—— 'Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending

Certain Union Legislative Acts COM/2021/206 final' (2021) <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206>

European Parliament, 'Resolution on the Protection of the Rights of the Individual in the Face of Developing Technical Progress in the Field of Automatic Data Processing' [1975] OJ C60/48

Experian, 'Credit Reference Agency Information Notice' (version 1, 23rd October 2017) (copy on file with author)

—— 'Making the Invisible Visible' (2018) <https://www.experian.co.uk/assets/consumer-credit-risk/making-the-invisible-visible.pdf>

—— 'Britain's Unseen Problem: 5.8 Million People 'Invisible' to the Financial System' (9 November 2018) <https://www.experianplc.com/media/latest-news/2018/britain-s-unseen-problem-58-million-people-invisible-to-the-financial-system/>

—— 'Credit Reference Agency Information Notice', (Version 1.1, 26 March 2020) <https://www.experian.co.uk/legal/crain/>

—— 'Meet the 5 Million 'Credit Invisible' Brits Still at Risk of Exclusion from the Financial System' (21 March 2022) <https://www.experianplc.com/media/latest-news/2022/meet-the-5-million-credit-invisible-brits-still-at-risk-of-exclusion-from-the-financial-system/>

—— 'Experian ESG Presentation' (June 27 2022) <https://www.experianplc.com/media/4157/experian_esg_presentation.pdf>

—— 'Instantly Improve Your Score with Experian Boost' <https://www.experian.co.uk/consumer/experian-boost.html>

—— 'Only Experian can raise your FICO score instantly—for free' <https://www.experian.com/consumer-products/score-boost.html>

—— 'Open Banking and Experian Boost' <https://www.experian.co.uk/consumer/experian-boost-open-banking.html>

—— 'Does Short-Term Buy Now Pay Later Credit Impact Your Credit Score?' <https://www.experian.co.uk/consumer/help-discover/discover/guides/short-term-buy-now-pay-later.html>

—— 'The Rental Exchange for Tenants' <https://www.experian.co.uk/business/customer-insights/risk-analysis/rental-exchange/tenant-information>

—— 'The Rental Exchange' <https://www.experian.co.uk/assets/rental-exchange/rental-exchange-main-brochure.pdf >

—— 'Your Free Experian Credit Score' <https://www.experian.co.uk/consumer/experian-credit-score.html>

— — 'Alternative Data Credit Trends and Beyond' <https://www.experian.com/consumer-information/alternative-financial-services>

— — and Oliver Wyman, 'Financial Inclusion and Access to Credit' (January 2022) <https://www.businesswire.com/news/home/20220112005355/en/Experian-and-Oliver-Wyman-Find-Expanded-Data-and-Advanced-Analytics-Can-Improve-Access-to-Credit-for-Nearly-50-Million-Credit-Invisible-and-Unscoreable-Americans>

Ezrachi A and Stucke ME, 'Artificial Intelligence & Collusion: When Computers Inhibit Competition' (2017) University of Illinois Law Review 1775

— — 'How Digital Assistants Can Harm our Economy, Privacy, and Democracy' (2017) 32 Berkeley Technology Law Journal 1239

Facebook, 'An Update on our Plans to Restrict Data Access on Facebook' (2018) <https://about.fb.com/news/2018/04/restricting-data-access/>

Fair By Design, 'No Interest Loan Scheme' <https://fairbydesign.com/no-interest-loan-scheme/>

Fairweather K, 'Redressing Inequality in Personal Credit Transactions: 1700-1974' in Barker K et al (eds) *Private Law and Power* (Hart 2016)

Fannie Mae, 'Fannie Mae Introduces New Underwriting Innovation to Help More Renters Become Homeowners' (August 11, 2021) <https://www.fanniemae.com/newsroom/fannie-mae-news/fannie-mae-introduces-new-underwriting-innovation-help-more-renters-become-homeowners>

— — 'FAQ: Positive Rent Payment History in Desktop Underwriter' <https://singlefamily.fanniemae.com/originating-underwriting/faqs-positive-rent-payment-history-desktop-underwriter>

Fanning T, 'The Tech Behind Borrowing Power' (*Zopa Blog*, 15 October 2019) <https://perma.cc/XL6F-E7TF?type=image>

— — 'Zopa Launches New Digital Bank, Offering Consumers a Compelling Alternative When They Need it Most' (*Zopa Blog*, 23 June 2020) https://www.zopa.com/blog/article/zopa-launches-new-digital-bank-offering-consumers-a-compelling-alternative-when-they-need-it-most

Farrell J and Shapiro C, 'Intellectual Property, Competition, and Information Technology' in Varian HR, Farrell J, and Shapiro C, *The Economics of Information Technology: An Introduction* (CUP 2004)

Financial Conduct Authority, 'Applying Behavioural Economics at the Financial Conduct Authority' (Occasional paper no. 1, April 2013) <https://bit.ly/33ghiit>

— — 'FCA's Regulatory Approach to Crowdfunding Over the Internet, and the Promotion of Non-Readily Realisable Securities by Other Media' (Policy Statement PS14/4, March 2014) <https://www.fca.org.uk/publication/policy/ps14-04.pdf>

—— 'Detailed Rules for the Price Cap on High-Cost-Short-Term Credit' (2014) PS 14/16 <https://www.fca.org.uk/publications/policy-statements/ps14-16-detailed-rules-price-cap-high-cost-short-term-credit>

—— 'Project Innovate: Call for Input' (Jul 2014) <https://www.fca.org.uk/publication/call-for-input/project-innovate-call-for-input.pdf>

—— 'Technical Annexes Supplement to CP14/10 Proposals for a Price Cap on High-Cost Short-Term Credit' (Jul 2014) <https://www.fca.org.uk/publication/consultation/cp-14-10-technical-annexes.pdf>

—— 'Wonga to Make Major Changes to Affordability Criteria Following Discussions with the FCA' (Press release, October 2 2014) <https://www.fca.org.uk/news/press-releases/wonga-make-major-changes-affordability-criteria-following-discussions-fca>

—— 'Call for Inputs on Big Data in Retail General Insurance' (Feedback Statement FS 16/5, September 2016) <https://www.fca.org.uk/publication/feedback/fs16-05.pdf>

—— 'Price Discrimination and Cross-Subsidy in Financial Services' (Occasional Paper No. 22, Sept. 2016) <https://www.fca.org.uk/publication/occasional-papers/op16-22.pdf>

—— 'Preventing Financial Distress by Predicting Unaffordable Consumer Credit Agreements: An Applied Framework' (Occasional Paper 28, July 2017) <https://www.fca.org.uk/publication/occasional-papers/op17-28.pdf

—— 'High-Cost Credit Review: Technical Annex 1' (July 2017) <https://www.fca.org.uk/publication/feedback/fs17-02-technical-annex.pdf>

—— 'Rent-to-Own Provider BrightHouse to Provide Over £14.8 Million in Redress to Around 249,000 Customers' (2017) <https://www.fca.org.uk/news/press-releases/rent-to-own-provider-brighthouse-14-8-million-redress-249000-customers>

—— 'Credit Card Market Study—Persistent Debt and Earlier Intervention—Feedback to CP 17/43 and Final Rules' (Policy Statement PS18/4, February 2018) <https://www.fca.org.uk/publication/policy/ps18-04.pdf>

—— 'Assessing Creditworthiness in Consumer Credit – Feedback on CP 17/27 and Final Rules and Guidance' (Policy Statement PS18/19, July 2018) <https://bit.ly/2SS9ijA>

—— 'Loan-Based ('Peer-to-Peer') and Investment-Based Crowdfunding Platforms: Feedback on Our Post-Implementation Review and Proposed Changes to the Regulatory Framework' (Consultation paper CP 18/20, July 2018) <https://www.fca.org.uk/publication/consultation/cp18-20.pdf>

—— 'Fair Pricing in Financial Services' (Discussion Paper DP18/9, October 2018) <https://www.fca.org.uk/publication/discussion/dp18-09.pdf>

—— 'Review of Retained Provisions of the Consumer Credit Act: Final Report' (2019) <https://www.fca.org.uk/publication/corporate/review-of-retained-provisions-of-the-consumer-credit-act-final-report.pdf>

—— 'PS19/14 Loan-Based ('Peer-to-Peer') and Investment-Based Crowdfunding Platforms: Feedback to CP18/20 and Final Rules' (Policy Statement PS19/14, June 2019) <https://www.fca.org.uk/publication/policy/ps19-14.pdf>

—— 'Reforming Conduct of Business Regulation' (Consultation Paper 06/19, 2019, chapter 28)

—— 'Fair Pricing in Financial Services: Summary of Responses and Next Steps' (Feedback Statement FS 19/04, July 2019) <https://www.fca.org.uk/publication/feedback/fs19-04.pdf>

—— 'Coronavirus: Information for Consumers with Personal Loans, Overdrafts and Other Forms of Credit' (2020) <https://www.fca.org.uk/consumers/coronavirus-information-personal-loans-credit-cards-overdrafts>

