

Categorizing Labour: How Platforms and Workers Co-construct Digital Markets

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To Cora, Noa, and my parents

Abstract

This project is an economic sociology perspective on the construction of online labour markets. I investigate classifications of labour as tools for market organization and sites of struggle between workers and platform firms.

Platform firms use classificatory devices such as recommender algorithms or quality labels to order their marketplaces and extract value. For millions of remote gig workers being classified matters because it directly affects their livelihoods. To investigate this tension, I ask *how and to what effect workers are classified in online labour markets*.

I address this question based on interface walk-throughs, worker interviews, and a survey across two online freelancing platforms. I problematize the view that classes in digital markets are primarily assigned automatically based on platform-specific, individual-level data, and thus removed from the social practices of those classified.

My first study shows how platform firms use classification systems to the effect of placing workers into discrete market categories. Consequential digital boundaries result from manual choices as well as automated algorithms. My second study theorizes quality labels that platforms attach to workers' profiles as market devices. I propose that these devices co-construct worker quality in the hiring process. To evaluate workers' experiences prior to platform work, administrators strategically fall back on conventional hiring techniques. My last study shows that centralized classification systems are circular and incomplete. It requires workers' informal categorical practices to complete the loop.

By integrating these studies, I arrive at my thesis that classifications of labour remain embedded in the social practices of the classified workers. By *putting the social back into classification*, I show how online markets are co-constructed by workers and platform firms alike. My research makes visible platform firms' classificatory power and their implicit value judgments on whose work counts, while also uncovering *categorical work* as an underappreciated form of worker agency.

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Abbreviations

ANA: American Nurses Association

CEDEFOP: European Centre for the Development of Vocational Training

CEO: Chief executive officer

Covid-19: Coronavirus Disease 2019

CrowdLearn: Project on skills formation and skills matching in online platform work

CSP: Classification of Socio-Professional Categories (France)

CUREC: Central University Research Ethics Committee

DMA: Digital Markets Act

DSA: Digital Services Act

EC: Economics of convention

INSEE: National Institute of Statistics and Economic Studies (France)

IS: Information systems

ISCO: International Standard Classification of Occupations

LMI: Labour market intermediary

NFT: Non-fungible tokens

NIC: Nursing Intervention Classification

NS-SEC: National Statistics Socio-Economic Classification (United Kingdom)

PCS: Classification of Professions & Socio-Professional Categories (France)

SEC: U.S. Securities and Exchange Commission

WWII: Second World War

Prologue

'We are brought on to a day in February, on which was held the yearly statute or hiring fair in the county-town of Casterbridge. At one end of the street stood from two to three hundred blithe and hearty labourers waiting upon Chance – [...] carters and waggoners were distinguished by having a piece of whip-cord twisted round their hats; thatchers wore a fragment of woven straw; shepherds held their sheep-crooks in their hands; and thus the situation required was known to the hirers at a glance.'

(Hardy, 1874, p.62)

Thomas Hardy's (1874) idealized description of a yearly hiring fair in a farming community in 19th century England suitably sets the scene for this research project. By reducing the complexities of the past, his literary account highlights several themes relevant for this thesis. On annual fairs as depicted in *Far from the Madding Crowd*, it was predominantly unmarried farm servants who hoped to be hired, housed and fed by prospective employers for a temporary period of time, ideally the entire upcoming year (Snell, 1985, p. 394). The labourers relied on easily recognizable symbols such as holding a sheep-crook or wearing a piece of woven straw to make their abilities as shepherds or thatchers known to prospective employers. In this way or another, categories and corresponding signals have always played a role in labour markets by defining occupations, skill sets and abilities, or the nature of an employer's demanded task or job vacancy. They provide workers, employers, and intermediaries with a necessary structure to compare and evaluate one another, and to make informed decisions who to work for or hire.

In this chapter of Hardy's (1874) classic, the protagonist, a shepherd named Gabriel Oak, fails to convince the attending farmers to hire him. His 'superior appearance' and

'dignified calm' were 'too good to be trustworthy' (Hardy, 1874, p. 58ff). Upon first impression, Gabriel does not match the ideals of what qualifies as a good bailiff, the service offered by him initially. In other words, Gabriel does not fit into the farmers' categorization of what constitutes a bailiff. In turn, Gabriel adapts his appearance and acquires a sheep-crook to instead offer his services as a shepherd. Although this bid remains unsuccessful as well, his behaviour underlines that market participants rarely accept their own market classification as set in stone but contest them by adapting their strategies in hope for better outcomes. These constant efforts of qualification by sellers, buyers, and intermediaries are thus an important element of any market. Stakeholders continuously aim to re-interpret classifications in their favour, compare the qualities of goods and services against the resultant categories, and evaluate the qualities of competing offers.

While such processes are interesting in and of themselves, research in the social sciences is generally justified by pointing towards the consequences of a phenomenon. As Gabriel Oak's unsuccessful bid for employment demonstrates, the categories adopted in a market setting can be to the detriment of some workers, irrespective of their actual abilities. While some workers get disadvantaged by hirers based on informally applied heuristics, for instance certain socio-economic markers, others profit as a result. As the fair ends, Gabriel Oak is forced to make ends meet by resorting to another skill, performing the flute for bystanders, and needs to continue his job hunt the next day in a neighbouring village. Since Hardy's (1874) view of hiring fairs and farm labourers can be considered romantic at best (Snell, 1985, p. 387ff), the real circumstances for a short-term labourer 'with almost no opportunity for upward social mobility in rural society' (Snell, 1985, p. 388) and without a job at the end of the day would have likely been even more dire.

Today, private firms have ‘revived’ hiring fairs for temporary labour and moved them online. They take place on digital platforms instead of local market squares. Gabriel has substituted his sheep-crook for self-descriptions, skill tags, experience badges, and reputation scores to be noticed, evaluated, and temporarily employed by a global pool of clients, sometimes only for a couple of minutes. While the hiring fairs described by Hardy were public affairs, attended by farm servants, employers, regional officials and bystanders alike (Roberts, 1988), these new online labour markets are not. Rather than employing categories and symbols which have grown collectively and informally over time, or have been prescribed by the state, Gabriel and his clients now rely on and navigate privately constructed and owned classification systems. They are encoded in digital interfaces and feed into proprietary search and recommender algorithms which shape the success and failure of workers on the platform.

Overall, this thesis sets out to understand how labour is formally and informally categorized on these new types of labour markets, how a contemporary Gabriel might adapt his behaviour to this new reality, and what implications these new types of labour classifications might have for work, markets, and society at large.

1. Introduction

'By throwing light on the way in which we distinguish entities from one another and thereby give them an identity, we can explore the very foundations of our social world, which we normally take for granted.'

(Zerubavel, 1991, p. 3f)

'Principles of division, inextricably logical and sociological, function within and for the purposes of the struggle between social groups; in producing concepts, they produce groups, the very groups which produce the principles and the groups against which they are produced.'

(Bourdieu, 1984/2010, p. 481)

In response to Russia's invasion of Ukraine which started on February 24, 2022, online freelancing platform firm Upwork announced the 'suspension of all business operations in Russia and Belarus, taking full effect by May.'¹ Its main competitor, Fiverr, followed their example by disallowing the opening of new and use of existing accounts in Russia.² Upwork and Fiverr are both providers of globally active, digital platforms. In this way, they match and facilitate remote transactions between workers and employers who are in need for on-demand services such as transcription or software development. According to the Online Labour Observatory, 2.6 percent of the global online freelancing workforce is supplied from Ukraine, another 2.2 percent from Russia (Stephany et al., 2021). The move of both platforms was praised as an expression of solidarity with the Ukrainian people. Mykhailo Fedorov, the Vice Prime Minister of Ukraine and Minister of Digital Transformation tweeted on March 7, 2022:

¹ <https://www.upwork.com/press/releases/statement-from-upwork-on-the-invasion-of-ukraine-and-operations-in-russia-and-belarus> (last accessed on December 29, 2022)

² <https://blog.fiverr.com/post/fiverr-suspends-business-in-russia> (last accessed on December 29, 2022)

'Thank you @UpWork for limiting the access to the platform in russia! Thank you for standing with us.'

At the same time, many individuals in Russia and Belarus were left without access to their primary source of income (Tiku & Vynck, 2022). One Russian worker summarized her situation in an official community forum:

'Upwork was my only way to earn money and a chance to move to another country. Unfortunately, it no longer exists. I hope you will reconsider your decision to ban work from Russia and Belarus. It literally deprived people of a chance for the future.'³

While this story is only a footnote to a war in which Russia has brought inconceivable suffering to the people of Ukraine, I include it to recognize the historic context in which I finalize my research. Besides, it also serves as an introduction to my doctoral project which studies platform work through the theoretical lens of categorization.

Over the past decade, millions of workers have taken up platform-mediated, remote gig work ranging from administrative support to highly specialised technology work (Kässi et al., 2021). The digital platforms that match and facilitate this form of remote contracting between workers and their clients tend to be owned and run by for-profit companies. These platform firms draw on a diverse set of tools to centrally manage their marketplaces (Aspers & Darr, 2022; Kirchner & Schüßler, 2019), including the categorization of work and classification of workers. Deciding on who gets access to a platform, as discussed above, is just one example of such boundary decisions (Gawer, 2020). For example, Fiverr matches and mediates the employment relationship between buyers and sellers of digital services via their platform, *fiverr.com*. Buyers range from private individuals to international corporations. They can browse for and purchase so-called 'gigs.' These digital services are offered by millions of sellers and

³ <https://community.upwork.com/t5/Upwork-Helps-Forum/Blocking-Russian-freelancers/m-p/1032259> (last accessed on December 29, 2022)

include anything that can be delivered remotely, from tarot reading to programming blockchain-based applications. To make its marketplace intelligible, increase efficiency, safeguard quality, and ultimately match the *right* sellers with the *right* clients, Fiverr constructs and codifies categories of work and classifications of workers into the digital interface and technological back end of its platform. Examples include classification systems of the services and skills available on the platform, the 'encoding' of online human behaviour for data collection and analysis (Alaimo & Kallinikos, 2017, p. 176; Flyverbom & Murray, 2018), the classificatory work that underpins search and recommender algorithms (Bechmann & Bowker, 2019), various forms of quality labels awarded to workers (Kässi & Lehdonvirta, 2022), and the categorical basis for the automated calculation of scores which capture workers' online reputation (Rahman, 2021; Wood & Lehdonvirta, 2022).

The resultant boundaries matter to all stakeholders. For platform firms and employers, these and other classificatory devices promise quicker, cheaper, and better matches, something that enables them to extract more value from workers (Fourcade & Healy, 2017). Platform firms thus 'translate' a continuous, social world into discrete data in the form of 'categories, measures and other representational forms' (Diaz-Bone et al., 2020; Kitchin, 2014, p. 1; Zerubavel, 1991). Once they operate at scale, platform firms like Monster, LinkedIn, Upwork, or Fiverr view users through a lens of 'scores, categories, and rankings' (Fourcade & Healy, 2013, 2017; Jürgenmeyer & Krenn, 2016, p. 179), all of which build on latent categorical practices (Bowker et al., 2019; Desrosières, 1998; Diaz-Bone, 2017; Espeland & Sauder, 2007; Power, 2004; Thévenot, 1984). For individual workers, being classified has even more immediate implications. Digital boundaries matter because they influence market outcomes and hold stratifying potential (Fourcade & Healy, 2013). On online labour platforms like

fiverr.com, for example, reputation scores (Rahman, 2021), platform-specific skill certificates (Kässi & Lehdonvirta, 2022), and individual recommendations (Barach et al., 2020) all impact workers' levels of material success online.

Consequently, there are potential tensions between for-profit platform firms and remote gig workers that deserve our attention. With their new-found strategic interest in the classification of labour (Beer, 2018; Birch et al., 2021; Fourcade & Healy, 2017), platform firms take up a role similar to bureaucratic organizations that have always classified labour at such scale on behalf of the state (Bourdieu, 2014, p. 9; Scott, 1998, pp. 76–102). It requires further investigation how and to what effect these platform firms put digital boundaries into practice (Cansoy et al., 2020; Fourcade & Healy, 2017). This is especially true because platform firms tend to make invisible the proprietary practices and assumptions underlying their classification systems (Diaz-Bone, 2017; Fourcade & Healy, 2017). The increased use of algorithms to dynamically categorize users further reduces transparency and removes human work from the public eye (Bechmann & Bowker, 2019; Cheney-Lippold, 2017). The resultant boundaries are thus somewhat disconnected from the users who rely on them for coordination and evaluation (Desrosières, 1990; Diaz-Bone, 2017).

It is currently unknown which workers' interests are at odds with the centralized classification systems constructed by private platform firms and how such systems intervene in individuals' everyday work practices (Fourcade & Healy, 2017). Such questions are particularly pertinent as platform firms construct boundaries based on previously unthinkable amounts of individual-level data on online behaviour and more abstract digital traces (Alaimo & Kallinikos, 2017; Cheney-Lippold, 2017; Flyverbom & Murray, 2018). This way, digital markets have a new moral dimension (Fourcade & Healy, 2017) that plays to the 'individualist mood' that 'holds the individual poor to be

personally responsible for their own misfortune' that gained traction from the late 20th century onwards (Douglas, 1979/1996, p. xxi). Distributional outcomes in online markets are more than ever portrayed as the deserved result of individual action rather than being shaped by structural inequalities (Fourcade & Healy, 2017).

In this thesis, I set out to investigate these and other questions surrounding the processes and effects of the categorization of work and classification of workers in digital marketplaces. I therefore ask: *How and to what effect are work and workers classified in online labour markets?* For the remainder of the introduction, I will provide motivation for this research question, discuss my theoretical and methodological approach, as well as give an overview of my thesis and its significance.

1.1 Importance of the topic

The story at the start of this chapter illustrates the importance of the research question above. Labour platforms have become essential infrastructures which millions of workers rely on for subsistence. Being classified by for-profit platform firms matters to the workers in question because it can directly influence their livelihoods.

Platforms are digital architectures that enable, organize, and intermediate the productive interaction of at least two parties, such as workers and employers (Dijck, 2018, p. 4; Srnicek, 2017, p. 43). They lie at the heart of a changing world of work. We can now search for a job, network with colleagues, or complete a project without ever leaving our homes. Efforts to digitize labour market processes include online job boards like *monster.com*, professional networking sites like *linkedin.com*, and marketplaces for remote contracting like *upwork.com*. Platforms are ubiquitous in our daily lives. As a result, 'Google, Facebook, and a handful of other corporate giants' are the 'modern-day equivalents of the railroad, telephone, and electric utility monopolies

of the late 19th and the 20th centuries' (Plantin et al., 2018, p. 306f). In the US, for example, 70% of companies in service industries are dependent on platforms either directly for their transactions (34%) or indirectly by connecting buyers and sellers (36%) (Kenney et al., 2021). For gig workers, platforms have become essential infrastructures which they rely on for subsistence (Dijck, 2018; Plantin et al., 2018), not unlike the Internet itself. From the 723 online freelancers surveyed for this thesis, more than 24% used *fiverr.com* or *upwork.com* as their primary source of income (chapter 4).

During the Covid-19 pandemic, remote work proliferated as companies adjusted to lockdowns and a significant share of such arrangements is being predicted to stay (Lund et al., 2021). My research empirically centres on the so-called *gig economy* because findings in this specific context have the potential to be precursors to changes in these more conventional work settings. The gig economy comprises all labour markets that are based on 'independent contracting that happens through, via, and on digital platforms' (Woodcock & Graham, 2020, p. 3). Gig work is also called *platform work* and includes location-dependent as well as location-independent service delivery. Food delivery and ridesharing are examples of locational platform work that rely on workers' availabilities at a specific time and location (Ramizo & Lehdonvirta, 2022). Online freelancing and microwork are examples of non-locational *online labour* (Wood et al., 2019a). *Microwork* is exemplified by the globally distributed workforce active on Amazon Mechanical Turk which is offered to clients as 'humans-as-a-service' to 'farm out massive volumes of small data processing tasks' (Irani, 2015, p. 2). In contrast, I exclusively study *online freelancing* (also known as *remote gig work* or *crowdwork*), that is geographically independent knowledge work (Kuek et al., 2015). What distinguishes *online labour markets* from other labour markets is the digital intermediation of supply and demand, often via platforms, and their exclusive focus on

remote work arrangements (Ramizo & Lehdonvirta, 2022). While the existence of distributed and global labour markets seems inevitable today, it is important to remember that even around the turn of the century predictions of such a possibility were still contested (Horton, 2010).

Especially in accounts referring to the so-called sharing economy (Schor & Vallas, 2021) or those rooted in economic theory, platforms are lauded for putting idle assets or labour power to use and support more efficient markets by reducing transaction costs (Sundararajan, 2016). In this view, labour platforms are another type of labour market intermediary (LMIs), as shown in Figure 1. Examples of LMIs range from public employment agencies to executive search firms or online job boards. More formally, LMIs are organizations that

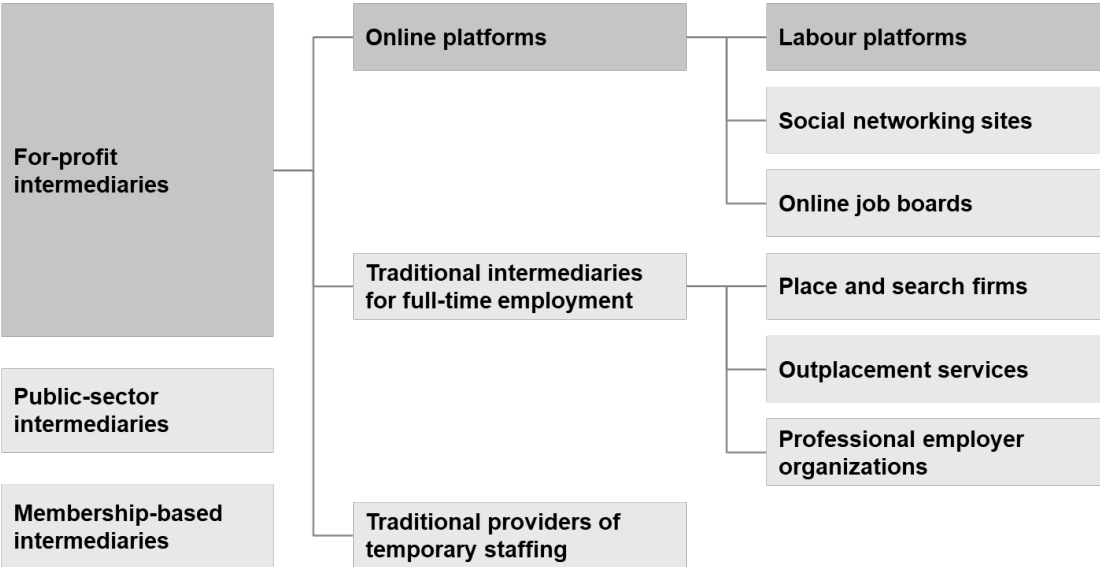
‘interpose themselves between workers and firms to facilitate, inform, or regulate how workers are matched to firms, how work is accomplished, and how conflicts are resolved’ (Autor, 2009, p. 2).

The use of private LMIs has become more prevalent as employers increasingly rely on so-called non-standard employment relationships that pose new uncertainties for employers (Bonet et al., 2013)⁴ such as temporary staffing (Hyman, 2018). In online labour markets, platform firms promote economic activity by reducing transaction costs which arise from information asymmetries between workers and employers in remote settings (Lehdonvirta et al., 2019; Pavlou et al., 2007). For example, platform firms decrease employer uncertainty about worker quality by enabling public client feedback (Pallais, 2014), standardizing and publishing platform-specific work histories (Agrawal

⁴ It should be noted that this view implies some standard form of employment (Ashford et al., 2007). Most commonly, it refers to a short period of job security characterized by full-time employment following WWII (Hyman, 2018, pp. 15–50). This perspective is somewhat idealistic given that during this period demographics like women, ethnic minorities, and immigrants all were structurally excluded from such *standard employment* (Hyman, 2018; Stanford, 2017).

et al., 2016), recommending workers (Horton, 2017) or attaching quality labels to their profiles (chapter 4). As a result, platforms have democratized online labour, for example by opening up outsourcing to individuals (rather than through outsourcing firms) in developing countries (Agrawal et al., 2016; Graham et al., 2017; Lehdonvirta et al., 2019) or connecting labour demand to rural areas (Braesemann et al., 2020).

Figure 1. Taxonomy of labour market intermediaries



Note. Adapted from Bonet et al. (2013). Focus on for-profit intermediaries with dark shading highlighting thesis focus.

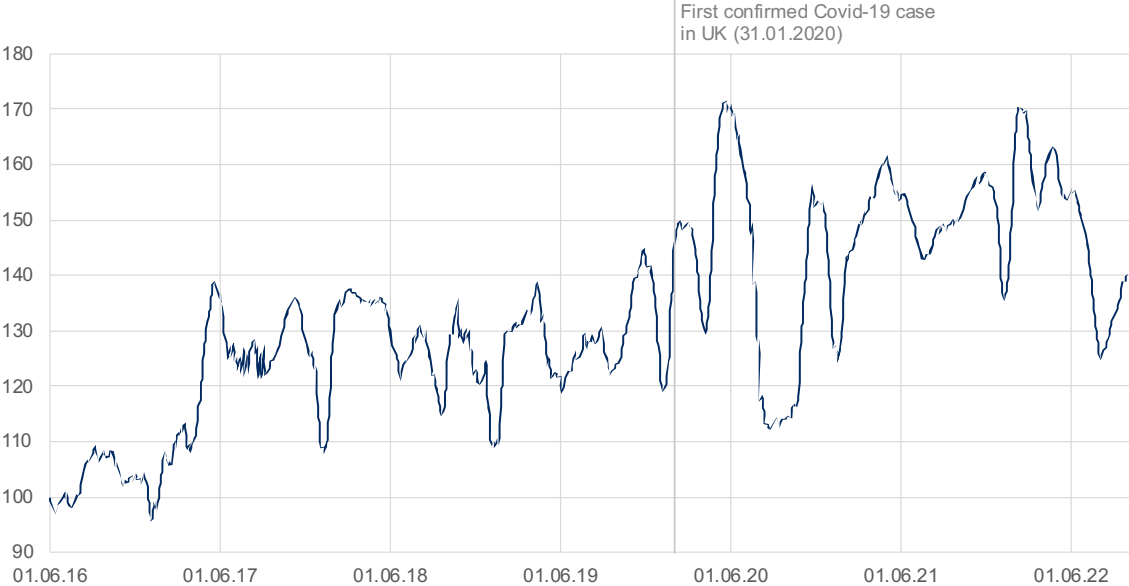
As a result, millions of workers rely on the (remote) gig economy for subsistence. About ten percent of the average European workforce reports to have engaged in some form of platform work before (Pesole et al., 2018). For many, such engagement is still limited in scope. Only 1.4 percent earn at least half their income through platforms or work on them for at least 20 hours per week (Pesole, 2021). In the US, about 1 percent of the workforce filed a tax report with income from platform work, with about half earning more than USD 2,500 that year (Collins et al., 2019). Although official employment statistics on online labour are even scarcer, it is safe to assume that millions of workers

are partaking worldwide. Globally, recent estimates put the number of workers who are registered on such platforms at about 163 million (Kässi et al., 2021). Of these workers, only 14 million are predicted to have completed at least one project, and about 3.3 million rely on platforms regularly. Such dependence was defined by the authors as having completed at least ten projects or earned at least \$1,000. These numbers are comparable to the sizes of the 2021 labour forces of the United States (164.8 million), Ghana (14.1 million), and Bulgaria (3.3 million), respectively. The geography of remote work is characterized by polarisation (Braesemann et al., 2022). Labour demand is concentrated in urban centres in North America, Europe, and Australia. The corresponding workforce, while globally distributed, is concentrated in Asia. In 2020, across four predominantly English-speaking platforms about 68% of all workers who had completed a project in the past month were located in Asia; 16% in Europe, 7% in North America, 5% in Africa, 3% in South America, and 1% in Oceania (Kässi & Lehdonvirta, 2018).

Evidence on the growth of online labour is mixed. Across the five largest and predominantly English-speaking platforms, 'accounting for at least 70% of all traffic to online labour platforms', and six Russian and Spanish language platforms, the number of new projects posted rose by almost 40% between May 2016 and October 2022, as visible in Figure 2 (Stephany et al., 2021, p. 3f). However, growth in the number of workers who can make a living from online freelancing is less pronounced (Kässi et al., 2021). The final impact of the Covid-19 pandemic on demand for online freelancing equally remains unknown. While the number of projects posted recovered quickly after an initial downturn, it remains volatile and had not yet reached pre-crisis levels in October 2022 (Figure 2). Further, jobs are scarcer as more people joined the marketplaces during the pandemic as other sources of employment were negatively

impacted by the crisis (Stephany et al., 2020). While the final impact of the pandemic on online labour markets is yet to be determined, it has introduced remote work to people’s lives more generally.

Figure 2. Number of new projects posted per day across leading online labour platforms (Jun 2016 – Oct 2022)



Note. Data taken from the Online Labour Index 2020 by Stephany et al. (2021). Data is a 28-day moving average normalized for May 2016 (100 = June 1, 2022). The index includes five predominantly English-speaking platforms which represent more than 70% of traffic and six platforms that are predominantly Spanish-speaking or Russian-speaking.

When platform firms categorize work or classify workers, it thus directly affects the life chances of millions of individuals. The consequences of being classified in online labour markets is comparable to the ‘classification situations’ in credit markets (Fourcade & Healy, 2013, p. 560). When for-profit companies assign individuals to discrete classes of credit risk it affects their cost of credit and thus their overall life chances. In fact, the influence of credit scores is no longer limited to financial markets but is used ‘off-label’ as a source of information in other contexts (Rona-Tas, 2017, p. 54), for example to inform hiring decisions (Kiviat, 2017). In the remote gig economy,

being classified has the potential to similarly influence an individual's market outcomes. Reputation scores, for example, affect workers' ability to attract visibility, create demand for their services, and earn a living online (Mosseri, 2020; Rahman, 2021; Wood et al., 2019a).

Given this observation, I am particularly motivated by potential negative impacts of platform work. These may include reductions of work quality (Wood et al., 2019a) including workers' autonomy (Jarrahi et al., 2020), enhanced dis-embeddedness (Tubaro, 2021; Wood et al., 2019b), increased insecurity around the principles of evaluation (Rahman, 2021; Stark & Pais, 2020; Wood & Lehdonvirta, 2022), as well as the reproduction of social inequalities (Demirel et al., 2020; Galperin, 2019; Shaw et al., 2022; Sutherland et al., 2020). More generally, however, the impact of platform work on workers is not uniform (Cansoy et al., 2020; Piasna & Drahokoupil, 2021; Schor et al., 2020). My project therefore seeks to identify how the classificatory practices of platform firms shape the experiences of remote gig workers while recognizing the heterogeneous character of this globally distributed workforce.