—— 'A New Consumer Duty' (Consultation Paper CP 21/36, December 2021) <https://www.fca.org.uk/publications/consultation-papers/cp21-36-new-consumer-duty-feedback-cp21-13-further-consultation>

—— 'Open Finance' (Feedback Statement FS21/7, 2021) <https://www.fca.org.uk/publications/feedback-statements/fs21-7-open-finance-feedback-statement>

—— 'FG21/1 Guidance for Firms on the Fair Treatment of Vulnerable Consumers' (2021) <https://www.fca.org.uk/publication/finalised-guidance/fg21-1.pdf>

—— 'The Woolard Review – A Review of Change and Innovation in the Unsecured Credit Market' (2021) <https://www.fca.org.uk/news/press-releases/fca-publishes-woolard-review-unsecured-credit-market>

—— 'Borrowers in Financial Difficulty Following the Coronavirus Pandemic- Key Findings' (2022) <https://www.fca.org.uk/publication/research/borrowers-in-financial-difficulty-following-coronavirus-pandemic-key-findings.pdf>

—— 'Credit Information Market Study: Interim Report and Discussion Paper' (MS191.2, 2022) <https://www.fca.org.uk/publication/market-studies/ms-19-1-2.pdf>

Feibelman A, 'Defining the Social Insurance Function of Consumer Bankruptcy' (2005) 13 American Bankruptcy Institute Law Review 129

Ferran E, 'The New Mandate for Supervision of Financial Services Conduct' (2012) 65 Current Legal Problems 411

Ferrari A, 'Losers Among the Losers: The Welfare Effects of the Great Recession Across the Cohorts' (ECB working paper series, December 2020) <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2509~a11c0ce310.en.pdf>

Feyen E et al, 'Fintech and the Digital Transformation of Financial Services: Implications for Market Structure and Public Policy' (BIS Working Paper No. 117, July 2021) <https://www.bis.org/publ/bppdf/bispap117.pdf>

Financial Services Authority, 'Treating Customers Fairly—Towards Fair Outcomes for Consumers' (2006) <https://www.fca.org.uk/publication/archive/fsa-tcf-towards.pdf>

—— 'Product Intervention' (Discussion Paper DP11/1, 2011) <https://www.fca.org.uk/publication/discussion/dp11_01.pdf>

Financial Stability Board, 'Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications' (2017) <https://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/>

FinReg Lab, 'The Use of Cash-Flow Data in Underwriting Credit' (2019) <https://finreglab.org/cash-flow-data-in-underwriting-credit-empirical-research-findings>

Fisher RA, 'The Use of Multiple Measurements in Taxonomic Problems' (1936) Annals of Eugenics 179

Foohey P and Martin N, 'Fintech's Role in Exacerbating or Reducing the Wealth Gap' (2021) University of Illinois Law Review 459

—— and Greene S, 'Credit Scoring Duality' (2022) 85 Law and Contemporary Problems 101

Fourcade M, 'Ordinal Citizenship' (2021) 72(2) British Journal of Sociology 154

Fracassi C and Magnuson WJ, 'Data Autonomy' (2021) 71 Vanderbilt Law Review 327

Franken SF, 'The Political Economy of the EC Consumer Credit Directive' in Niemi J, Ramsay I and Whitford W C (Eds) *Consumer Credit, Debt and Bankruptcy: Comparative and International Perspectives* (Hart 2009)

Frankfurt H, 'Equality as a Moral Ideal' (1987) 98(1) Ethics 21

—— *On Inequality* (Princeton 2016)

Freedman S and Jin GZ, 'Learning by Doing with Asymmetric Information: Evidence From Prosper.com' (2011) <http://www.nber.org/papers/w16855>

Frost J et al, 'BigTech and the Changing Structure of Financial Intermediation' (BIS Working Papers no. 779, 2019) <https://www.bis.org/publ/work779.pdf>

Furman J, 'Unlocking Digital Competition: Report of the Digital Competition Expert Panel' (2019) <https://www.gov.uk/government/publications/unlocking-digital-competition-report-of-the-digital-competition-expert-panel>

Fuster A et al, 'Predictably Unequal? The Effects of Machine Learning on Credit Markets' (2022) 77(1) The Journal of Finance 5

Fuster GG, *The Emergence of Personal Data Protection as a Fundamental Right of the EU* (Springer 2014)

G20, '2008 G20 Communique' <http://www.g20.utoronto.ca/2008/2008communique1109.html>

Gabaix X and Laibson D, 'Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets' (2006) 121(2) Quarterly Journal of Economics 505

Gal MS and Elkin-Koren N, 'Algorithmic Consumers' (2017) 30(2) Harvard Journal of Law and Technology 309

— — and Aviv O, 'The Competitive Effects of the GDPR' (2020) 16 Journal of Competition Law and Economics 349

Galindo J and Tamayo P, 'Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modelling Applications' (2000) 15 Computational Economics 107

Gambacorta L et al, 'How do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm' (2019) <https://www.bis.org/publ/work834.pdf>

— — et al, 'Data vs Collateral', BIS Working Paper No. 881 (Sept. 01, 2020), <https://www.bis.org/publ/work881.htm>

Gardner J, 'Austerity, Inequality and High-Cost Credit: Understanding the Role of a Social Minimum, in Gardner J, Gray M, and Moser K (eds) *Debt and Austerity* (Edward Elgar 2021)

Gardner J, 'Liberals and Unlawful Discrimination' (1989) 9(1) Oxford Journal of Legal Studies 1

Gardner J, Gray M, and Moser K (eds) *Debt and Austerity* (Edward Elgar 2021)

Gathergood J, 'Debt and Depression: Causal Links and Social Norm Effects' (2012) 122 The Economic Journal 1094

— — and Guttman-Kenney B, 'Can we Predict Which Consumer Credit Users Will Suffer Financial Distress?' (FCA Occasional Paper 20, August 2016), <https://www.fca.org.uk/publication/occasional-papers/occasional-paper-20.pdf>

— — Guttman-Kenney B, Hunt S, 'How Do Payday Loans Affect Borrowers? Evidence from the U.K. Market' (2019) 32(2) The Review of Financial Studies 496

Gelpi R and Julien-Labroyère F, *The History of Consumer Credit: Doctrines and Practices* (Palgrave Macmillan 2000)

Geslevich Packin N and Lev-Aretz Y, 'On Social Credit and the Right to Be Unnetworked' (2016) Columbia Business Law Review 339.

Gillis TB, 'The Input Fallacy' (2022) 106 Minnesota Law Review 1175

— — and Simons J, 'Explanation < Justification: GDPR and the perils of privacy' (2019) 2(1) Pennsylvania Journal of Innovation 71

Godfrey G et al, 'Banker's Confidentiality—A Dying Duty but Not Dead Yet' (2016) 17 Business Law International 173

Goertzel B and Pennachin C (Eds) *Artificial General Intelligence* (Springer 2005)

Goldberg I, 'Privacy Enhancing Technologies for the Internet III: Ten Years Later', in Acquisti et al (eds) *Digital Privacy: Theory, Technologies and Practices* (New York 2007)

Golding E, Green R and McManus D, 'Imperfect Information and the Housing Finance Crisis' (2008) <https://www.jchs.harvard.edu/research-areas/working-papers/imperfect-information-and-housing-finance-crisis>

Good I J, 'Speculations Concerning the First Ultraintelligent Machine' (1966) 6 Advances in Computers 31

Goode RM, 'The Consumer Credit Act 1974' (1975) 34(1) Cambridge Law Journal 79

—— 'Usury in English Law' (1982) 1 Arizona Journal of International and Comparative Law 38

—— 'The Banker's Duty of Confidentiality' (1989) Journal of Business Law 269

Goodfellow I, Bengio Y, Courville A, *Deep Learning* (MIT 2015)

Goodman B and Flaxman S, 'EU Regulations on Algorithmic Decision-Making and a "Right to Explanation"' (2017) <https://doi.org/10.1609/aimag.v38i3.2741>

Google, 'Why Google Collects Data' <https://policies.google.com/privacy?hl=en-US#whycollect>

Graeber D, *Debt: The First 5000 Years* (Melville House 2014)

Gray M and Suri S, *Ghost Work: How to Stop Silicon Valley from Building a New Underclass* (Houghton Mifflin Harcourt 2019)

Gray M, Moser K, and Gardner J, 'Understanding Low-Income Debt in a High-Income Country' in Gardner J, Gray M, and Moser K (eds) *Debt and Austerity* (Edward Elgar 2021)

Grice A, 'War on Wonga: We're Putting You Out of Business, Archbishop of Canterbury Justin Welby Tells Payday Loans Company' *Independent* (25 July 2013) <https://www.independent.co.uk/news/uk/home-news/war-on-wonga-we-re-putting-you-out-of-business-archbishop-of-canterbury-justin-welby-tells-payday-loans-company-8730839.html>

Guardian, 'Wonga 2.0? Meet the New Breed of Payday Lenders' *Guardian* (Apr 14 2018) <https://www.theguardian.com/money/2018/apr/14/wonga-mark-2-new-breed-of-payday-lenders-oakam>