1.2 Theoretical approach

My project offers an economic sociology perspective on digital markets (Fligstein & Dauter, 2007). It is fundamentally concerned with the construction and maintenance of such markets (Çalışkan & Callon, 2010) and their social order (Beckert, 2009). Markets are the preferred social 'mechanism for the production and allocation of goods and services' under competition (Beckert, 2009, p. 245). Examples range from weekly produce markets to abstract structures like national labour markets or the market for 'CryptoPunk' NFTs. Labour markets serve the specific purpose of matching people to tasks, projects or jobs demanded by an employer or client under competition. In their

simplest form, they comprise a network which connects employers, who are looking to hire for a vacancy, project or task, and workers, who seek a contractual agreement to temporarily sell their labour power (Tilly & Tilly, 1994). Labour markets connect organizations with external talent but also organize internal work allocation (Doeringer, 1985, pp. 1–2). Examples of external labour markets are corporates competing for graduate talent to fill entry-level positions or freelancers advertising their services to clients online. Short-term, project-based staffing in consulting companies typifies an internal labour market. The latter are most pronounced in organizations which fill core positions exclusively from within their own ranks, like the military (Tilly & Tilly, 1994).

In this context, I view categories and classifications, for now defined as ‘organized architectures of categories’ (Diaz-Bone, 2017, p. 238), as context-specific, social institutions (Berger & Luckmann, 1966/1991; Douglas, 1986). They are constructed and negotiated within communities or by experts to order society (Alaimo & Kallinikos, 2021; Bowker & Star, 2000a). They are equally fundamental to the construction and maintenance of markets (Beckert & Musselin, 2013; Callon et al., 2002; Douglas, 1979/1996). Compared to other markets, sociologists ascribe a special status to labour markets based on their social embeddedness. On the one hand, labour markets are embedded in social communities and impacted by our social ties (Granovetter, 1985). These structures not only influence job search but can explain varying levels of productivity or what are deemed fair wages for given tasks (Granovetter, 2005). On the other hand, work is fundamental to the human condition itself and labour markets thus impossible to disentangle from society at large. Polanyi even considered the commodification of labour in market-settings as a ‘fictitious’ exercise insofar as workers unlike other production inputs ‘cannot be shoved about, used indiscriminately, or even left unused, without affecting [...] the human individual’ (1944, p.76). In his view, labour

as a commodity could never be separated from the 'physical, psychological, and moral entity "man".' Labour markets are of utmost importance because people rely on them not only for subsistence but their identity and social status (Swedberg, 2010).

I start from the premise that foregrounding how humans demarcate the world into recognizable entities allows exploring the foundations of social reality itself (Zerubavel, 1991). The symbolic boundaries we draw can turn into social barriers that cement, construct, contest or crush inequalities ingrained in society (Lamont & Molnár, 2002). For example, during the Covid-19 pandemic, the second major event that unfolded during my time as a doctoral student, how we categorized and valued work got called into question. Workers were temporarily classified based on the essential nature of their jobs for society instead of the level of skill or education associated with an occupation. The latter is the norm in capitalist societies. Early during this global health crisis, this symbolic shift in how to classify labour had material consequences. In Germany, medical staff, cashiers in supermarkets, and others at the frontlines of the health crisis received not only social recognition but preferential access to resources ranging from protective gear and childcare to bonus pay.

Evidently, the way we demarcate the world around us is more than a basis for making our experiences intelligible (Hannan et al., 2019; Zerubavel, 1991). By adopting a category, we valorise one perspective at the expense of multiple others (Bowker & Star, 2000a). It informs how we evaluate and value one another, and ultimately how material resources are distributed (Boltanski & Thévenot, 2006; Lamont, 2012). In this way, my project is related to the academic tradition of studying class formation in labour markets (Boltanski, 1987; Bourdieu, 1984/2010; Desrosières, 1998; Goldthorpe, 1980; Marx & Engels, 1948/2018; M. Weber, 1922/2021). It comes to no surprise that

individuals and social groups engage in 'classification struggles' to shape the 'meaning of the social world' in pursuit for better outcomes in life (Bourdieu, 1984/2010, p. 481).

Any study of categories and classifications is therefore always also about power. When platform firms construct platform infrastructure, they codify certain categories or classification systems. This act 'freezes a certain state of the power relations,' and in discontinuous form 'reproduces [...] the generally gradual and continuous differences which structure the established order' (Bourdieu, 1984/2010, p. 482). Not unlike maps, the categories and classifications of labour 'transform as well as merely summarize the facts that they portray' (Scott, 1998, p. 87). Thus, platform firms and their employees who classify work and workers hold power. For example, 'describing and recording someone's task', as commonly done in remote gig work, 'may mean controlling or surveilling their work', while looser classifications are often afforded 'to those with the most power and discretion [...] to set their own terms' (Bowker & Star, 2000a, p. 46).

Then, *power* in the context of categorization and digital platforms is about 'the current configuration of structural privilege and structural oppression' (D'Ignazio & Klein, 2020, p. 24). Translated to the context of platform work, classificatory power could mean that classification systems as codified by platform firms and their employees will work better for some while structurally disadvantaging others (Star, 1990). After all, socio-technical systems are always built in a specific cultural and social context (MacKenzie & Wajcman, 1999). Categories and classifications are 'social forms' that help us 'make disparate things hold together, thus generating things of another order' (Desrosières, 1998, p. 22). Questions of power then ask about 'whose metaphor brings worlds together, and holds them there' (Star, 1990, p. 52).

1.3 Methodological approach and field sites

My integrated doctoral project studies platform work through the lens of categorization and classification. It is integrated in the sense that it comprises three standalone studies (chapters 3–5) whereby each study contributes to a specific debate in the platform economy literature. These empirical chapters are connected by a common theoretical context, categorization and classification in (online) labour markets (chapter 2), and I ultimately integrate their findings to arrive at an overarching thesis (chapter 6). As mentioned before, the research question that ties all chapters together is: *How and to what effect are work and workers classified in online labour markets?*

I address this question through triangulation (Yin, 2013) of four distinct sources of data, most of which capture the perspectives of remote gig workers. My primary methods of data collection included a walk-through of the digital interfaces of two globally operating online freelancing platforms (Light et al., 2018), as well as in-depth, digital interviews and an online survey with workers active on either of two target platforms. These primary sources of data are contextualized by a set of supportive data including my own observations over three years as a client on both platforms (e.g., Rahman, 2021), the use of internet archives (www.archive.org), and secondary document analysis.

My project was thus largely a *qualitative* effort insofar as it can be considered an

‘iterative process in which improved understanding to the scientific community is achieved by making new significant distinctions resulting from getting closer to the phenomenon studied’ (Aspers & Corte, 2019, p. 139).

This definition allows me to reflect on specific dimensions of my research design. My process was iterative in two ways. Being a research assistant in a more general project on skill development and matching allowed me to engage with data on remote gig workers’ informal practices from the outset of my project. I thus iterated between first

evidence and theories of classification and platform work from the very beginning. The survey, for example, was piloted with a handful of workers before roll-out, and the analysis of secondary worker transcripts informed the construction of my directional interview guide (cf. appendix A.1). Second, I adopted a grounded theory approach for coding my data as an inherently iterative form of analysis (Corbin & Strauss, 1990). I subsequently got closer to the phenomenon of categorization in online labour markets by subscribing to a pragmatist methodology (Overdevest, 2011) that foregrounded workers' practices and interactions with centralized classification systems. In-depth interviews are a helpful method to learn about workers' practices but also their interaction with symbolic systems (Lamont & Swidler, 2014). Theoretical sampling of workers for these interviews further allowed me to strategically capture significant dimensions of the phenomenon (Foley et al., 2021). As a result, I was able to make novel distinctions such as a generalized break-down of the labour process across both platforms (cf. Table 8 in appendix A.2) or the identification of four classes of workers that differ categorically in their experiences of platform work (chapter 3). While it is difficult for me to be the judge of whether my project yielded an 'improved understanding to the scientific community' (Aspers & Corte, 2019, p. 155), my empirical studies all contribute to distinct theoretical debates in the literature.

That said, I would like to acknowledge that my emphasis on workers' perspectives only offers a partial view of the phenomenon at hand. My project could have benefitted from collaboration with one or more platform firms. Access to upper management or the group of technology workers (Dorschel, 2022) who design the digital infrastructure of platform work would have provided an essential perspective. It would have allowed me to build theory also based on tech workers' motivations and values encoded in their centralized classification systems, as well as their own embeddedness in a specific

social and cultural context. Similarly, such collaboration might have yielded access to transaction data which would have allowed for a more rigorous econometric study design in chapter 4 and testing for a causal relationship between quality labels and market outcomes (e.g., Kässi & Lehdonvirta, 2022). Unfortunately, I was unable to secure such a collaboration, mainly because the classification systems of labour are part of a proprietary digital infrastructure that platform firms claim as their own competitive advantage. As a second-best alternative, I followed scholars such as Bowker and Star (2000; Star, 1999, p. 384ff) in their methodological suggestions such as ‘identifying master narratives and “others”’ frozen into the platform interface, ‘surfacing invisible work’ on the user-side, and drawing on inferences from ‘paradoxes of infrastructure’ as experienced by these workers.

Data collection

Each of my empirical studies has an individual methods section. At this stage, I thus only briefly summarize the primary and secondary sources of data included in my project. For an overview, Table 1 lists research question(s), strategy, and data included in each of the subsequent chapters. While analysis unfolded iteratively throughout (Corbin & Strauss, 1990), my actual data collection was separated in two parts.

In the first phase of research, I collected data as a researcher working on a project investigating skill matching and development of online freelancers funded by the European Centre for the Development of Vocational Training (Cedefop, 2020). I was tasked with preparing, piloting, conducting, and validating an online survey of 1,002

Europe-based online freelancers active on *upwork.com*, *fiverr.com*, and two further platforms, *peopleperhour.com* and *twago.com* (Margaryan et al., 2022).⁵

In this thesis, I include only a subsample of the original survey responses (n=723) provided by workers active across either *upwork.com* or *fiverr.com*. In chapter 4, I only included responses from workers who consented to matching survey responses with scraped data from their platform profiles and were still active at the time of scraping (n=448). The (non-random) sampling approach (Lehdonvirta et al., 2021) and the potential limitations of online surveys such as selection bias (Bethlehem, 2010) are detailed in that same study. Combining survey responses with worker profiles allowed me to investigate associations between quality labels and workers' labour market attachment and activity. More generally, the survey responses provided some quantitative context in this introduction, the literature review, and integrated discussion. As part of my work as a research assistant, I additionally gained access to transcripts of semi-structured interviews with workers (n=41) and experts (n=25, including n=7 platform representatives) which provided me with contextual information, especially on the everyday work process and skills matching on the platforms. As part of the research project, I also managed to establish a relationship with one of the platforms which contextualized my findings.

⁵ I would like to acknowledge the support of the responsible principal investigators, Prof Anoush Margaryan and Prof Vili Lehdonvirta, who supervised the entire process, and to Susanne Klausning who supported me with conducting the survey. It should be noted that core elements of the survey distributed to workers which were not used for this thesis, especially on workers' learning practices, were primarily based on work done by Prof Anoush Margaryan.

Table 1. Overview of research strategies by chapter

Chapter	Research questions	Research approach	Data
<i>Categorization and classification in (online) labour markets (literature review)</i>			
2	How, and to what effect, are work and workers classified in conventional LMs?	'Integrative' literature review (Snyder, 2019, p. 335f)	Zotero database with 1,011 items (platform economy, classification, markets)
<i>Explaining heterogeneous outcomes in platform work: A categorical approach (study I)</i>			
3	<ul style="list-style-type: none"> • How, do platform firms categorize work and classify workers? • Do such practices produce heterogeneity in workers' market outcomes? 	3 years as a registered platform client <ul style="list-style-type: none"> • Interface walk-through (Light et al., 2018) • In-depth worker interviews 	<ul style="list-style-type: none"> • Interface walk-through notes, screenshots, and contextual documents • Interview transcripts (n=28)
<i>Platform-certified: How worker quality is constructed online (study II)</i>			
4	Why do online labour platforms attach quality labels to workers' profiles?	Mixed-methods design: <ul style="list-style-type: none"> • In-depth worker interviews • Online worker survey 	<ul style="list-style-type: none"> • Interview transcripts (n=39) • Survey responses (n=723) • Scraped worker profile (n=448)
<i>Completing the loop: How workers co-construct digital markets (study III)</i>			
5	<ul style="list-style-type: none"> • How do centralized classification systems feature in workers' everyday work practices? • How, if at all, do workers' informal categorical practices co-construct online markets? 	In-depth worker interviews	<ul style="list-style-type: none"> • Phase 1: Interview transcripts (n=41) • Phase 2: Interview transcripts (n=28)
<i>Putting the social back into classification: An integrated discussion (discussion)</i>			
6	How and to what effect are work and workers classified in online LMs?	Integration of findings	Use of all available materials

Note. LM stands for *labour market*.