Gurney P, 'The Battle of the Consumer in Postwar Britain' (2005) 77(4) Journal of Modern History 976

Guseva A and Rona-Tas A, 'Uncertainty, Risk, and Trust: Russian and American Credit Card Markets Compared' (2001) 66(5) American Sociological Review 623

Hacker J, 'Privatizing Risk Without Privatizing the Welfare State: The Hidden Politics of Social Welfare Retrenchment in the United States' (2004) 98 American Political Science Review 243

Hand DJ, 'Classifier Technology and the Illusion of Progress' (2006) 21(1) Statistical Science 1

—— and Henley WE, 'Can Reject Inference Ever Work?' (1993) 5(1) IMA Journal of Management Mathematics 45

—— and Henley WE, 'Statistical Classification Methods in Consumer Credit Scoring: A Review' (1995) 160(3) Journal of the Royal Statistical Society 523

Hardy Q, 'Big Data for the Poor' *New York Times* (July 2012) <https://bits.blogs.nytimes.com/2012/07/05/big-data-for-the-poor/>

Hartfree Y and Collard S, 'Poverty, Debt and Credit: An Expert-led review—Final Report to the Joseph Rowntree Foundation' (March 2014) <https://www.bristol.ac.uk/media-library/sites/geography/migrated/documents/pfrc1404.pdf>

Hau H et al, 'How FinTech enters China's Credit Market' (2019) 109 AEA Papers and Proceedings 60 <https://www.aeaweb.org/articles?id=10.1257/pandp.20191012>

Haugeland J, *Artificial Intelligence: The Very Idea* (MIT Press 1985)

Hausman D, McPherson M, and Satz D, *Economic Analysis, Moral Philosophy and Public Policy* (3rd Edition, CUP 2017)

Hayek F, 'The Pretence of Knowledge' (1989) 79(6) American Economic Review 3

Hellman D, 'Big Data and Compounding Injustice' Journal of Moral Philosophy (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3840175>

—— 'Indirect Discrimination and the Duty to Avoid Compounding Injustice' in Collins H and Khaitan T (eds), *Foundations of Indirect Discrimination Law* (Hart 2018)

Henley WE and Hand DJ, 'Construction of a K-Nearest Neighbour Creditscoring System' (1997) 8(4) IMA Journal of Management Mathematics 305

Herrine L, 'Credit Reporting's Vicious Cycles' (2016) 40 NYU Review of Law and Social Change 305

Hills J, 'The Last Quarter Century: From New Right to New Labour' in Glennerster H, Hills J, Piachaud D, and Webb J, 'One Hundred Years of Poverty' (2004) <https://eprints.lse.ac.uk/3913/1/One_hundred_years_of_poverty.pdf>

Hirsch F, *The Social Limits of Growth* (HUP 1976)

Hirshleifer J, 'The Private and Social Value of Information and the Reward to Inventive Activity' (1971) 61(4) American Economic Review 561

HM Treasury, 'A New Approach to Financial Regulation—Consultation on Reforming the Consumer Credit Regime' (2010) <https://www.gov.uk/government/consultations/a-new-approach-to-financial-regulation-reforming-the-consumer-credit-regime>

—— 'Review of the Money Advice Service' (2015) <https://www.gov.uk/government/publications/review-of-the-money-advice-service>

—— 'Financial Inclusion Report: 2020-2021' <https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1038537/Financial_Inclusion_Report_2020-21.pdf>

—— 'Regulation of Buy-Now Pay-Later: Consultation' (2021) <https://www.gov.uk/government/consultations/regulation-of-buy-now-pay-later-consultation>

—— 'Reform of the Consumer Credit Act: Consultation' (9 December 2022) <https://www.gov.uk/government/consultations/reform-of-the-consumer-credit-act-consultation>

—— 'Regulation of Buy-Now Pay-Later: Consultation Response' (2022) <https://www.gov.uk/government/consultations/regulation-of-buy-now-pay-later-consultation>

Hochstein M, 'Fintech (the Word, That Is) Evolves' *American Banker* (5 October 2015) <https://www.americanbanker.com/opinion/fintech-the-word-that-is-evolves>

Hockett RC and Omarova ST, 'The Finance Franchise' (2017) 102 Cornell Law Review 1143

Hodgman DR, 'Credit Controls in Western Europe: An Evaluative Review' (Credit Allocation Techniques and Monetary Policy, Federal Reserve Bank of Boston Conference Series No. 11, 1973)

Hoff K and Stiglitz J (1990) 'Imperfect Information and Rural Credit Markets: Puzzles and Policy Perspectives' (1990) 4(3) World Bank Economic Review 235

Holloman C, 'Your Facebook Updates Now Determine Your Credit Score' *Guardian* (August 28 2014) <https://www.theguardian.com/media-network/media-network-blog/2014/aug/28/social-media-facebook-credit-score-banks>

Hudon M, 'Should Access to Credit be a Right?' (2009) 84 Journal of Business Ethics 17

Hunt R, 'What's in the File? The Economics and Law of Consumer Credit Bureaus' (Federal Reserve Bank of Philadelphia Business Review, Second Quarter, 2002)

Hurley M and Adebayo J, 'Credit Scoring in the Era of Big Data' (2016) 18 Yale Journal of Law and Technology 148

Hyman L, 'Debtor Nation: How Consumer Credit Built Postwar America' (2008) 9(4) Enterprise & Society 614

Hyman L, 'The Politics of Consumer Debt: U.S. State Policy and the Rise of Investment in Consumer Credit, 1920-2008' (2012) 644 Annals of the American Academy of Political & Social Science 40

Hyman L, *Borrow: The American Way of Debt* (Vintage Books 2012)

Information Commissioner's Office, 'Investigation Into Data Protection Compliance in the Direct Marketing Data Broking Sector' (2020) <https://ico.org.uk/media/action-weve-taken/2618470/investigation-into-data-protection-compliance-in-the-direct-marketing-data-broking-sector.pdf>

— — 'Enforcement Notice' (2020) <https://ico.org.uk/media/action-weve-taken/enforcement-notices/2618467/experian-limited-enforcement-report.pdf>

— — 'Data Protection Impact Assessments' <https://bit.ly/3nJlPUH>

— — 'Guide to Data Protection—Exemptions' <https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/exemptions/>

— — 'How Do We Apply Legitimate Interests in Practice?' <https://bit.ly/32a8gEt>

— —'Investigation Into Data Analytics for Political Purposes', <https://ico.org.uk/action-weve-taken/investigation-into-data-analytics-for-political-purposes/>

— — and Financial Conduct Authority, 'Memorandum of Understanding Between the Financial Conduct Authority and the Information Commissioner' (Feb 18, 2019) <https://ico.org.uk/media/about-the-ico/documents/2614342/financial-conduct-authority-ico-mou.pdf>

Ince H and Aktan B, 'A Comparison of Data Mining Techniques for Credit Scoring in Banking: A Managerial Perspective' (2010) 10(3) Journal of Business Economics and Management 233

International Monetary Fund, 'Global Financial Stability Report October 2017: Is Growth at Risk?' (October 2017) <https://www.imf.org/en/Publications/GFSR/Issues/2017/09/27/global-financial-stability-report-october-2017>

Iscenko Z et al, 'Economics for Effective Regulation' (FCA Occasional Paper No. 13, March 2016) <https://www.fca.org.uk/publication/occasional-papers/occassional-paper-13.pdf>

Iversen T and Rehm P, 'Information and Financialization: Credit Markets as a New Source of Inequality' (2022) 0(0) Comparative Political Studies 1

Iyer R et al, 'Screening Peers Softly: Inferring the Quality of Small Borrowers' (2016) 62(6) Management Science 1554

Jack RB, *Banking Services: Law and Practice. Report by the Review Committee* (Cmnd 622, 1989)

Jack W and Suri T, 'Mobile Money: The Economics of M-Pesa' (2011) National Bureau of Economic Research Working Paper 16721 <https://www.nber.org/system/files/working_papers/w16721/w16721.pdf>

Jacob K and Schneider R, 'Market Interest in Alternative Data Sources and Credit Scoring' (The Center for Financial Services Innovation, December 2006) <https://s3.amazonaws.com/cfsi-innovation-files/wp-content/uploads/2017/02/05053225/The-Predictive-Value-of-Alternative-Credit-Scores.pdf>

Jaffee DM and Russell T, 'Imperfect Information, Uncertainty and Credit Rationing' (1976) 90 Quarterly Journal of Economics 651

Jagtiani J and Lemieux C, 'Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks' (FRB of Philadelphia Working Paper No 18-13, 2018) <https://ssrn.com/abstract=3178459>

— — and Lemieux C, 'The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform' (FRB of Philadelphia Working Paper No. 18-15, 2018) <https://ssrn.com/abstract=3178461>

— —, Lambie-Hanson L, and Lambie-Hanson T, 'Fintech Lending and Mortgage Credit Access' (2019) <https://doi.org/10.21799/frbp.wp.2019.47>

Janardana J, 'An Update on P2P at Zopa' (*Zopa Blog*, 6 December 2021) <https://www.zopa.com/blog/article/an-update-on-p2p-at-zopa>

Jansen M, Nguyen H, and Shams A, 'Rise of the Machines: The Impact of Automated Underwriting' (Fisher College of Business Working Paper No. 2020-03-019, 2021) <https://ssrn.com/abstract=3664708>

— —, Nagel F, Yannelis C, Zhang A, 'Data and Welfare in Credit Markets' (2022), <https://ssrn.com/abstract=4015958>

Tullio Jappelli and Marco Pagano, 'The Role and Effects of Credit Information Sharing' in Bertola G, Disney R, and Grant C (eds) *The Economics of Consumer Credit* (MIT Press 2006), 347-372

Jarrow R and Protter P, 'Fair Microfinance Loan Rates' (2019) 19(4) International Review of Finance 909

Jayne L, 'What We'll Build in 2019' (*Monzo Blog*, 29 January 2019) <https://monzo.com/blog/2019/01/29/2019-features>

Jentzsch N, 'The Regulation of Financial Privacy: The United States vs Europe' (ECRI Research Report No. 5, 2003) <https://www.ceps.eu/ceps-publications/regulation-financial-privacy-united-states-vs-europe/>

— — *Financial Privacy: An International Comparison of Credit Reporting Systems* (2nd Edition, Springer 2007)

Jones R, 'Ratesetter Savers Claim Loans Being Sold Off "On the Cheap"' *Guardian* (6 February 2021) <https://www.theguardian.com/money/2021/feb/06/ratesetter-savers-investments-metro-bank>

Joseph Rowntree Foundation, 'Dragged Down by Debt: Millions of Low-Income Households Pulled Under by Arrears While Living Costs Rise' (October 2021) <https://www.jrf.org.uk/report/dragged-down-debt-millions-low-income-households-pulled-under-arrears-while-living-costs-rise>

JP Morgan, 'JPMorgan Chase Commits £1.2 Million to Fair4All Finance to Expand No Interest Loan Scheme for people on low incomes' (2022) <https://www.jpmorganchase.com/news-stories/jpmc-commits-1-2-million-to-fair4all-finance-to-expand-no-interest-loan-scheme>

Kahn A, 'The Tyranny of Small Decisions: Market Failures, Imperfections, and the Limits of Economics' (1966) 19(1) Kyklos International Review for Social Sciences 23

Kahneman D, *Thinking Fast and Slow* (Farrar, Straus and Giroux 2011)

Kaldor N, 'Marginal Productivity and the Macroeconomic Theories of Distribution: Comment on Samuelson and Modigliani' (1966) 33 Review of Economic Studies 309

Kaldor N, *The Scourge of Monetarism* (OUP 1982)

Kalifa R, 'The Kalifa Review of UK FinTech' (2021) <https://www.gov.uk/government/publications/the-kalifa-review-of-uk-fintech>

Kaminski M E, 'The Right to Explanation, Explained' (2019) 34(1) Berkeley Law and Technology Journal

Kaplow L and Shavell S, 'Why the Legal System is Less Efficient than the Income Tax in Redistributing Income' (1994) 23 Journal of Legal Studies 667

Kearns M and Roth A, *The Ethical Algorithm* (OUP 2020)

Kelly-Lyth A, Abraha H, and Adams-Prassl J, 'From 'Code' to 'Guidance': Revising the Instrument on Data and Employment' (2022) 51 Industrial Law Journal 744

Khandani AE, Kim AJ, and Lo AW, 'Consumer Credit Risk Models via Machine Learning Algorithms' (2010) 34(11) Journal of Banking and Finance 2767

King D and Jacobs LR, *Fed Power: How Finance Wins* (OUP 2016)

King T, Aggarwal N, Taddeo M and Floridi L, 'Artificial Intelligence Crime: An Interdisciplinary Analysis of Foreseeable Threats and Solutions' (2020) 26 Science and Engineering Ethics 89

Kingsford-Smith D and Dixon O, 'The Consumer Interest and the Financial Markets' in Moloney N, Ferran E and Payne J (eds) *The Oxford Handbook of Financial Regulation* (OUP 2015)

Kiviat B, 'The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores' (2019) 84(6) American Sociological Review 1134

Kleinberg J, Mullainathan S, Raghavan M, 'Inherent Trade-offs in the Fair Determination of Risk Scores' (2016) <https://arxiv.org/abs/1609.05807>

—— et al, 'Human Decisions and Machine Predictions' (2018) 133(1) The Quarterly Journal of Economics 237

Knight F H, *Risk, Uncertainty, and Profit* (Houghton Mifflin 1921)

Korobkin R B and Ullen T S, 'Law and Behavioral Science: Removing the Rationality Assumption from Law and Economics' (2000) 88 California Law Review 1051

Krippner G K, *The Financialization of the American Economy* (2005) 3 Socio-Economic Review 173

—— *Capitalizing on Crisis: The Political Origins of the Rise of Finance* (HUP 2011)

—— 'Democracy of Credit: Ownership and the Politics of Credit Access in Late Twentieth-Century America' (2017) 123 American Journal of Sociology 1

Krueger D and Perri F, 'On the Welfare Consequences of the Increase in Inequality in the United States' (2003) 18 NBER Macroeconomics Annual 83

—— 'Does Income Inequality Lead to Consumption Inequality? Evidence and Theory' (2006) 73(1) The Review of Economic Studies 163

Kuznets S, 'Economic Growth and Income Inequality' (1955) 45(1) American Economic Review 1

Laibson D, 'Golden Eggs and Hyperbolic Discounting' (1997) 112(2) Quarterly Journal of Economics 443

Lambrecht A and Tucker C, 'Can Big Data Protect a Firm from Competition?' (2015) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2705530>

Lamont J, 'Distributive Justice' (1996) <https://plato.stanford.edu/entries/justice-distributive/>

Langenbucher K, 'Responsible AI Credit Scoring: A Legal Framework' (2020) 25 European Law Review 1

Lauer J, *Creditworthy: A History of Consumer Surveillance and Financial Identity in America* (New York 2017)

Laurer M and Seidl T, 'Regulating the European Data-Driven Economy: A Case Study on the General Data Protection Regulation' (2020) 13(2) Policy and Internet 257

Lawler R, 'Why Fintechs are Buying up Legacy Financial Services Companies' *TechCrunch* (August 2021) <https://techcrunch.com/2021/08/16/why-fintechs-are-buying-up-legacy-financial-services-companies/>

LeCun Y, Bengio Y, and Hinton G, 'Deep Learning' (2015) 251 Nature 436

Lee MSA and Singh J, 'Spelling Errors and Non-Standard Language in Peer-to-Peer Loan Applications and the Borrower's Probability of Default' (2020) <https://papers.ssrn.com/abstract=3609834>

Lending Club, 'Lending Club Closes Acquisition of Radius Bankcorp' (1 February 2021) <https://ir.lendingclub.com/news/news-details/2021/LendingClub-Closes-Acquisition-of-Radius-Bancorp/default.aspx>

Lerman J, 'Big Data and its Exclusions' (2013) 66 Stanford Law Review Online 55

Lessig L, *Code and Other Laws of Cyberspace: Version 2.0* (Basic Books 2006)

Leviathan Y and Matias Y, 'Google Duplex: An AI System for Accomplishing Real-World Tasks Over the Phone' (*Google Research Blog*, 8 May 2018) <https://bit.ly/2rznYXJ>

Leyshon A and Thrift N, 'Lists Come Alive: Electronic Systems of Knowledge and the Rise of Credit Scoring in Retail Banking' (1999) 28(3) Economy and Society 434

Liberti J M and Petersen M A, 'Information: Hard and Soft' (2019) 8(1) The Review of Corporate Finance Studies 1

Lindop N, *Report of the Committee on Data Protection. Chairman: Sir Norman Lindop. Presented to Parliament by the Secretary of State for the Home Department by command of Her Majesty* (Cmnd 7341, 1978)

Lippert J, 'ZestFinance Issues Small, High-Rate Loans, Uses Big Data to Weed Out Deadbeats' *Washington Post* (11 Oct 2014) <https://wapo.st/2J6ugVc>

Lipton Z C, 'The Mythos of Model Interpretability' <https://dl.acm.org/doi/pdf/10.1145/3236386.3241340>

Lister R, *Poverty* (Polity Press 2004)

Lombardi M, Mohanty M, and Shin I, 'The Real Effects of Household Debt in the Short and Long Run' (BIS Working Paper no. 607, January 2017) <https://www.bis.org/publ/work607.pdf>

Lynskey O, *The Foundations of EU Data Protection Law* (OUP 2015)

Macey J, 'Fair Credit Markets: Using Household Balance Sheets to Promote Consumer Welfare' (2022) 100 Texas Law Review 683

Mackenzie D and Wajcman J, *The Social Shaping of Technology* (1985)