In the second phase of research, I collected data as an active and registered user of the platforms *upwork.com* and *fiverr.com* over a period of 3 years (2019–22). As classification systems have a tendency to escape our attention (Zerubavel, 1991), it was necessary to systematically make boundaries visible again at the level of the interface (van Dijck, 2013) as well as through workers' experiences, for example when infrastructures fail (Bowker & Star, 2000a) or lead to strange consequences (Seberger & Bowker, 2021). Thus, I collected data via walk-throughs of the platform interface from the perspective of workers and employers (Light et al., 2018), conducted in-depth interviews with workers across both target platforms (n=28), and recorded evidence through digital archival work including the use of the Wayback Machine (www.archive.org) as a basis for contextual document analysis. This second phase of data collection forms the empirical core of my thesis. Again, my exact sampling approach for each study is detailed in the respective chapters.

Virtual sites of research

Data was collected across two virtual sites of research: *upwork.com* and *fiverr.com*. My sampling frame thus included remote gig workers that are active on at least one of these two online labour platforms. My decision to limit the sampling frame to two specific platforms was pragmatically driven. On the one hand, I referred to literature on case research. Data collection across two platforms enabled me to ensure that inferred findings were at least generalizable across two similar cases (Yin, 2013). As I will explain, corroboration of evidence on categorical practices is especially helpful for these two platforms because they differ in significant dimensions of how they categorize labour. The inclusion of two platforms further acknowledges that platforms are characterized by heterogeneity which researchers should account for in their study designs (Gegenhuber et al., 2020; Schor, 2020). However, while other studies on the

remote gig economy extend their sampling frame to workers across any form of online labour platform (e.g., Wood & Lehdonvirta, 2022), my scope was more limited due to the difficulty of making classification systems visible in the first place (Bowker & Star, 2000a). I decided against adding more platforms to my sample due to the costly nature—in terms of time, money, and complexity—of the process of denaturalizing classification systems across platforms via interface walk-throughs, interviews, and supplementary document analysis.

Upwork and Fiverr are examples of platform firms that specialize in intermediating remote, per-project (or per-task) work contracts between online freelancers and their clients through the provision of digital platforms. Figure 3 shows the landing pages of both marketplaces from the perspective of a non-registered page visitor. Both platforms facilitate the entire transaction from workers' self-presentation and employers' initial search to their means of communication, the contractual framework, as well as the provision of technology for managerial oversight, payments, and feedback on the completed service. The types of services offered on these marketplaces range from administrative support such as virtual assistance or data entry to specialised offerings like writing and translation, media design, legal consulting, or software development. I selected Upwork and Fiverr as sites of research because they are sufficiently similar while displaying important theoretical differences (Eisenhardt, 2021).

They share many similarities. Both companies are publicly listed and generate most of their revenues through the provision of an online freelancing marketplace. As platform intermediaries, both 'can charge membership fees, levy ad valorem charges on payments and charge buyers and sellers for using the market (e.g., for listing a job, taking a skills test or applying for a job)' (Horton, 2010, p. 517). They cater to a global

market and a broad range of skills (as opposed to specialist platforms which focus solely on one industry, for example design). Unsurprisingly, their stock price is highly correlated and subject to the same macro dynamics. During the Covid-19 pandemic, both platforms increased in popularity. For example, stock prices of Upwork and Fiverr respectively grew more than 500 and 800% between Jan 1, 2020, and July 1, 2021.⁶ However, in December 2022, both have lost more than 80% of their share price compared to their individual peaks in 2021.⁷ Online freelancers equally treat them as close substitutes. All but one worker who I interviewed were either aware of the other platform or had gone as far as testing it as an alternative. In a survey with 1,002 workers across four different online labour platforms, 9% of respondents indicated to be active on both platforms simultaneously (Cedefop, 2020).

On the other hand, both platforms are sufficiently distinct to accentuate different dimensions of online labour and allow for theoretically fruitful cross-comparisons. Most importantly, Upwork and Fiverr propagate contrasting visions of remote gig work. Upwork's CEO, Hayden Brown, emphasizes the ongoing human relations underlying hybrid work arrangements:

'We're in the midst of a once-in-a-lifetime, tectonic shift in how work gets done [... We are] relentlessly focused on helping freelancers and companies connect and reach their full potential through meaningful work relationships.'⁸

⁶ Between Jan 1, 2020, and July 1, 2021, Upwork's share price rose from 9.18 to 57.83 USD. During the same time span, Fiverr's share price increased from 26.09 to 240.82 USD.

⁷ Upwork's share price fell from a USD 58.29 high on June 1, 2021, to USD 9.91 on December 1, 2022. This marked a decrease of 83% (<https://finance.yahoo.com/quote/UPWK/>, last accessed on December 29, 2022). Fiverr's share price fell from a USD 269.96 high on February 1, 2021, to USD 28.04 on December 1, 2022. This marked a decrease of almost 90% (<https://finance.yahoo.com/quote/UPWK/>, last accessed on December 29, 2022).

⁸ Press release 'Upwork Introduces Work Marketplace' (2021: [https://www.upwork.com/press/releases/upwork-introduces-work-marketplace-category#:~:text=\(Nasdaq%3A%20UPWK\)%20today%20announced,help%20them%20achieve%20more%20together](https://www.upwork.com/press/releases/upwork-introduces-work-marketplace-category#:~:text=(Nasdaq%3A%20UPWK)%20today%20announced,help%20them%20achieve%20more%20together;); last accessed on Dec 19, 2022).

On the contrary, Fiverr's CEO, Micha Kaufman, likens their business model to 'traditional e-commerce businesses like Etsy and Amazon.'⁹ As a company, Fiverr defines its mission along similar lines:

'Our mission is to change how the world works together. We started with the simple idea that people should be able to buy and sell digital services in the same fashion as physical goods on an e-commerce platform.'¹⁰

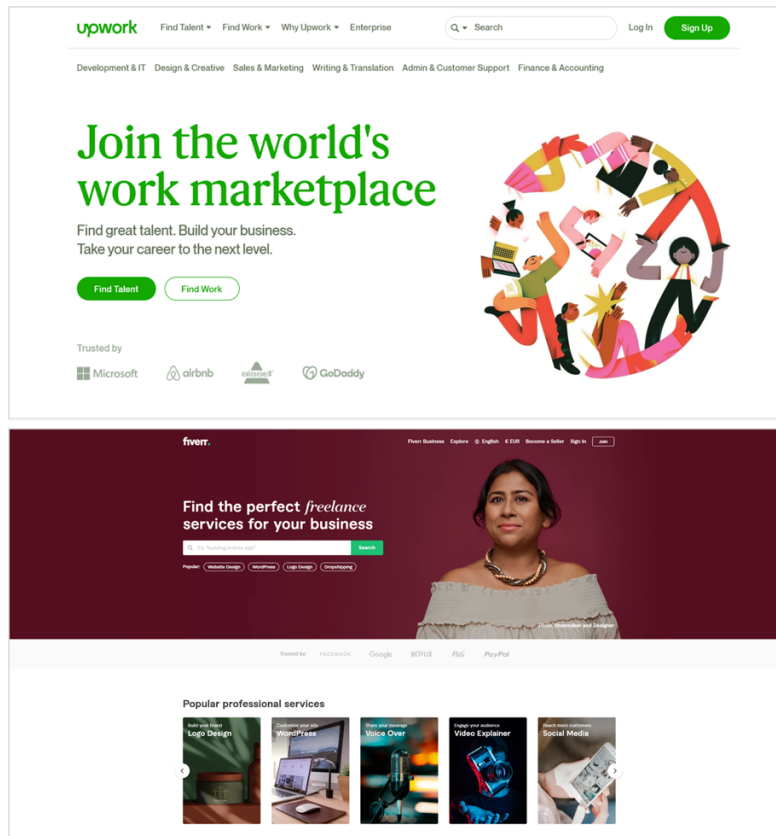
In practice, clients on *fiverr.com* can choose from millions of gigs offered and pre-specified by a large number of sellers, while freelancers and their skill sets used to be the sole focal point on *upwork.com*. Either freelancers directly apply for a pre-specified project of a potential employer, or the latter actively search for freelancers with the right skill set. Recently, both platforms have started to converge in their platform interfaces. Upwork, for instance, introduced a 'Project Catalogue' which closely resembles the logic of Fiverr's gigs. Yet, the financials of the platforms still match their original strategies. According to their 2020 SEC filings and recent investor presentations, Fiverr's average client spent USD 205 compared to Upwork's average of USD 5,850 in 2020, while generating USD 0.7bn and 2.5bn in user spend respectively.¹¹ Hence, while Fiverr attracted more clients than Upwork, these clients on average spent considerably less money.

⁹ Quote from a TechCrunch interview with Fiverr's CEO Micha Kaufman published on June 14, 2019 (https://techcrunch.com/2019/06/14/fiverr-ceo-interview/?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAABmP6XWUJvfzxaG5Tr58waR-vg84z9OHem_1fRk7R9-MaT6uNaxpZRtFAca7xts7KnRHNXJaY9cll8bZpEHEOUTF6m1N9ZUiJPYkEYKsWliUd1gpk13c1YdkKrRepWTjFleh_t5YrhgBBcbaHj3ggN5VBDBu1lexJ2aoFR-e8zfi, last accessed on September 22, 2021).

¹⁰ https://d18rn0p25nwr6d.cloudfront.net/CIK-0001762301/00738e6b-3fbb-4875-9237-c98820d9db34.html#FVRR20F1220_HTM_D1E1987_ANCHOR (last accessed on June 24, 2021)

¹¹ Upwork Annual Report (2020), Fiverr F-20 SEC filing (2020), Upwork Investor Day presentation (2021; <https://investors.upwork.com/static-files/11fe6ce1-8c50-40e5-9f4e-2710de4e27c8>, last accessed on November 1, 2021)

Figure 3. Screenshot of Upwork's and Fiverr's landing pages



Note. The screenshots were taken on Sep 21, 2021. They only show a selection of each dynamic landing page directed to via upwork.com and fiverr.com respectively.

Ethical considerations

I applied for and received ethical clearance for the survey (SSH OII C1A 19 004) as well as the digital fieldwork on upwork.com and fiverr.com (SSH_OII_CIA_20_67) by the Central University Research Ethics Committee (CUREC). While specific ethical considerations are selectively discussed in each study, two overarching themes emanated from my CUREC application.

First, some gig workers are subjected to precarious working conditions (Anwar & Graham, 2020; Schor et al., 2020; Sutherland et al., 2020). I designed my research project to neither exploit nor worsen their situation. Since globally operating labour

platforms are characterized by an oversupply of labour (Graham & Anwar, 2019), I decided against offering my own labour power and applying for projects for observatory purposes. At the same time, recruitment of online freelancing required remuneration of participants as platforms do not allow listings of unpaid projects and rewarding people for their time is in accordance with the culture of online freelancing. Payments of approximately 7.50 GBP for a twenty-minute survey and at least 15 GBP for a one-hour interview were chosen to comply with living wages even in more expensive cities like London.

Second, drawing on categorization and classification as a theoretical lens comes with ethical responsibilities. In the context of social network analysis, Hogan (2021, p. 10f) reminds us that by using analytical tools to merge personal experiences ‘across contexts in unanticipated or unexpected ways’ can be unsettling for participants:

‘We are disassembling and reassembling [their] social world in front of them, and by implication, we are doing much the same to their sense of identity in the world. Doing so is not an unambiguous good. But it is unambiguously a form of power.’

Just like network analysis, the analytical lens of categorization allows for powerful recombination of information about social life. In my first study, for instance, I identify and theorize the segmentation of the online workforce. While most participants surely will enjoy being likened to a *platform superstar*, *being excluded* is less flattering. Since I believe it to be paramount to share my research with those who participated, the wording, inclusion of identifiable quotes (even for the participants themselves), and the interpretation of my results must be considered carefully.

Limitations

Although I research categorization and classification of labour online, my own approach to this project already presupposes a certain conceptualization of what work

means. The analytical focus on labour markets implicitly acknowledges that not all work, defined as 'human effort that adds use value to goods and services' (Tilly & Tilly, 1994, p. 291), is organized through market mechanisms. Tilly and Tilly (1994) highlight that work can equally be pursued as part of household production, engagement in the informal economy, or volunteering. These other forms of organization are by no means negligible. For example, between the age of 20 and 64 only about 58% of work activities of an average American are organized through labour markets or the informal economy; roughly 37% are dedicated to housework and around 5% are spent volunteering (U.S. Bureau of Labor Statistics, 2019).¹²

That said, any strict dichotomies between formal and informal economic activities, or paid and unpaid human effort fail to adequately portray the complexities of economic reality, especially in the platform economy (Williams & Nadin, 2012). In emerging economies like Mexico and Panama, platform firms actively shape the shift from the informal to the formal economy for services like driving or cleaning (C. E. Weber et al., 2021). Similarly, platforms purposefully organize online labour to blur the boundaries of paid and unpaid activities. In the platform economy, the cost of idle time, for example when looking through projects advertised on a freelancing marketplace or waiting for customers as a ride-hailing driver, is largely born by workers (Prassl, 2018, p. 76f). Remote gig workers (n=125) working from Sub-Saharan Africa and Southeast Asia, for instance, reported to spent an average 16 hours per week on uncompensated activities involved in acquiring remote tasks and projects (Wood et al., 2019b). Hence,

¹² Calculations done by the author based on the U.S. Time Use Survey (U.S. Bureau of Labor Statistics, 2019). Housework includes 'Household activities', 'Purchasing goods and services' and 'Caring for and helping household members.' Volunteering includes 'Caring for and helping nonhousehold members' and 'Organizational, civic, and religious activities.' Work organized through the informal sector or labour markets includes 'Working and work-related activities' and 'Educational activities.' Other activities are excluded from the analysis.

it is necessary to acknowledge that my analysis is grounded in observations on a particular type of work.