MacNeil I, 'Rethinking Conduct Regulation' (2015) 30(7) Butterworths Journal of International Banking and Financial Law 413

Madden M, Gilman M, Levy K, and Marwick A, 'Privacy, Poverty, and Big Data: Matrix of Vulnerabilities for Poor Americans' (2017) 95(1) Washington University Law Review 53

Maglieri G, 'The Concept of Fairness in the GDPR: A Linguistic and Contextual Interpretation' (2020) Proceedings of FAT* ACM 154

Magnuson WJ, *For Profit* (Basic Books 2021)

Majone G, 'The Rise of the Regulatory State in Western Europe' (1994) 17 Western Europe Politics 77

Mak V, 'Financial Services and Consumer Protection' in Flesner C T (ed) *Research Handbook on EU Consumer and Contract Law* (Edward Elgar 2016)

Mann RJ, *Charging Ahead: The Growth and Regulation of Payment Card Markets Around the World* (CUP 2006)

— — 'Bankruptcy Reform and the Sweat Box of Credit Card Debt' (2007) University of Illinois Law Review 375

Manning RD, *Credit Card Nation: The Consequences of America's Addiction to Debt* (Basic Books 2000)

Marchant GE, Allenby BR, and Herkert JR (eds), *The Growing Gap Between Emerging Technologies and Legal-Ethical Oversight: The Pacing Problem* (Springer 2011)

Marcus G and Davies E, *Rebooting AI: Building Artificial Intelligence We Can Trust* (Paragon 2019)

Marron D, '"Lending by Numbers": Credit scoring and the Constitution of Risk Within American Consumer Credit' (2007) 36(1) Economy and Society 103

Marx K, *Das Kapital* (1867)

Maryland Department of Labor, 'Evaluation Rules and Alternative Methods of Determining Creditworthiness' (September 2 2021) <https://content.govdelivery.com/accounts/MDDLLR/bulletins/2ef8d8c>

Mayer-Schönberger V and Cukier K, *Big Data: A Revolution That Will Transform How We Live, Work and Think* (John Murray 2013)

McCarthy J et al, 'A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence' (1955) <http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf>

McLannahan B, 'Being 'Wasted' on Facebook May Damage Your Credit Score' *Financial Times* (Oct 14 2015) <https://www.ft.com/content/d6daedee-706a-11e5-9b9e-690fdae72044>

McLaurin WR, 'The Sequence From Invention to Innovation and its Relation to Economic Growth' (1953) 67(1) The Quarterly Journal of Economics 97

McMahan HB et al, 'Communication-Efficient Learning of Deep Networks From Decentralized Data' (2016) <arXiv:1602.05629>

Melzer BT, 'The Real Costs of Credit Access' (2011) 126 The Quarterly Journal of Economics 517

Metcalf J, 'Translation Tutorial. Engineering for Fairness: How a Firm Conceptual Distinction Between Unfairness and Bias Makes it Easier to Address Un/Fairness' (ACM FAT*, Feb 2019) <https://par.nsf.gov/biblio/10112010>

Meyer M, 'The Right to Credit' (2018) 26(3) The Journal of Political Philosophy 304

Mian A and Sufi A, *House of Debt* (University of Chicago Press 2014)

—— and Verner E, 'Household Debt and Business Cycles Worldwide' (2017) Quarterly Journal of Economics 1755

Micklitz H, 'The Public and the Private – European Regulatory Private Law and Financial Services' (2014) 10(4) European Review of Contract Law 473

Mittelstadt B, 'From Individual to Group Privacy in Big Data Analytics' (2017) 30 Philosophy and Technology 475

Mnohoghitnei I et al, 'Embracing the Promise of Fintech' (Bank of England Quarterly Bulletin, 2019) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3419994>

Moloney N, 'Regulating the Retail Markets' in Moloney N, Ferran E, and Payne J (eds) *The Oxford Handbook of Financial Regulation* (OUP 2015)

Molony J T, *Report of the Committee on Consumer Protection* (Cmnd 1781, 1962)

Morgenson G, 'Held Captive by Flawed Credit Reports' *New York Times* (Jun 21 2014) <https://nyti.ms/2QaYxrG>

Morozov E, *To Save Everything, Click Here: The Folly of Technological Solutionism* (Public Affairs, 2014)

Morse A, 'Peer-to-Peer Crowdfunding: Information and the Potential for Disruption in Consumer Lending' (2015) 7 Annual Review of Financial Economics 463

Murray A, 'Nodes and Gravity in Virtual Space' (2011) 5 Legisprudence 195

National Consumer Law Center, 'Even the Catch-22s Come with Catch-22s: Potential Harms and Drawbacks of Rent Reporting' <https://www.nclc.org/wp-content/uploads/2022/10/IB_Catch_22_Rent.pdf>

Netzer O, Lemaire A, and Herzenstein M, 'When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications' (2019) 56(6) Journal of Marketing Research 960

New York Times Editorial Board, 'The Race-Based Mortgage Penalty' *New York Times* (Mar 7 2018) <https://www.nytimes.com/2018/03/07/opinion/mortage-minority-income.html>

Nissenbaum H, 'From Preemption to Circumvention: If Technology Regulates, Why Do We Need Regulation (and Vice Versa)' (2011) 26 Berkeley Technology Law Journal 1367

Norman F, 'History of Information Policy' (1999) <http://www.laits.utexas.edu/~anorman/long.extra/information/history.html>

Nozick R, *Anarchy, State, and Utopia* (Basic Books 1974)

O'Dwyer R, 'Are You Creditworthy? The Algorithm Will Decide' (2018) *Undark* (5 July 2018) <https://undark.org/2018/05/07/algorithmic-credit-scoring-machine-learning/>

O'Neil C, *Weapons of Math Destruction* (Crown Books 2016)

O'Neill T, 'The Birth of Predictor—Machine Learning at Zopa' (*Zopa Blog*, 21 October 2016) <https://perma.cc/8EXJ-JETA>

Odinet CK, 'Consumer Bitcredit and Fintech Lending' (2018) 69 Alabama Law Review 100

—— 'Predatory Fintech and the Politics of Banking' (2021) 106 Iowa Law Review 1739

Ofcom, 'Adults' Media Use and Attitudes Report' (2022) <https://www.ofcom.org.uk/__data/assets/pdf_file/0020/234362/adults-media-use-and-attitudes-report-2022.pdf>

Office of Fair Trading, 'Irresponsible Lending—OFT guidance for creditors' (2011) <https://webarchive.nationalarchives.gov.uk/ukgwa/20140402162813/http://www.oft.gov.uk/OFTwork/publications/publication-categories/guidance/consumer_credit_act/oft1107>

Office of National Statistics, 'Regional Gross Disposable Household Income, UK: 1997 to 2018' <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/bulletins/regionalgrossdisposablehouseholdincomegdhi/1997to2018>

—— 'Regional Gross Disposable Household Income: Local Authorities by ITL1 Region' <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/datasets/regionalgrossdisposablehouseholdincomelocalauthoritiesbyitl1region>

—— 'Average Household Income, UK: Financial Year Ending 2021' <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances

/incomeandwealth/bulletins/householddisposableincomeandinequality/financialyearending2021)>

— — 'Wealth and Assets Survey QMI' <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/debt/methodologies/wealthandassetssurveyqmi>

Ogus A, *Regulation: Legal Form and Economic Theory* (Oxford: Clarendon Press 1994)

Ohm P, 'Broken Promises of Privacy: Responding to the Surprising Failure of Anonymization' (2010) 57 UCLA Law Review 1701

Öhman C and Aggarwal N, 'What if Facebook Goes Down? Ethical and Legal Considerations for the Demise of Big Tech' 9(3) Internet Policy Review

Olson P, 'The Algorithm That Beats Your Bank Manager' *Forbes* (March 15, 2011) <https://www.forbes.com/sites/parmyolson/2011/03/15/the-algorithm-that-beats-your-bank-manager/?sh=606b2ef61ae9>

Omarova ST, 'New Tech v. New Deal: Fintech as a Systemic Phenomenon' (2019) 36 Yale Journal on Regulation 735

Oreopoulos P and Salvanes KG, 'Priceless: The Nonpecuniary Benefits of Schooling' (2011) 25(1) Journal of Economic Perspectives 159

Óskarsdóttir M et al, 'The Value of Big Data for Credit Scoring: Enhancing Financial Inclusion Using Mobile Phone Data and Social Network Analytics' (2019) 74 Applied Soft Computing 26

Ots H, Liiv I, Tur D, 'Mobile Phone Usage Data for Credit Scoring' in Robal T, Haav H M, Penjam J, Matulevičius R (eds) *Databases and Information Systems* (Springer 2020)

Packin NG and Aretz YL, 'On Social Credit and the Right to Be Unnetworked' (2016) Columbia Business Law Review 339

Padilla J and Pagano M, 'Sharing Default Information as a Borrower Discipline Device' (2000) 44 European Economic Review 1951

Pagano M and Jappelli T, 'Information Sharing in Credit Markets' (1993) XLVIII Journal of Finance 1693