As always, the results of my project are shaped by my empirical choices. By relying on Upwork and Fiverr as empirical cases, I concentrate on two publicly listed companies who are market leaders in the provision of online freelancing platforms. They have exceptional power when it comes to platform design choices, for instance due to workers being reluctant to change platforms as reputation remains non-transferable.

By focusing on online freelancing platforms, I prioritize knowledge work, which comprises more complex and longer projects, over what I earlier defined as microwork, that is less specialized, piece-meal tasks distributed to a crowd (Howcroft & Bergvall-Kåreborn, 2019; Irani, 2015). My assumption was that platforms that facilitate knowledge work allow for more social interaction between workers and clients, mainly because the stakes for successful matches are higher due to more significant project costs and lengths. To explore informal categorical work by workers, more interactions imply more room for agency and were methodologically desirable. Still, future research will need to extend my findings to workers with less visibility and autonomy than the average remote knowledge worker (Gruszka & Böhm, 2020; Gupta, 2017; Irani, 2015).

1.4 Overview of the thesis

In the next chapter, I survey the literature to understand *how and to what effect work and workers are classified in conventional labour markets*. I define conventional labour markets as those not typically associated with the gig economy. For my review, I use the fact that theories of classification have a long tradition in research on labour markets (Desrosières & Thévenot, 1979; Marx & Engels, 1948/2018) and build up my argument from three examples. I discuss a socio-professional classification of

occupations devised by experts within the French state bureaucracy (e.g., Amossé, 2013), a community-based classification of nursing interventions that originated as part of the professionalization of the occupation (e.g., Bowker & Star, 2000a), and the categorization of ideal candidates by intermediaries active in executive search (e.g., Finlay & Coverdill, 2007). To generalize from these examples, I relate research on categorization and classification, (labour) markets, and the platform economy. By drawing on sociology from Durkheim to Bourdieu, I show that market participants construct boundaries to make labour markets intelligible, shape the distribution of resources, and exercise control. By transferring the findings to the phenomenon of online labour markets, I conclude that digitization has brought about changes to who classifies labour, how categories and classifications are constructed, and on what basis. As a result, I show how it may be argued that so-called classification situations (Fourcade & Healy, 2017) in digital market-settings are somewhat removed from the social practice and context of the classified workers.

Following my literature review, I present three original studies that investigate questions at the intersection of categorization and platform work. Chapter 3 studies how categorical practices by platform firms shape heterogeneity in workers' market outcomes. Chapter 4 examines quality labels that platform firms attach to workers' online profiles as one such practice in detail. Chapter 5 completes the picture by investigating how workers' informal categorical practices co-construct online markets.

In chapter 3, I study how labour platforms categorize labour to produce heterogeneity in workers' market outcomes. This study is positioned in relation to a growing debate on how to explain the diversity of experiences reported by platform workers (Cansoy et al., 2020; Schor et al., 2020). Based on a walk-through of the platform interfaces of *upwork.com* and *fiverr.com* (Light et al., 2018) and in-depth worker interviews (n=28),

I uncover that platform firms categorize work and workers to the effect of institutionalizing distinct classes of online freelancers. My finding contributes to the platform economy literature by theorizing heterogeneity in outcomes as categorical but actively shaped by the choices of platform firms. This theorization offers a new dimension to extant scholarship that explains heterogeneity by referring to either categorical differences between workers, or a continuous conceptualization of success largely influenced by the accumulation of various experience metrics as measured by the platform firm. My novel theorization of output heterogeneity allows the distinction of four classes of workers who differ substantially in their experiences of remote gig work. I discuss how the acknowledgement of such platform-constructed heterogeneity offers a means to examine the generalizability of extant theories of online labour.

In my second empirical study (chapter 4), I examine *to what effect online labour platforms attach quality labels to workers' profiles*. As millions of workers engage in remote gig work, it is paramount to understand how such platform-constructed labels intervene in the hiring or labour process. This mixed-method study includes worker interviews as a primary method (n=39) and supplements it with a dataset that combines Europe-based workers' responses to an online survey with data scraped from their online profiles across two points in time (n=448). I find that workers who have been labelled by the platform experience greater labour market attachment and activity. Some scholars theorize quality labels as signals that reduce transaction costs and ultimately employer uncertainty in the hiring process (Lehdonvirta et al., 2019). Others subsume quality labels under practices of algorithmic management (Stark & Pais, 2020). Instead, I propose that quality labelling is an act of market categorization that co-constructs workers' competencies at the hiring stage. As market devices (Callon et

al., 2007; Karpik, 2010), quality labels have the effect of making otherwise singular workers commensurable and provide a basis for employer evaluation.

My third study (chapter 5) challenges the previous two chapters insofar as it foregrounds the limitations of centralized classification systems. It shows how the construction and maintenance of online markets also requires workers' informal categorical practices. The chapter asks *how centralized classification systems feature in workers' everyday work practices* and *how, if at all, workers' informal categorical practices co-construct online markets*. Based on 28 primary and 41 secondary in-depth worker interviews, I challenge the predominant view that workers' informal categorical practices are best understood as reactions to a centralized platform infrastructure imposed on them. My first contribution lies in demonstrating how centralized classification systems in digital market-settings remain incomplete. Building on this observation, I then demonstrate how only workers' informal categorical practices complete the *classificatory loop*. Reflecting on these empirical results, my third contribution to the academic debate lies in extending Bowker and Star's (2000, p. 310f) concept of 'categorical work' to digital market-settings. I identify this expanded form of *categorical work* as an underappreciated element of digital market construction (Çalışkan & Callon, 2010).

At last, in chapter 6, I reflect on my previous findings to arrive at an overarching thesis. I problematize the view identified in my literature review that classification systems in digital market-settings are somewhat removed from the social communities that they affect. Such a statement can be inferred from the observation that classes are primarily assigned as the result of opaque and (partially) automated processes and flow from platform-specific, individual-level data (e.g., Cheney-Lippold, 2017; Diaz-Bone, 2017; Fourcade & Healy, 2017). I discuss the evidence collected across all chapters and

show how classifications of labour in online freelancing markets continue to be embedded in the social practices and contexts of those classified. By *putting the social back into classification*, I argue that the centralized classification infrastructure of labour platforms is in fact partially co-constructed and enacted by the workers themselves. I draw implications for workers (on how to succeed in online labour markets), platform firms (on how to construct better marketplaces), and regulators (on how to use the concept of categorical work for holding platform firms accountable).

1.5 Significance of the research

In sum, my project contributes to academic debate threefold. First, I demonstrate how the sociology of classification is a useful lens to analyse and make sense of the platform economy. In this way, I connect recent discussions on classifications as social institutions in digital market-settings with economic sociological debates on market construction and class formation. However, rather than essentializing machine learning technologies, my findings underline that online markets are organized through manual, expert-based classification just as much as through automatically assigned categories as proxies for community-based knowledge such online reputation (Wood & Lehdonvirta, 2022). By making visible categories and classifications codified into the platform infrastructure, I foreground platform firms' classificatory power and their implicit value judgments on whose work counts. This way, I start the discussion on for whom these classification systems of labour do not work well, or worse, who is excluded from participation altogether.

As a second contribution, my project translates Bourdieu's notion of 'classification struggles' (Bourdieu, 1984/2010, p. 481ff) to the context of platforms as digitally mediated workplaces. By centring around workers' varied experiences in platform

work, I provide evidence for how platform firms construct classification systems to the effect of placing workers into discrete market categories that influence their market outcomes and livelihoods. However, I show how workers themselves engage in what I call *categorical work* to navigate and shape the digital infrastructure of platform work. My unique contribution thus lies in uncovering a previously underappreciated form of worker agency specific to the digital age.

My third contribution concerns the construction and maintenance of digital marketplaces. My project uncovers that platform firms only do half of the work in constructing online markets. At least the centralized classification systems constructed by platform firms remain incomplete due to their necessary level of standardization, their circular nature, and the evaluative frictions that flow from them. I therefore argue that digital markets are partially co-constructed and enacted by workers and their informal classificatory practices. In this way I concretize the limitations of classification systems in digital settings, and outline boundaries of the classificatory power enjoyed by platform firms. My project thus provides a concrete and in-depth demonstration of the circularity of digital infrastructure based on machine learning and some societal implications that follow (Beer, 2022; Fourcade & Johns, 2020).

2. Categorization and classification in (online) labour markets

2.1 Introduction

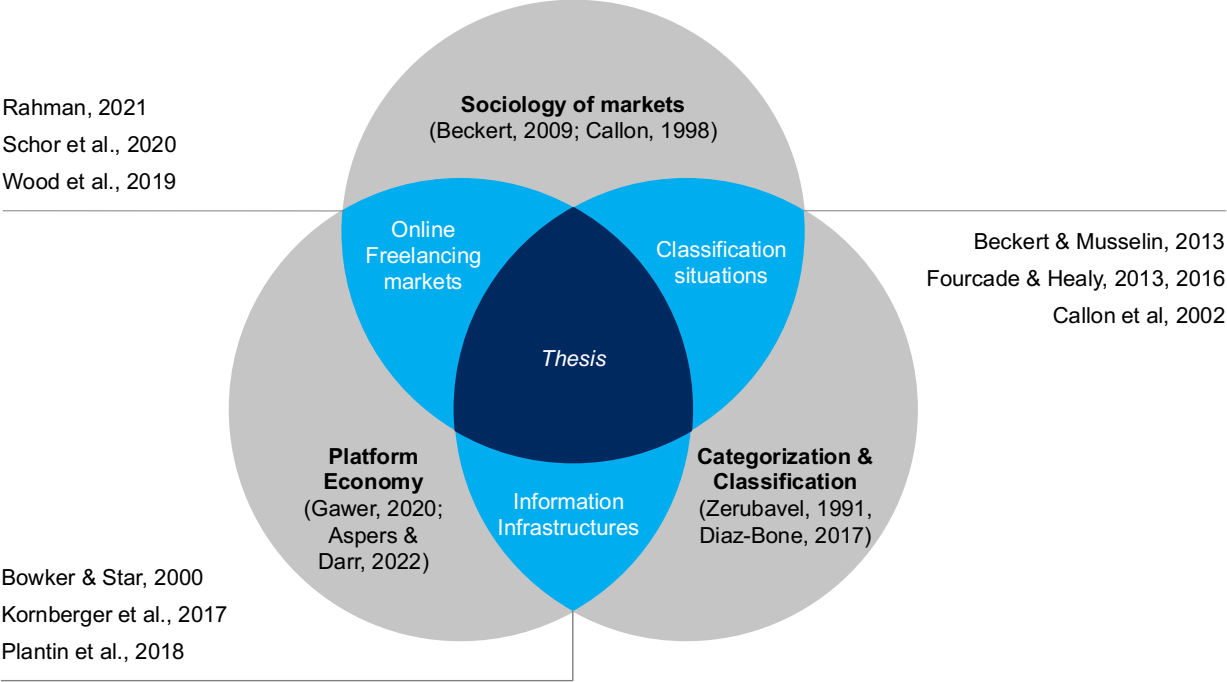
The classification of workers based on their position in the labour market is not a new phenomenon. It is a common feature of sociological debate. Marx viewed capitalist societies as characterized by a fundamental antagonism between a capitalist ('bourgeoisie') and a working ('proletariat') class.¹³ The classes are characterized by their ownership of the means of production and the lack thereof (Marx & Engels, 1948/2018, p. 6). Weber proposed a more dynamic social reality of 'class situations', wherein a social class is defined by similar life chances in a given 'market situation' (Weber, 1922/2021, p. 85). And despite suggestions for other ways to classify society (e.g., Savage et al., 2013), the 'Goldthorpe schema' (Goldthorpe, 1980) developed at Nuffield College in Oxford still forms the foundation for the UK National Statistics Socio-Economic Classification (NS-SEC) which assigns class status based on employment status and occupation.¹⁴ Only recently, a debate has started around whether 'tech workers' of various kinds are becoming a 'new' class of their own (Dorschel, 2022; Lehdonvirta, 2022; Stark & Pais, 2020). In this literature review, I thus first pose the question *how, and to what effect, work and workers are classified in conventional labour markets*. By 'conventional labour markets', I simply refer to all labour markets that are generally not considered part of the gig economy. Since I hope to draw implications for my research on classification in online markets, I then consider what

¹³ Marx did not limit his writing to these two classes only, but he identified them as the most fundamental ones.

¹⁴ <https://www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticsocioeconomicclassificationnssecrebasedonsoc2010> (last accessed on Jan 5, 2023)

these findings would mean in the case of online labour. In this way I hope to provide a unifying theoretical frame which connects my empirical studies (chapters 3, 4 and 5) and sets up my integrated discussion and overall thesis (chapter 6).

Figure 4. Positioning of the thesis in existing literatures



Note. I would like to acknowledge that I was introduced to this type of visualization by colleagues who presented their doctoral work at the Oxford Internet Institute, Dr Corinne Cath-Speth and Dr Kate Sim.

I take an economic sociology perspective and mainly review research on categorization and classification, the sociology of (labour) markets, and the platform economy (Figure 4). This intersection is a necessarily incomplete selection from a large body of available literature. I chose contributions based on their significance for explaining market construction and dynamics. For example, I focus on how the legal classification of platform workers as independent contractors shapes working conditions and market dynamics (Lehdonvirta, 2016), but not on the legal debate itself (Cherry, 2016). Similarly, I only selectively draw on cognitive psychology (Murphy,

2002), research on the ethics of gig work (Tan et al., 2021), and more technical perspectives like computer linguistics (Hannan et al., 2019). Overall, I was limited to English and German publications, as well as translations of non-English works.¹⁵

2.2 Defining categorization and classification

In everyday life, we constantly demarcate the world around us into recognizable entities: Is something an apple or a banana, someone a friend or enemy, an experience 'profane' or 'sacred' (Durkheim, 1912/1995, p. 34)? Our continuous world only becomes distinct and meaningful because we engage in such acts of division (Zerubavel, 1991). Categorization is thus foundational to how humans perceive the world. The Oxford English Dictionary describes categorization as an action which '[places entities] in a category.'¹⁶ Categories differ from concepts. Concepts are 'mental representations of classes of things' and 'the glue that holds our mental world together' (Murphy, 2002, pp. 1, 5). They link knowledge and past occurrences with present experiences and thus allow the grouping of 'objects (a relative, a present), acts (an apology, a crime), or events (a game, a conference)' (Zerubavel, 1991, p. 5) as fitting a mental representation (Hannan et al., 2019, p. ix; Murphy, 2002, p. 1). This reliance on concepts and categories when making sense of the world is a cognitive fact rather than some 'second-best alternative to collecting and analysing more detailed information' (Hannan et al., 2019, p. x). Categorization is the act of us making distinctions (Zerubavel, 1991, pp.1f). The resultant categories lump entities together

¹⁵ This practical choice limited my ability to engage with primary materials central to the '*economics of convention*' (EC) only published in French. Instead, I drew on available reviews (e.g., Diaz-Bone, 2018). EC is a pragmatic, institutional approach in the field of economic sociology. It has introduced a framework to analyse socio-economic coordination and institutions under uncertainty based on underlying and frequently re-negotiated conventions (Diaz-Bone, 2017).

¹⁶ <https://www.oed.com/view/Entry/28876?redirectedFrom=categorization#eid9843444> (last accessed on May 26, 2019).

that share a set of determined characteristics given a specific context (Jacob, 2004).

More precisely,

‘a category is a set of objects that have been recognized as fitting a concept. How an object is categorized is the realization of a probabilistic process that depends on the set of concepts that the person holds’ (Hannan et al., 2019, p. ix).

Categories are flexible, allow for fuzzy boundaries and thus partial membership (Hannan, 2010; Jacob, 2004).

Classifications on the other hand are formally defined systems of categories, sometimes referred to as ‘organized architectures of categories’ (Diaz-Bone, 2017, p. 238). At least theoretically, classification follows a ‘consistent, unique classificatory principle’ while resulting in a ‘mutually exclusive’ and ‘complete’ segmentation of things or people (Bowker & Star, 2000a, p. 10). Thus, classification conceptually differs from categorization (Jacob, 2004): On the one hand, categorization is a creative process of demarcating entities along grades of similarity given some context. The lines of distinction are fuzzy, and membership of an entity is flexible because it is assigned based on context-dependent and context-independent criteria. Members can be ordered based on typicality of some represented concept. A classification on the other hand considers each member of a class an equally typical member of that class. Class membership is mutually exclusive and assigned based on general, context-independent principles. The resultant class boundaries are in theory rigid, clearly defined, and result in a hierarchical structure.

Thus, in theory, *concepts*, *categories*, *classifications*, and *standards* have a constitutive relationship to one another (Figure 5). A mental representation of what constitutes an ‘occupation’ is a necessary condition for categorizing nursing as such. Once several categories are systematically related to one another, they comprise a

classification system (Bowker & Star, 2000a, p. 10f). On an online job board like *indeed.com*, nursing might be only one formalized class of hospital jobs available. Such an occupational classification is specific to one context. Instead, the International Standard Classification of Occupations (ISCO) is a classificatory standard for collaboration across time, place, and contexts. While not all classifications become standards, every standard proliferates at least one underlying classification (Bowker & Star, 2000a, p. 13ff).

Figure 5. Differentiating concepts, categories, classifications, and standards

	Concept	Category	Classification	Standard
Definition	'Mental representations of classes of things' (Murphy, 2002)	'Set of objects that have been recognized as fitting a concept' given some context (Hannan et al, 2019)	'Organized [hierarchical] architectures of categories' (Diaz-Bone, 2019)	'[S]et of agreed-upon rules for the production of [...] objects' which spans place, time, and more than one community of practise (Bowker & Star, 2000)
Characteristics	<ul style="list-style-type: none"> Used to categorize the subjects, objects, and situations we encounter (Hannan et al, 2019) 	<ul style="list-style-type: none"> Probabilistic assignment based on similarity/context Boundaries are fuzzy Partial membership ok Groups of similarity 	<ul style="list-style-type: none"> Assignment via consistent classificatory principle Boundaries are rigid Classes mutual exclusive Hierarchical structure 	<ul style="list-style-type: none"> Often enforced by law Difficult to change
Example	<i>Occupation</i>	<i>Nursing as an occupation</i>	<i>Classification of hospital jobs on an online job board</i>	<i>International Standard Classification of Occupation</i>

Note. The figure is based on contributions by several authors (Bowker & Star, 2000a; Diaz-Bone, 2017; Hannan et al., 2019; Jacob, 2004; Murphy, 2002; Zerubavel, 1991). Grey shading signifies tangential relevance for this thesis.

In practice, the boundary between categories and classifications remains often blurry. While the terms are regularly used interchangeably, a pragmatic differentiation between both concepts is necessary to present a clear argument in this project. Since it might well be impossible to identify any classification system which fulfils the formal definition given above, I will follow the approach identified by Bowker and Star (2000a, p. 13). They define a classification system as 'anything consistently called a classification system and treated as such' (Bowker & Star, 2000a, p. 13). Hence, I will

speak of *classification* whenever something is treated as a classification system by the involved parties or the researchers describing it. Conversely, I consider *categorization* a necessary condition for classification. Thus, whenever I write about classification it implies an underlying subset of categorization, but not the other way around.

2.3 Boundaries in conventional labour markets

Three examples illustrate the role and socio-economic influence of socially constructed boundaries in labour markets: an occupational classification introduced by the French state, the classificatory work done by executive search firms globally, and the U.S. Nursing Interventions Classification (NIC). Drawing on concrete cases helps to foreground boundaries which ‘are normally taken for granted and, as such, usually manage to escape our attention’ (Zerubavel, 1991, p. 3).

Socio-professional categories in France

As noted earlier, there is a long tradition of research on how employment status is linked to social class (Erikson & Goldthorpe, 1992). Outside the UK, the ‘Classification of Socio-Professional Categories’ (CSP) is a well-studied French example of how employment status impacts life chances, and why it is difficult yet essential to study such classification systems. Originally, it was an occupational classification constructed for the administration of the census in 1954 at the French National Institute of Statistics and Economic Studies, INSEE (Amossé, 2013). Its objective was to ‘categorise individuals according to their professional situation, taking account of several criteria: their profession, economic activity, qualification, hierarchical position and status.’¹⁷

¹⁷ <https://www.insee.fr/en/metadonnees/definition/c1758> (last accessed on July 15, 2021).

The classification has been ‘overhauled’ as the ‘Classification of Professions & Socio-Professional Categories’ (PCS) in 1982, and further updated as recently as 2020 (Amossé, 2022). The PCS comprise four levels: eight aggregate socio-professional groups, 24 partially aggregated socio-professional categories, 42 socio-professional categories, and almost 500 professions. For example, a municipal police officer (531b) is subsumed under ‘police and military’ (53), the aggregated socio-professional category ‘civil service employee’ (51), and the socio-professional group ‘employees.’¹⁸ Each profession lists a description, most typical occupational designations included in a class (e.g., municipal police officer, chief of municipal police), assimilated cases (e.g., investigator at the municipal police, ‘*garde champêtre*’) and professions explicitly excluded from a class (e.g., national police officer).¹⁹ To this day, they remain a legitimate ‘collective cognitive device’ in French everyday life (Diaz-Bone, 2017, p. 240) and the ‘benchmark [...] for analysing social stratification, social classes, and the working world’ (Amossé, 2022).

The French socio-professional categories are an exemplar of an expert-based classification of labour constructed by a state bureaucracy to yield abstract, statistical categories necessary to govern their people (Desrosières, 1998; Scott, 1998). Historically, the CSP was introduced against the backdrop of a growing, centralized state who needed more and better information about its citizens. In Europe during the 19th century, this trend was first closely linked to the rise of census activity and increased quantification of society (Desrosières, 1998, p. 147f; Espeland & Sauder, 2007). States draw on categories and classifications to structure, simplify, and make legible the land, things, and citizens it governs (Scott, 1998, p.76). Bureaucratic

¹⁸ Translation by the author.

¹⁹ <https://www.insee.fr/fr/information/2497952> (last accessed on April 21, 2021).

categories are foundational to 'state simplifications', standardized abstractions of a complex reality, which take the form of statistics, censuses, and other government records designed to inform governance, exert control over the citizens, and allow for state interventions (Scott, 1998, p.77). In other words, for the state to govern, 'reality must be reduced to schematic categories' (Scott, 1998, p. 76f). Only social distinctions facilitate a move from singular citizens to the general (Desrosières, 1990).

For my thesis, there are two essential debates that emanated from the academic contributions by experts employed at the INSEE. These included French thinkers like Bourdieu (1984/2010), Desrosières (1998; Desrosières et al., 1983), Boltanski (1987), and Thévenot (Boltanski & Thévenot, 1983; Thévenot, 1984). First, these authors highlighted that naturalization of categories hides the human practices and judgments inherent to their construction (Diaz-Bone, 2017). The reworking of the CSP in the 1970s was thus foremost a concentrated effort to denaturalize official categories (Amossé, 2013). It was a response to growing pressures to reflect social hierarchies in occupational classifications which at this point in time were still closely aligned with everyday language (Amossé, 2013). The project was notably influenced by Bourdieu's call for social scientists to rely on statistical categories to uncover inequalities in society, while retaining a reflexive mindset towards said tools (Desrosières, 2003, as cited in Amossé, 2013, Diaz-Bone, 2018). Second, researchers at the INSEE underlined that classifications of labour are subject to 'classification struggles' (Bourdieu, 1984/2010, p. 481ff). Individuals and social groups have a history of reacting to being classified and trying to shape their own classifications (Boltanski, 1987; Boltanski & Thévenot, 1983). In the case of the CSP, political struggles for better representation occurred in the public arena, for example whenever occupational groups struggled for being recorded as a distinguished entity (Boltanski, 1987).

Ultimately, these struggles can be traced back to the power of symbolic boundaries to have material effects and constitute the social order (Lamont & Molnár, 2002).

Executive search

Executive search firms, also called headhunters, exemplify how intermediaries can occupy powerful positions in information networks of labour markets. They exploit workers' and employers' imperfect information and engage their corporate clients in qualifying what makes a good candidate for a vacancy. Just like platform firms, headhunters intermediate the hiring process of workers and employers (Khurana, 2002). They are often paid by employers only if their respective candidate is actually hired for the position in question (Finlay & Coverdill, 2007, p. 1f). Early sociological work ascribed only limited significance to formal job matching services such as the ones provided by executive search firms, employment agencies, and through advertisements. It considered personal networks as the most reliable path to finding a new job (Granovetter, 1995, p. 26). However, more recent evidence suggests that executive search firms are relevant labour market intermediaries with '80 – 90% of Fortune 250 or FTSE 100 companies pay[ing] headhunters to find their CEO' and worldwide revenues of the industry having increased fivefold from 1991 to about 15 \$bn in 2018.²⁰

Executive search firms concentrate on three activities to position themselves between workers and employers in the information network of labour markets (Coverdill & Finlay, 2014). First, they establish a working relationship with employers to source

²⁰ Statistics were taken from the article '*Take me to a leader – Corporate headhunters are more powerful than ever*' (The Economist, Feb 6, 2020). The authors sourced the revenue numbers from AESC, the Association of Executive Search and Leadership Consultants: <https://www.economist.com/briefing/2020/02/06/corporate-headhunters-are-more-powerful-than-ever> (last accessed on March 15, 2021).

search orders. Then, they identify fitting candidates from their databases, informal networks or through other means such as cold-calling or social media searches. Last, they facilitate the match between their candidate and the company, for instance by preparing the candidate for their interview. Faulconbridge et al. (Faulconbridge et al., 2009, p. 801) argue that through these activities executive search firms not only facilitate matching but shape the definition of who classifies as talented and fit for an executive role, and is conversely 'admitted to the networks that provide access to elite executive positions'. Similarly, Coverdill and Finlay (Coverdill & Finlay, 2014, p. 15) state that 'headhunters clearly become involved in shaping—not just understanding—job definitions and selection criteria', for example through repeat interactions with employers. These interactions are used to align on candidate characteristics, to ensure fit with the company and their interviewers, as well as to identify so-called 'hot buttons'. The latter are skills or experiences that are not explicitly called out in job specifications, but nevertheless 'serve as markers of a candidate's ability to do *the* job, not just a job of the sort being filled' and thus are likely to make a candidate stand out from an otherwise homogenous shortlist of potential hires (Coverdill, 1998, p. 107).