Peppet S R, 'Freedom of Contract in an Augmented Reality: The Case of Consumer Contracts' (2012) 59 UCLA Law Review 676

Perez C, 'The Double Bubble at the Turn of the Century: Technological Roots and Structural Implications' (2009) 33 Cambridge Journal of Economics 779

Petersen MA and Rajan RG, 'The Benefits of Lending Relationships: Evidence from Small Business Data' (1994) 49(1) Journal of Finance 3

— — 'Does Distance Still Matter? The Information Revolution in Small Business Lending' (2002) LVII(6) The Journal of Finance 2533

Pfaffenberger B, 'Technological Dramas' (1992) 17 Science, Technology, & Human Values 282

Philippon T, 'The FinTech Opportunity' (2016) <https://www.nber.org/papers/w22476>

Piketty T, *Capital in the 21st Century* (HUP 2014)

— — and Saez E, 'Inequality in the Long Run' (2014) 344(6186) Science 838

Pistor K, 'A Legal Theory of Finance' (2013) 41 Journal of Comparative Economics 315

Polayni K, *The Great Transformation: The political and economic origins of our time* (Beacon 1957 / Farrar 1944)

Poon M, 'Scorecards as Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated' (2007) 55(2) The Sociological Review 284

Posner E, 'The Boundaries of Normative Law and Economics' (2021) 38(2) Yale Journal on Regulation 657

— — and Hynes R M, 'The Law and Economics of Consumer Finance' (2001) 4 American Law and Economics Review 168

Posner R A, 'The Value of Wealth: A Response to Dworkin and Kronman' (1980) 9 Journal of Legal Studies 243

— — 'Utilitarianism, Economics and Legal Theory' (1979) 8(1) The Journal of Legal Studies 103

— — *Economic Analysis of Law* (9th Edition, Wolters Kluwer 2014)

Prasad M, *The Land of Too Much: American Abundance and the Paradox of Poverty* (HUP 2012)

Prelec D and Loewenstein G, 'The Red and the Black: Mental Accounting of Savings and Debt' <https://www.cmu.edu/dietrich/sds/docs/loewenstein/redblack.pdf>

Proud L, 'Peer-to-Peer Lending's Demise is Cautionary Tale' *Reuters* (13 December 2021) <https://www.reuters.com/markets/asia/peer-to-peer-lendings-demise-is-cautionary-tale-2021-12-13/>

Rahman S, 'Combining Machine Learning with Credit Risk Scorecards' (*FICO Blog,* March 24 2022) <https://bit.ly/2JDKObw>

Rajan RG, 'Has Financial Development Made the World Riskier?' (NBER Working Paper 11728, 2005) <https://www.nber.org/papers/w11728>

— — *Fault Lines: How Hidden Fractures Still Threaten the World Economy* (Princeton 2011)

— — and Zingales L, 'The Tyranny of Inequality' (1995) 76(3) Journal of Public Economics 521

Ramsay I, *Consumer Protection: Text and Materials* (Weidenfeld and Nicholson 1989)

— — 'Consumer Credit Law, Distributive Justice and the Welfare State' (1995) 15(2) Oxford Journal of Legal Studies 177

— — 'Bankruptcy and Consumer Credit in the Declining Welfare State' in Wilhelmsson T and Hurri S (eds), *From Dissonance to Sense: Welfare Expectations, Privatisation, and Private Law* (Routledge 1999)

— — 'Changing Policy Paradigms of EU Consumer Credit and Debt Regulation', in Leczykiewicz D and Weatherill S (eds) *The Images of the Consumer in EU Law: Legislation, Free Movement and Competition Law* (Hart 2016)

— — *Personal Insolvency in the 21st Century* (Bloomsbury 2017)

— — and Williams T, 'Peering Forward, 10 Years After: International Policy and Consumer Credit Regulation' (2020) 43 Journal of Consumer Policy 209

Rawls J, *A Theory of Justice* (Belknap 1971)

Regan S et al, 'Model Behaviour. Nothing Artificial—Emerging Trends in the Validation of Machine Learning and Artificial Intelligence Models' (2017) <https://accntu.re/2HQcFzi>

Reidenberg J, 'Lex Informatica: The Formulation of Information Policy Rules Through Technology' (1998) 76(3) Texas Law Review 553

Reinhart CM and Rogoff KS, *This Time is Different: Eight Centuries of Financial Folly* (Princeton 2009)

Richards NM and Solove DJ, 'Privacy's Other Path: Recovering the Law of Confidentiality' (2007) 96 Georgetown Law Journal 123

Robeyns I, 'The Capability Approach' <https://plato.stanford.edu/entries/capability-approach/>

Robinson D and Yu H, 'Knowing the Score: New Data, Underwriting, and Marketing in the Consumer Credit Marketplace' (*Upturn*, October 2014), <https://www.upturn.org/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf>

Rolf E et al, 'Balancing Competing Objectives with Noisy Data: Score-Based Classifiers for Welfare-Aware Machine Learning' (2020) <https://arxiv.org/abs/2003.06740>

Romer PM, 'Endogenous Technological Change' (1990) 98(5) Journal of Political Economy S71

Roth AE, 'Repugnance as a Constraint on Markets' (2007) 21(3) Journal of Economic Perspectives 37

Roussi A, 'Kenyan Borrowers Shamed by Debt Collectors Chasing Silicon Valley Loans' *Financial Times* (September 9 2020) <https://on.ft.com/2FtPY95>

Rouvroy A and Poullet Y, 'The Right to Informational Self-determination and the Value of Self-Development: Reassessing the Importance of Privacy for Democracy' in Gutwirth S et al (eds) *Reinventing Data Protection?* (Dordrecht; London 2009)

Rowlingson K, 'High-Cost Credit in the UK: What's the Problem and How Should Policy Respond?' in Gardner J, Gray M, and Moser K (eds) *Debt and Austerity* (Edward Elgar 2021)

Ruddick G, 'Facebook Forces Admiral to Pull Plan to Price Car Insurance Based on Posts' *Guardian* (Nov 2 2016) <https://www.theguardian.com/money/2016/nov/02/facebook-admiral-car-insurance-privacy-data>

Rudin C, 'Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead' (2019) 1(5) Nature Machine Intelligence 206

Russell S and Norvig P, *AI: A Modern Approach* (3rd Edition, Prentice Hall 2010)

Ryll L et al, 'Transforming Paradigms. A Global AI in Financial Services Survey' (2020) <https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/transforming-paradigms/>

Ryman-Tubb N, 'An Overview of Credit Scoring Techniques' (2000) 21(1/2) Credit Control 39

Sadhwani A, Giesecke K and Sirignano J A, 'Deep Learning for Mortgage Risk' (2021) 19(2) Journal of Financial Econometrics 331

Saez E and Zucman G, 'Wealth Inequality in the United States Since 1913: Evidence from Capitalized Income Tax Data' (2016) 131(2) Quarterly Journal of Economics 519

Sahay R et al, 'The Promise of Fintech: Financial Inclusion in the Post Covid-19 era' (IMF Working Paper No. 20/09, 2020) <https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2020/06/29/The-Promise-of-Fintech-Financial-Inclusion-in-the-Post-COVID-19-Era-48623>

Sain-Jones L and Maynard Jr GP, 'Unfulfilled Promises of the Fintech Revolution' (2023) 111 California Law Review (forthcoming) < https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4031044>

Salganik M et al., 'Measuring the Predictability of Life Outcomes with a Scientific Mass Collaboration' (2020) 117 (15) Proceedings of the National Academy of Sciences 8398

Sandel MJ, *The Tyranny of Merit: What's Become of the Common Good?* (Macmillan 2020)

Schumpeter J, *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process* (McGraw-Hill 1939)

Schwartz PM and Peifer K, 'Transatlantic Data Privacy Law' (2017) 106 Georgetown Law Journal 115

Seamster L and Charron-Chénier R, 'Predatory Inclusion and Education Debt: Rethinking the Racial Wealth Gap' (2017) 4(3) Social Currents 199

Seelye A et al, 'Computer Mouse Movement Patterns: A Potential Marker of Mild Cognitive Impairment' (2015) 1(4) Alzheimers Dement (Amst) 472

Selbst A, 'An Institutional View of Algorithmic Impact Assessments' (2021) 35(1) Harvard Journal of Law and Technology 1

Sen AK, 'The Impossibility of a Paretian liberal' (1970) 78(1) Journal of Political Economy 152

—— 'Equality of What?' in McMurrin (ed), *Tanner Lectures on Human Values* (CUP 1979)

—— *Inequality Re-Examined* (Harvard 1992)

—— *The Idea of Justice* (Harvard 2009)

Senior AW et al, 'Improved Protein Structure Prediction Using Potentials from Deep Learning' (2020) 577 Nature 706

Shearing C, 'A Constitutive Conception of Regulation' in Grabosky PN and Braithwaite J (eds) *Business Regulation and Australia's Future* (Canberra 1994)

Shelter, 'How to Rent with a Poor Credit Score' <https://england.shelter.org.uk/housing_advice/private_renting/how_to_rent_with_a_poor_credit_history>