The powerful intermediary role of executive search firms is relevant because 'through their governance actions, [they] render powerful the resources of certain individuals and render less powerful the knowledge and experience of others' (Faulconbridge et al., 2009, p. 807). Executive search firms are no neutral facilitators, but actively shape labour market outcomes. They contact white males more often than females or minorities (Dreher et al., 2011). This practice mediates pay advantages from external job change enjoyed by white male candidates compared to female or minority male pendants at statistically significant levels. Similarly, headhunters co-construct ideal physical characteristics of executive candidates (Meriläinen et al., 2015), emphasize

the importance of certain geographical signals such as select educational institutions, reputable corporations or international biographies (Faulconbridge et al., 2009), and value candidates job titles over actual accomplishments (Hamori, 2010). They co-construct these hierarchies of value through a mixture of work practices and reliance on technology. Workers who do not conform to their ideals, for instance, are simply not included into internal databases, the basis for their matchmaking services (Cappelli & Hamori, 2014; Faulconbridge et al., 2009). In the age of *linkedin.com*, headhunters use such platforms to 'poach[...] specialized superstar talent, [...] while active job seekers are relegated to the hyper-competitive and impersonal "black hole" of the online job boards' (McDonald et al., 2019, p. 93).

In sum, the case of executive search illustrates the role of labour market intermediaries which generate and extract value by acting as and themselves using so-called market devices (Callon et al., 2007; Karpik, 2010). Their business model builds on easing the informational burden on employers by reducing the number of candidates, variables of evaluation, and uncertainty around these variables. However, these intermediaries do not neutrally broker information, but co-construct the evaluative landscape of a labour market (Bessy & Chauvin, 2013).

The professionalization of nursing in the U.S.

The Nursing Interventions Classification (NIC) serves as an exemplar for a concentrated effort of professionalization within a specific occupational community (Bowker et al., 1996; Bowker & Star, 2000a, p. 229ff). It is a 'comprehensive, research-based, standardized classification of interventions that nurses perform' recognized by

the American Nurses' Association (ANA) and published by Elsevier.²¹ The seventh edition of the NIC includes 565 interventions—defined as 'any treatment based upon clinical judgment and knowledge that a nurse performs to enhance patient/client outcomes'—and more than 13,000 subsumed activities (Butcher et al., 2018, p. 2).²² It provides 'a manifesto for nursing as an organized occupation, a basis for a scientific domain, and a tool for organizing work practices' (Bowker & Star, 2000a, p. 31). To fulfil these aims, functional classifications of work have to navigate three particular challenges: comparability, visibility, and control (Bowker et al., 1996). The experts who designed the NIC had to balance the standardization of practices (sufficient for comparisons across place and time) with local specificity, explicitly making visible core interventions while avoiding to highlight those considered to banal for inclusion, and weighing the benefits of transparency against the risks of workplace surveillance and loss of discretionary decision making (Bowker & Star, 2000a, p. 240ff). Examples of workplace surveillance could range from simple impact analyses of nursing interventions to ranking nurses based on their perceived efficiency. Borrowing MacKenzie's language (2006), these considerations highlight that classifications as 'act[s] of professional practice' (Abbott, 1988, p. 40) are rarely if ever only cameras which simply record existing work practices in a standardized manner. Instead, they behave more like engines which drive the convergence of 'map and [...] territory' (Bowker & Star, 2000a, p. 254).

²¹ <https://nursing.uiowa.edu/cncce/nursing-interventions-classification-overview> (last accessed on Jan 9, 2023).

²² As a complement to the NIC, the Nursing Outcomes Classification (NOC) was subsequently introduced to standardize the impact measurement of nursing interventions (<http://www.nursing.uiowa.edu/cncce/nursing-outcomes-classification-overview>, last accessed on May 10, 2021)

Due to their normative nature, these classifications have politics (Suchman, 1993). Even within a single community of practice—nursing—there is rarely consensus on how to best categorize a shared occupational reality. While categories and classifications of a particular social group become naturalized to its members over time and use (Bowker & Star, 2000a, p. 310f), these cognitive distinctions can by definition only ever be an abstraction of human experience (Zerubavel, 1991, p. 2). Next to more fundamental debates about the nature of nursing and strategic implications of the NIC, disagreements about the classification have been rooted in its various envisioned applications. Stakeholders' requirements differ with use ranging from daily, local practice (e.g., recording interventions), scientific research (e.g., studying the impact of interventions across contexts), management (e.g., cost and time-efficiency of interventions), and input to ever more pervasive information systems (e.g., integration with hospital software) (Bowker & Star, 2000a, p. 31). Classifications are thus information infrastructures which are best understood as a continuous process evolving over time, mainly based on user feedback (Butcher et al., 2018, p. 3). Once we interpret classification systems as information infrastructures, it becomes clear that they are relational in nature and become 'a system in design and use, not the one without the other' (Bowker & Star, 2000a, p. 292).

Despite the complexities in classifying nursing interventions, the researchers and practitioners who designed the system recognized its imminent need: 'If we cannot name it, we cannot control it, practice it, teach it, finance it, or put it into public policy' (Butcher et al., 2018; Clark & Lang, 1992, p. 109). The emergence of information systems in healthcare settings tied classifications ever more intimately to visibility. As Bowker and Star (2000a, pp. 227–282) manage to show, a standardized and transparent means of communicating nursing services was required, or else nursing

would have simply been excluded from new digital records. It would have likely yielded some of its professional jurisdiction to other healthcare groups. As an input for information infrastructure, classifications of work can simultaneously be seen as tools of communication across multiple communities of practice, while equally being devices of erasure leaving behind those people or activities defined as irrelevant (Bowker & Star, 2000a, p. 282). The case of the NIC highlights that while classifications are contested and imperfect in the sense that they cannot serve everyone equally, they nevertheless are pragmatic solutions to real challenges that can ‘work reasonably well for many people at particular times’ (Star et al., 1998, sec. 7).

2.4 The process of categorizing labour

In response to the first part of my research question—*how* work is categorized—I argue that the three examples above and the broader sociological literature on categorization and classification suggest that the process of constructing boundaries is characterized by three inherent tensions. First, distinctions are both socially constructed and ‘real’ facts in that actors view them as such and alter their actions accordingly (Desrosières, 1998). Second, categories and classifications are mundane, yet highly political and contested amongst individuals and groups who construct, implement or apply them, and those who are being classified (Boltanski & Thévenot, 1983; Bourdieu, 1984/2010). Third, the organization of labour markets relies on formalized categories, classifications, and standards just as much as on the local and informal categorical practices by workers, employers, and intermediaries (Aspers & Darr, 2022; Beckert, 2009; Beckert & Musselin, 2013; Bowker & Star, 2000a; Fligstein, 2002).

Tension 1: The social construction of boundaries

Sociologists highlight the social—as opposed to natural or logical—character of classification. In their study on ‘primitive’ classifications, Durkheim and Mauss state:

‘Society was not simply a model which classificatory thought followed; it was its own divisions which served as divisions for the system of classification. The first logical categories were social categories; the first classes of things were classes of men, into which these things were integrated’ (Durkheim, 1963/2010, p. 48).

Any symbolic representation is inevitably a simplification of the ‘wildness and complexity of what is represented’ (Bowker & Star, 2000a, p. 232). Our language ‘builds up classification schemes to differentiate objects’ (Berger & Luckmann, 1966/1991, p. 55). Humans thus continuously gauge which differences are negligible, or which similarities deemed sufficient for objects to be grouped together (Jenkins, 2000). The necessary ‘rules of irrelevance’ are socially learned (Goffman, 1961, p. 19ff). Put differently, boundaries usually ‘rest on some social convention’ and are ‘social artifacts’ (Zerubavel, 1991, p. 62). The more comfortable we feel in a social setting the more familiar and natural its categories and conventions seem. The social categories of any community become more naturalized as a function of our membership in that particular group .

Thus, boundaries are deeply rooted in their cultural and historical context. In ‘The Order of Things’, Foucault proposes that all classification rests ‘upon a sort of historical *a priori*’ which sets the boundaries of what can be known, provides the theoretical base for seeing the world, and ‘defines the conditions in which [one] can sustain a discourse about things that is recognized to be true’ (Foucault, 1966/2002, p. 172). For example, Foucault reasons that there was a shift from grouping species based on similarity in the 16th century to designating species based on their relation to and difference from ‘all other possible designations’ in the 17th century and onwards (Foucault, 1966/2002,

p. 157). In the latter case, 'to know what properly appertains to one individual is to have before one the classification – or the possibility of classifying – all others', while in the former 'each species identified itself by itself, expressed its individuality independently of all the others' (Foucault, 1966/2002, p. 157f).

Desrosières and Thévenot similarly conclude that social boundaries cannot be reduced to logic or empirics alone (Desrosières & Thévenot, 1979; as cited in Diaz-Bone, 2018, p. 62ff). Classifications of work, for example, differ in core theoretical assumptions like their dimensionality. In 20th century Britain, for example, workers were classified along a unidimensional hierarchy of abilities, while French '*social space*' was conceptualized along two dimensions representing,

'a combination of the levels of income and training [...and an opposition of] non-wage earners to wage earners, and wage earners in the public sector [...] to those in firms' (Desrosières, 1998, pp. 263f, 270f).

The social, contextual, and historical character of classifications is often forgotten. Categories and classifications are taken for granted, especially once they 'have disappeared into infrastructure [and] into habit' (Bowker & Star, 2000a, p. 319; Thévenot, 2016). Therefore, as workers and others accept them as natural or real categories, they become real in their consequences (Bowker & Star, 2000a).

Tension 2: The politics of classification

To make visible the human practices sustaining classification systems, Desrosières and Thévenot introduced the metaphor of the *statistical chain* (Desrosières & Thévenot, 2002; as cited in Diaz-Bone, 2018). They follow Bourdieu in focusing on the practices underlying classification. The statistical chain thus is a metaphor to foreground the people entrusted with constructing a classification, citizens providing and workers recording survey responses, experts encoding them into general classes,

and representatives of occupational groups politicising the individual categories (Desrosières et al., 1983; as cited in Diaz-Bone, 2018, p. 63). The ‘general categories’ produced by states, are not necessarily equivalent to the ‘particular forms’ flowing from interpretations of individuals in their application (Thévenot, 1984, p. 4). Given the chance, individuals tend to struggle against being classified, although this tension between them and those tasked with recording and encoding their responses is rarely recognized (Boltanski & Thévenot, 2006, p. 2). The latter engage in qualification, which

‘transforms a case, with its complexity and opaqueness into an element of a class of equivalence, capable of being designated by a common noun and integrated as such into larger mechanisms’ (Desrosières, 1998, p. 246).

Examples of such qualification are plentiful. Judges and lawyers place individual cases into the wider classes of the law, doctors assign causes of death to classes in the International Classification of Diseases, and educational institutions assign students to categories such as grades or levels of certification (Desrosières, 1998, p. 247). Since assigning particular cases to general classes by reference to official instructions can be ambiguous, these workers in the statistical chain struggle with uncertainty and end up resorting to workarounds such as ‘statistical approximation, [... or attempting to] ‘unveil[...] the identity of the person concealed behind the questionnaire’ (Boltanski & Thévenot, 1983, 2006, p. 5).

Categories and classifications thus have politics (Suchman, 1993), both in their construction and use. They carry with them an invisible, historic, and social context which motivate ‘classification struggles’ between affected individuals and social groups at the societal level who seek to improve their symbolic and material standing (Bourdieu, 1984/2010, p. 481ff). State classifications like the CSP discussed before are thus not just projected onto some social reality but are the result of proactive efforts

by social actors to secure status recognition and distributional advantages. The French professional class of 'cadres', for example, emerged only from the concerted efforts of a small sub-group of engineers at a given historical context, and is therefore non-existent outside French (Boltanski, 1987). Producers of classifications are thus always constrained by the practical uses of their tools and the resistance of those being classified (Bowker & Star, 2000a, p. 106; Desrosières & Thévenot, 1979, as cited in Diaz-Bone, 2018, p. 62ff).

Tension 3: Formal versus informal boundaries

Another reoccurring theme in the three exemplars is the tension between formal classification standards and the informal and local practices and needs of its users (Bowker & Star, 2000a). Codified state classifications are challenged by those being classified (Boltanski & Thévenot, 1983). Workers, employers, and intermediaries alike co-construct the qualities of and preferences for labour and often formalize them as market devices (Beckert & Musselin, 2013; Callon et al., 2002; Muniesa et al., 2007). Local practitioners challenge and re-purpose standardized classifications of work practices (Bowker & Star, 2000a). Professional groups secure their status through cultural boundary work as much as legal categorization by the state (Abbott, 1988). In other words, informal categorical practices by workers and employers are as essential to the functioning of labour markets as more formalized classification systems. In fact, they are two sides of the same coin once classifications are viewed as information infrastructures which relate the formal and the informal (Bowker & Star, 2000a), and arise whenever 'local practices are afforded' by global standards (Star & Ruhleder, 1996, p. 114). As such, research which foregrounds categories and classifications in labour markets lends itself to a pragmatic study of the actual practices of workers, employers and intermediaries involved, as well as the market devices they use in their

efforts of ‘constructing and reconstructing meaning through the interplay of action and structure/environment’ (Overdeest, 2011, p. 535).

Bourdieu considered both official systems of classifications as well as tacit classificatory schemes equally powerful to maintain order:

‘Official systems of classification [...] do explicitly and systematically what the classificatory schemes did tacitly and practically. [...] Classificatory *discretio*, like law, freezes a certain state of the power relations which it aims to fix forever by enunciating and codifying it. [...] it makes its own [...] contribution to the maintenance of that order only because it has the specifically symbolic power to make people see and believe which is given the imposition of mental structures.’ (Bourdieu, 1984/2010, p. 482)

As information systems, mix up ‘the conventional and the formal, the hard technical problems of storage and retrieval[, and] the hard interactional problems of querying and organizing’ (Bowker & Star, 2000a, p. 7), the diverse language and local context of their production is formalized into code. One concrete example is the use of skill requirements scraped from online job advertisement data for the creation of occupational classifications based on natural language processing (Djumalieva et al., 2018). As in any statistical analysis, data scientists make implicit and explicit assumptions about the equivalence of content across categories that emerge from diverse social contexts and define formal rules on how to address the phenomenon of fuzzy boundaries in our language .