Shiller R, *Irrational Exuberance* (3rd edition, Princeton 2016)

Shrivastava A et al, 'Learning from Simulated and Unsupervised Images through Adversarial Training' (2016) <arXiv:1612.07828>

Silver D et al, 'Mastering the Game of Go with Deep Neural Networks and Tree Search' (2016) 529 Nature 484

Simon H, *Models of Man: Social and Rational; Mathematical Essays on Rational Human Behavior in a Social Setting* (Wiley 1957)

Sithigh DM and Siems M, 'The Chinese Social Credit System: A Model for Other Countries?' (2019) 82(6) Modern Law Review

Skiba PM, 'Regulation of Payday Loans: Misguided?' (2012) 69 Washington & Lee Law Review 1023

—— and Tobacman J, 'Payday Loans, Uncertainty, and Discounting: Explaining Patterns of Borrowing, Repayment, and Default' (Vanderbilt law and economics research paper no. 08-33, 2008) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1319751>

—— and Tobacman J, 'Do Payday Loans Cause Bankruptcy?' (2019) 62 Journal of Law & Economics 485 (2019)

Solove DJ, 'Privacy Self-Management and the Consent Dilemma' (2013) 126 Harvard Law Review 1880

Spence M, 'Job Market Signaling' (1973) 87(3) The Quarterly Journal of Economics 355

Spooner J, *Bankruptcy: The Case for Relief in an Economy of Debt* (CUP 2019)

Srinivas V and Schoeps J-T, 'Platform Banking as a New Business Model' (2019) <https://www2.deloitte.com/us/en/pages/financial-services/articles/platform-banking-as-a-new-business-model.html>

Starks M et al, 'Price Discrimination in Financial Services. How Should We Deal with Questions of Fairness?' (Financial Conduct Authority, July 2018) <https://bit.ly/2W783jl>

Statt N, 'Apple Updates Safari's Anti-Tracking Tech with Full Third-party Cookie Blocking' *The Verge* (March 24, 2020) <https://bit.ly/2GXWTZ0>

Steering Committee on Reciprocity, 'Principles of Reciprocity Version 41' <https://www.scoronline.co.uk/key-documents/>

Sternberg Greene S, 'Stealing Identity from the Poor' (2021) 106 Minnesota Law Review 51

Stigler GJ, 'The Theory of Economic Regulation' (1971) 2(1) Bell Journal of Economics and Management Science 3

Stiglitz J, 'Regulation and Failure' in Moss DA and Cisternino J (eds), *New Perspectives on Regulation* (Cambridge MA 2009)

— — and Weiss A, 'Credit Rationing in Markets with Imperfect Information' (1981) 71(3) The American Economic Review 393

— — and Weiss A, 'Asymmetric Information in Credit Markets and its Implications for Macro-Economics' (1992) 44(4) Oxford Economic Papers 694

Stokes R, 'The Genesis of Banking Confidentiality' (2011) 32(2) The Journal of Legal History 279

Strandburg KJ, 'Free Fall: The Online Market's Consumer Preference Disconnect' (2013) University of Chicago Legal Forum 95

— — 'Monitoring, Datafication, and Consent: Legal Approaches to Privacy in the Big Data Context' in Lane J et al. (eds.) *Privacy, Big Data, and the Public Good: Frameworks for Engagement* (CUP 2014)

Sullivan TA, Warren E, Westbrook JL, *As We Forgive Our Debtors* (Beard Books 1999)

Sunstein C, 'Boundedly Rational Borrowing' (2006) 73(1) University of Chicago Law Review 249

— — *After the Rights Revolution: Reconceiving the Regulatory State* (HUP 1993)

— —, Jolls C, and Thaler RH, 'A Behavioural Approach to Law and Economics' (1998) 50 Stanford Law Review 1471

Taibi AT, 'Banking, Finance, and Community Economic Empowerment: Structural Economic Theory, Procedural Civil Rights, and Substantive Racial Justice' (1994) 107 Harvard Law Review 1463

Tan ZM et al, 'The Ethical Debate About the Gig Economy' (2021) 65 Technology in Society

Tang H, 'Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?' (2019) 32(5) The Review of Financial Studies 1900

Taylor P, 'Volume of Data/Information Created, Captured, Copied, and Consumed Worldwide from 2010 to 2025' (*Statista*, 8 Sept 2022) <https://www.statista.com/statistics/871513/worldwide-data-created/>

Telefonica Digital España SLU, 'Computer-Implemented Method, a System and Computer Program Products for Assessing the Credit Worthiness of a User' (US20170039637A1) <https://patents.google.com/patent/US20170039637A1/en?oq=US20170039637A1>

Tesler L, 'Adages and Coinages' <https://www.nomodes.com/Larry_Tesler_Consulting/Adages_and_Coinages.html>

Thaler RH and Sunstein CR, *Nudge: Improving Decisions About Health, Wealth, and Happiness* (Yale University Press 2008)

The New York Fed, 'Quarterly Report on Household Debt and Credit' (2022) <https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/hhdc_2022q1.pdf>

Thelen K, *How Institutions Evolve: The Political Economy of Skills in Germany, Britain, the United States, and Japan* (CUP 2012)

Thomas G, *Loss Coverage: Why Insurance Works Better With Some Adverse Selection* (CUP 2017)

Thomas L C, *Consumer Credit Models: Pricing, Profit, and Portfolios* (OUP 2009)

— —, Crook J, and Edelman D, *Credit Scoring and Its Applications* (2nd edition, Society for Industrial and Applied Mathematics 2017)

Tims A, 'A Tiny Error in Your Address Could Wreck Your Credit Rating' *Guardian* (10 October 2022) <https://www.theguardian.com/money/2022/oct/10/a-tiny-error-in-your-address-could-wreck-your-credit-rating>

Tirole J, *The Theory of Corporate Finance* (Princeton 2006)

TransUnion, 'Credit Reference Agency Information Notice' <https://www.transunion.co.uk/legal/privacy-centre/pc-credit-reference>

Trumbull G, 'National Varieties of Consumerism,' (2006) 47(1) Jahrbuch für Wirtschaftsgeschichte / Economic History Yearbook 77

—— 'Regulating for Legitimacy: Consumer Credit Access in France and America' (Harvard Business School BGIE Unit Working Paper, 2010) <https://ssrn.com/abstract=1705550>

—— 'Credit Access and Social Welfare: The Rise of Consumer Lending in the United States and France' (2012) 40(1) Politics & Society 9

Tsamados A et al, 'The Ethics of Algorithms: Key Problems and Solutions' (2022) 37 AI & Society 2015

Turing AM, 'Computing Machinery and Intelligence' (1950) LIX (236) Mind 433

Turner et al, 'Optimizing Neural Networks for Risk Assessment' Patent number US10133980B2, November 2018 <https://patentimages.storage.googleapis.com/33/7d/5c/8e298e321906a8/US10133980.pdf>

Turner MA, Walker P, Moore K, 'Addition is Better than Subtraction' (*Policy and Economic Research Council*, 2020) <https://www.perc.net/wp-content/uploads/2020/06/credit-data-suppression-deletion-addition.pdf>

U.K. Home Office, *Computers and Privacy* (Cmnd 6353, 1975)

—— *Data Protection, the Government's Proposals for Legislation* (Cmnd 8539, 1982)

UK Cabinet Office, 'Scaling Community Lenders: The Role of Social Investment' (2015) <https://www.gov.uk/government/publications/scaling-community-lenders-the-role-of-social-investment>

UK Department for Digital, Culture Media & Sport, 'Data: A New Direction—Consultation' (2021) <https://www.gov.uk/government/consultations/data-a-new-direction>

—— 'Data: A New Direction—Government Response to Consultation' (2022) <https://www.gov.uk/government/consultations/data-a-new-direction>

—— 'National Data Strategy' (2020) <https://www.gov.uk/government/publications/uk-national-data-strategy/national-data-strategy>

UK Insolvency Service, 'Individual Voluntary Arrangement Outcomes, 1990 to 2013' (Statistical Release, 12 November 2014) <https://www.gov.uk/government/statistics/individual-voluntary-arrangement-outcome-statistics>

UK Office for Artificial Intelligence, 'National AI Strategy' (2021) <https://www.gov.uk/government/publications/national-ai-strategy>

UK Parliament House of Commons Library, 'Poverty in the UK: Statistics' (13 April 2022) <https://commonslibrary.parliament.uk/research-briefings/sn07096/>

UK Parliament, 'Household Debt: Key Economic Indicators' (Research Briefing, 28 October 2022) <https://commonslibrary.parliament.uk/research-briefings/sn02885/>

—— 'Household Debt: Statistics and Impact on Economy' (Research briefing, 5 December 2022) <https://commonslibrary.parliament.uk/research-briefings/cbp-7584/>

Ulph D and Vulkan N, 'Electronic Commerce and Competitive First-Degree Price Discrimination' (2000) cited in Varian HR, Farrell J, and Shapiro C *The Economics of Information Technology: An Introduction* (CUP 2004)

United Nations, 'UN Sustainable Development Goals' <https://sdgs.un.org/goals/goal10>

Ustun B, Spangher A and Liu Y, 'Actionable Recourse in Linear Classification' (Proceedings of the Conference on Fairness Accountability and Transparency, Atlanta, January 2019) <https://arxiv.org/abs/1809.06514>

Van Loo R, 'Digital Market Perfection' (2019) 117 Michigan Law Review 815

—— 'Privacy Pretexts', Cornell Law Review (forthcoming) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4048919>

—— 'Rise of the Digital Regulator' (2017) 66 Duke Law Journal 1267

Varian HR, 'Competition and Market Power' in Varian HR, Farrell J, and Shapiro C *The Economics of Information Technology: An Introduction* (CUP 2004)

—— *Intermediate Microeconomics: A Modern Approach* (7th Edition, W.W. Norton and Company 2006)

Veljanovski C, 'The Regulation Game' in Veljanovski C (ed) *Regulators and the Market: An Assessment of the Growth of Regulation in the UK* (London: Inst. of Economic Affairs 1991)

Verma A, 'Pulse from Aire: The Opportunity the Ecosystem is Waiting For' *Medium* (29 July 2020) <https://medium.com/aire-life/pulse-the-opportunity-the-ecosystem-is-waiting-for-f68c534d7f1a>

Verma et al, 'Artificial Intelligence System with Hierarchical Machine Learning for Interaction Session Optimisation' (2021) US Patent no. US 10977711 B1 <https://patents.google.com/patent/US10977711B1/en?oq=US+Patent+no.+US+10977711+B1+>

Vinge VS, 'The Coming Technological Singularity: How to Survive in the Post-Human Era' (1993) <https://edoras.sdsu.edu/~vinge/misc/singularity.html>

Wachter S and Mittelstadt B, 'A Right to Reasonable Inferences: Re-Thinking Data Protection Law in the Age of Big Data and AI' (2019) 2 Columbia Business Law Review

——, Mittelstadt B, and Floridi L, 'Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation' (2017) 7(2) International Data Privacy Law 76

Wagner G and Eidenmüller H, 'Down by Algorithms? Siphoning Rents, Exploiting Biases and Shaping Preferences—The Dark Side of Personalized Transactions' (2019) 86 University of Chicago Law Review 581

Waldmeir P, 'Tackle the 'Credit Invisibles' to Help Close the Racial Wealth Gap', *Financial Times* (November 28, 2022) <https://www.ft.com/content/ee7e19bd-631e-4575-b0b7-8b747f74185a>

Waldron J, 'Locating Distribution' (2003) 32(1) The Journal of Legal Studies 277

Wang et al, 'A Comparative Assessment of Ensemble Learning for Credit Scoring' (2011) 38 Expert Systems with Applications 223

Wang J C, 'Technology, the Nature of Information, and FinTech Marketplace Lending' (Federal Reserve Bank of Boston Current Policy Perspectives No. 18-3, 2018) <https://www.bostonfed.org/publications/current-policy-perspectives/2018/technology-nature-of-information-fintech-marketplace-lending.aspx>

Warren A and Dearnley J, 'Data Protection Legislation in the United Kingdom: From Development to Statute 1969–84' (2005) 8(2) Information, Communication and Society 238

Warren E, 'Unsafe at Any Rate' (2007) <https://democracyjournal.org/magazine/5/unsafe-at-any-rate/>

— — and Bar-Gill O, 'Making Credit Safer' (2008) 157(1) University of Pennsylvania Law Review 1

Wei Y et al, 'Credit Scoring with Social Network Data' (2015) 35(2) Marketing Science 234

West D, 'Neural Network Credit Scoring Models' (2000) 27(11-12) Computers and Operations Research 1131

Westin AF, *Privacy and Freedom* (Athenaeum 1967)

Whateley L, 'Facebook Can Hit Your Mortgage Chances' *The Times of London* (Jan 09 2016) <https://www.thetimes.co.uk/article/facebook-can-hit-your-mortgage-chances-z2cd9s65p08>

Whitman JQ, 'The Two Western Cultures of Privacy: Dignity Versus Liberty' (2004) 113 Yale Law Journal 1150

Whitworth D, 'I Was Refused a Home Testing Kit After a Credit Check' *BBC News* (7 November 2020) <https://www.bbc.com/news/business-54841185>

Wiedemann A, 'A Social Policy Theory of Everyday Borrowing: On the Role of Welfare States and Credit Regimes' (2021) 0(0) American Journal of Political Science 1

— — *Indebted Societies* (Princeton 2021)

Wiener N, *Cybernetics: Or Control and Communication in the Animal and the Machine* (MIT Press 1948)

Wilkinson R and Picket K, *The Spirit Level: Why Greater Equality Makes Societies Stronger* (Bloomsbury 2011)

Winner L, *Autonomous Technology: Technics-Out-of-Control as a Theme in Political Thought* (MIT Press 1978)

—— *The Whale and the Reactor* (University of Chicago Press 1986)

Wood Z, 'Brighthouse Admits Affordability Checks are Hurting Business Model' *Guardian* (Oct 4 2016) <https://www.theguardian.com/money/2016/oct/04/brighthouse-admits-affordability-checks-are-hurting-business-model>

Woolard C, 'Testimony of Christopher Woolard at the Hearing before the Task Force on Financial Technology of the Committee on Financial Services' (Jun 25 2019) <https://www.govinfo.gov/content/pkg/CHRG-116hhrg39497/html/CHRG-116hhrg39497.htm>

—— 'The FCA and Innovation' (May 22, 2015) <https://www.fca.org.uk/news/speeches/fca-and-innovation>

Wright G, 'Introducing the Buy Now Pay Later Bureau from Experian' (*Experian Blog*, Jan 26 2022) <https://www.experian.com/blogs/news/2022/01/26/buy-now-pay-later-bureau/>

Wu CC, 'Credit Invisibility and Alternative Data: Promises and Perils' (National Consumer Law Center, July 2019) <https://www.nclc.org/wp-content/uploads/2022/08/ib-credit-invisib-alt-data-july19.pdf>

—— et al, *Fair Credit Reporting* (10th edition, National Consumer Law Center 2022)

Yadav Y and Brummer C, 'Fintech and the Innovation Trilemma' (2019) 107 Georgetown Law Journal 235

Yaffe-Bellany D, 'How Sam Bankman-Fried's Crypto Empire Collapsed' *New York Times* (Nov 14 2022) <https://www.nytimes.com/2022/11/14/technology/ftx-sam-bankman-fried-crypto-bankruptcy.html>

Yamarik S, El-Shagi M, Yamashiro G, 'Does Inequality Lead to Credit Growth? Testing the Rajan Hypothesis Using State-Level Data' (2016) 148 Economic Letters 63

Younger KG, *Report of the Committee on Privacy (Younger Committee)* (Cmnd 5012, 1972)

Yuan L, 'How Cheap Labor Drives China's AI Ambitions' *New York Times* (25 November 2018) <https://www.nytimes.com/2018/11/25/business/china-artificial-intelligence-labeling.html>

Zarsky T, 'Incompatible: GDPR in the Age of Big Data' (2017) 47(4) Seton Hall Law Review

Zeller M, 'Determinants of Repayment Performance in Credit Groups: The Role of Program Design, Intragroup Risk Pooling, and Social Cohesion' (1998) 46(3) Economic Development and Cultural Change

Zellermayer O, 'The Pain of Paying' (PhD thesis, 1996) <https://www.researchgate.net/publication/280711796_The_Pain_of_Paying>

Zest AI, 'A Lender's Roadmap to AI Adoption' (2020) <https://assets.website-files.com/5fd0851c241bd8619aefc08f/602868b79f875613cf85b260_Lender%27s%20Roadmap%20to%20AI%20adoption%20ZestAI.pdf>

— — 'More Data is Useful But Not All Data is Equally Important' <https://www.zest.ai/insights/alternative-data-is-dead-long-live-inclusive-data>

Zetsche DW et al, 'From FinTech to Techfin: The Regulatory Challenges of Data-Driven Finance' (University of Hong Kong Faculty of Law Research Paper No. 2017/007, 2017) <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2959925>

Zinman J, 'Restricting Consumer Credit Access: Household Survey Evidence on Effects Around the Oregon Rate Cap' (2010) 34(3) Journal of Banking and Finance 546

Zittrain J, *The Future of the Internet—And How to Stop it* (Yale University Press, 2008)

Zopa, 'Coronavirus and My Investment' (2022) <https://www.zopa.com/coronavirus-and-my-investment>

— — and Clearscore, 'Clearscore and Zopa Launch First-in-Market Open Banking Partnership to Provide Credit to Those That Need it Most' (2021) <https://www.innovatefinance.com/news/clearscore-and-zopa-launch-first-in-market-open-banking-partnership-to-provide-credit-to-those-that-need-it-most/>

Zucman G, 'Global Wealth Inequality' (2019) (11) American Economic Review 109