2.5 The effects of categorizing labour

After having established that categorization and classification in labour markets are social and contested processes which are rooted in informal, human categorical work, I proceed to the second part of the research question: To what effect is labour categorized and classified in conventional labour markets?

In the following, I argue that categorization and classification matter because of their consequences for the individual. This overarching theme of social science research into boundaries has been summarized by Lamont and Molnár as:

‘the search for understanding the role of symbolic resources [...] in creating, maintaining, contesting, or even dissolving institutionalised social differences’ (Lamont & Molnár, 2002, p. 168).

I posit that the ways in which categories touch people’s lives can be subsumed under the perspectives of *information*, *division*, and *control*.

Perspective 1: Information – making labour markets intelligible

First and foremost, categories and classifications are social institutions which inform and order the human experience (Douglas, 1986; Durkheim, 1963/2010; Hannan et al., 2019; Zerubavel, 1991). In the seminal work *Primitive Classification*, Durkheim goes as far as viewing classifications to be equivalent to the social order. He considers them purely informational in nature:

‘Their object is not to facilitate action, but to advance understanding, to make intelligible the relations which exist between things’ (Durkheim, 1963/2010, p. 48).

Douglas extends Durkheim’s work by highlighting the institutional character of classifications. Categories and classifications determine what entities count as sufficiently similar to be grouped together (Douglas, 1986). While the informational value of classifications stays a key element in her work, she also highlights the normative character of categorical work. In her view, for example, ‘dirt’ is a relational concept and best understood as ‘matter out of place’ which makes it a ‘by-product of a systematic ordering and classification of matter’ which ‘reject[s] inappropriate elements’ (Douglas, 1966/2002, p. 44).

In labour markets, categories also first and foremost communicate essential information (Diaz-Bone, 2017). Market participants need a way to distinguish between types of work, workers, and employers. This use of categories is not a choice or strategy but quite simply how human cognition functions (Hannan et al., 2019, p. x). Categories ease the informational burden on workers and employers who make hiring decisions under the constraints of their bounded rationality (Simon, 1990). Grouping similar entities together as categories can increase the efficiency of searches by reducing transactions costs, for example via signalling (Pissarides, 1984; Spence, 1973). To simplify verification and raise the bar for falsification, occupational symbols such as credentials or job titles tend to be approved by acknowledged institutions (Goffman, 1951), one reason why online platform-curated signals are more efficient than self-reported alternatives (Lehdonvirta et al., 2019).

Since quality is generally uncertain in labour markets (Beckert, 2019), workers and employers rarely if ever make decisions based on perfect information based on some underlying reality. Instead, they are actively involved in qualifying one another (Beckert & Musselin, 2013). Only by collectively establishing similarities and differences workers and their skill sets become comparable (Callon et al., 2002). Categories and classifications always 'come from action and in turn from relationships' (Bowker & Star, 2000a, p. 285). Hiring decisions are enabled only through this singularization of otherwise indistinguishable vacancies, workers, and employers (Beckert & Musselin, 2013; Callon et al., 2002). A worker thus has the opportunity to differentiate herself from others, singularizing her abilities and services as much as possible to virtually become the monopolist of one particular employer transaction (Callon, 2016). Yet, she also needs to communicate her appeal to a broad set of employers which also requires her use of standardized and easily recognizable symbols.

The study of classifications of labour is paramount because such 'infrastructure does more than make work easier, faster, or more efficient; it changes the very nature of what is understood by work' (Bowker & Star, 2000a, p. 108). Once qualified, workers are judged based against the expectations tied to a certain role. Market categories are sticky because non-role confirming behaviour can be punished (Zuckerman, 1999). In the film industry, for instance, being typecast can increase actors' chance of getting employed by signalling a relevant skill set in a respective genre only at the beginning of their careers (Zuckerman et al., 2003). In online labour markets, the categories of previous projects help employers to judge the effort and experience of available freelancers. Leung (2014) shows that employers consider some erraticism in a freelancer's work history desirable, while too much or none is being punished by non-employment. Further, classifications always render invisible some workers or work activities (Star & Strauss, 1999). Such invisibility can affect whether one's work is perceivable as such before law, by one's personal environment, or as a service offered in a market-setting (Gruszka & Böhm, 2020). As a worker, being visible in a pool of competitors is ultimately the necessary condition for being hired (van Doorn, 2017).

Perspective 2: Division – securing access to resources

Meaningful information always necessitates simplification and distinction of the social world. Not by accident, information has famously been defined as 'a difference that make a difference' (Bateson, 1970/2015). Information and division are two sides of the same coin. Bourdieu and Weber are two authors who viewed classification primarily as a means of distinction. In contrast to Durkheim, Bourdieu notes that the symbolic and social order are not equivalent—'the order of words never exactly reproduces the order of things' (Bourdieu, 1984/2010, p. 481)—mainly because classifications are also

constitutive of the social order. According to him (Bourdieu, 1984/2010, p. 6f), it is cultural tastes that 'fulfil a social function of legitimating social differences':

'Social subjects, classified by their [own] classifications, distinguish themselves by the distinctions they make between the [...] distinguished and the vulgar, in which their position in the objective classifications is expressed or betrayed.'

Weber instead focuses on the power of markets to classify. He likens someone's '*class situation*' to their '*market situation*', thus highlighting equal life chances in market-settings as the most important commonality of social class:

'[T]he kind of chance in the market is the decisive moment which presents a common condition for the individual's fate.' (Weber, 2021, p. 85)

Both thinkers are insofar aligned as they acknowledge that classification has politics and is associated with struggles by real people or groups of people for symbolic recognition, better economic outcomes, and a more advantageous social order. Bowker and Star acknowledge this dimension of struggle by noting that

'one group's visibility [in a given classification system] comes at the expense of another's suffering.' (2000a, p. 320)

Classifications are always hierarchical and contain implicit 'orders of worth' (Boltanski & Thévenot, 2006) which can serve as symbolic justifications for social inequalities.

Next to their informational value, individuals and groups draw on symbolic boundaries to regulate access to resources such as material rewards, recognition, and increased life chances (Lamont & Molnár, 2002). For example, occupational groups have economic incentives to shield themselves from unregulated entry and protect its legally acknowledged area of jurisdiction. Gieryn (1983, p. 791), for example, suggests that 'boundary work' as a 'stylistic resource for ideologists of a profession or occupation' is utilized to increase their own authority or power into domains previously occupied by

other groups. Specifically professions, loosely understood as 'exclusive occupational groups applying somewhat abstract knowledge to particular cases', stand in competition to one another and claim jurisdiction over certain problems and solutions by referring to abstract knowledge specific to their own profession (Abbott, 1988, p. 8). The continuous reconstitutions of boundaries are acts of categorization to protect existing or gain better distributional outcomes for one's profession over another.

Distributional outcomes can equally be affected by formalized structures in labour markets. The chosen division of labour, that is the matching of people to tasks in an organization, codified in job titles and their role descriptions, impacts professional success within a hierarchy. In their job title analysis of the Californian civil service system, Strang and Baron (1990) show that such titles influence individuals' opportunities including wages and career prospects within an organization. The system, however, is not necessarily shaped by technological deliberations as might be expected but 'social, political, administrative, and historical factors' (Strang & Baron, 1990, p. 491). Even in a public hierarchy like the Californian civil service 'bureaucratization and rationalization do not necessarily eradicate ascription' based on personal characteristics, but instead codify it into its division of labour based on 'job descriptions, job ladders, patterns of pay progression and the like' (Barnett et al., 2000, p. 132). As a result, women and men respond by observing different mobility and career patterns within the system (Barnett et al., 2000). More generally, sites where categories with stratification potential are negotiated generally give way to politics and 'opportunity hoarding' by privileged social groups. Well-off families identify academic tracking or gatekeeping by schools as means to preserve and re-enforce a lucrative status quo (Domina et al., 2017). Occupational groups seek favourable recognition

(Boltanski, 1987). Manual workers dispute with knowledge workers over divisions of labour in production plants (Vallas, 2001).

Perspective 3: Control – controlling the worker

Last, those who hold power to categorize and classify exercise control over those classified (Lamont et al., 2015). For example, classifying a worker's tasks 'may mean controlling or surveilling their work, and may imply an attempt to take away discretion' (Bowker & Star, 2000b, p. 161). Especially Foucault (1977, pp. 144–149) considered classification a necessary condition of discipline:

'In discipline, the elements are interchangeable, since each is defined by the place it occupies in a series, and by the gap that separates it from the others. The unit is [...] the *rank*: the place one occupies in a classification [...] Discipline is an art of rank [...] It individualizes bodies by a location that does not give them a fixed position, but distributes them and circulates them in a network of relations'

This way, the power to classify always has a normative dimension. As noted before, the construction of social classifications is an important function and tool of the rational state (Bourdieu, 2014). By drawing on the support of the entire force of the state bureaucracy and executive, state classifications are not mere observations of public life, but social fabrications with the normative power to shape and even become people's lived realities:

'The categories used by state agents are not merely means to make their environment legible; they are an authoritative tune to which most of the population must dance.'
(Scott, 1998, pp. 82–83)

In labour markets, classifications are equally employed as tools of governance. That is, they help actors in positions of power—for example employers or labour market intermediaries—to shape incentives and influence the actions of those partaking in a market (Foucault, 1977; Fourcade & Healy, 2013; Power, 2004). The choice of

categories employed to structure a labour market as well as organization shape incentives and the type of order achieved (Ahrne et al., 2015; Kornberger et al., 2017; Miller & Power, 2013; Power, 2004). Performance measurement and accounting, for example, are essential to governing organizations. In this context, Power (2004, p. 767) points out that 'all measurement systems are made possible by calibration, understood as the creation and determination of quanta' which in turn require classification. Such workplace evaluation tools and their underlying classifications are never neutral and have, for instance been demonstrated to increase gender bias in performance evaluations (Rivera & Tilcsik, 2019).

Once they are backed by credible 'market organizers' (Ahrne et al., 2015), such as states, an employer, and even profit-seeking third parties, formal categories tend to impact behaviour. In educational institutions, for example, certain student characteristics are selected 'out of multidimensional human variation' and codified into social categories such as 'learning disability', 'honours courses', or 'English language learner' leading in turn to categorical inequality (Domina et al., 2017, p. 316ff). Students adapt their behaviour in response to given categories because the latter affect their motivation and self-identity. Similarly, workers change their behaviour because they fear repercussions once they ignore category-specific obligations. Zuckerman (1999), for example, concludes that market participants are punished for neglecting role-conforming behaviour in market settings that are highly reliant on critics and analysts like stock markets. Similarly, CEO pay is often related to the performance of a company relative to comparatively similar peers. As similarity tends to be defined by the companies' boards, the chosen market categories are not only collectively constructed, but chosen to follow self-serving and strategic objectives (Porac et al., 1999).

2.6 The case of online labour

Taken together, I view categories and classifications as social institutions (Alaimo & Kallinikos, 2021; Bowker & Star, 2000a; Douglas, 1986; Durkheim, 1963/2010) that are essential to the construction and organization of labour markets (Beckert & Musselin, 2013; Fligstein, 2002). They are constructed by a specific communities, set of experts, and by extension even by machine learning algorithms and a given dataset (Alaimo & Kallinikos, 2021; Cheney-Lippold, 2011, 2017). As a result, categories and classifications always codify a ‘certain cultural and historical standard’ or context (Bechmann & Bowker, 2019, p. 3). How do these findings map onto online labour markets? To answer this question, I draw on additional research on the platform economy to arrive at the theoretical starting point of my empirical work: In online labour markets the *who* (does the categorizing), *how* (is the categorizing done), and *what* (is being categorized) have changed with digitization.

In comparison to conventional labour markets, *online labour markets* emerge whenever those supplying and demanding remote tasks match digitally (Ramizo & Lehdonvirta, 2022), a process predominantly intermediated by platform firms. They provide socio-technical infrastructure to facilitate exchange from initial search to the provision of matching recommendations, collaboration tools or payment solutions, and services like dispute resolution or short-term loans to workers. Platforms like *upwork.com* or *fiverr.com* are digital marketplaces for remote services. Marketplaces are an ‘organized place—physical or digital—for trade’ (Aspers et al., 2022). In contrast to markets, digital marketplaces are characterized by a high degree of organization (Ahrne et al., 2015; Kirchner & Schüßler, 2019) and a dedicated place, the website of the platform. Transactions of online freelancing services tend to be structured on a per-

project or per-task basis and cover a broad spectrum of knowledge work such as administrative services, logo design or computer programming (Kuek et al., 2015).

Who: From states to platform firms

As labour markets have moved online, who classifies workers has changed. Millions of workers and employers now match and transact online (Kässi et al., 2021) and thus they rely on platform firms to organize these digital marketplaces (Kirchner & Schüßler, 2019). In their efforts to centrally construct platform infrastructure (Aspers & Darr, 2022), private (or publicly listed) companies suddenly have a strategic interest in and the effective power over classification systems of labour as 'investments in forms' (Thévenot, 1984). They codify what constitutes online labour (Pongratz, 2018), attach quality labels to workers' profiles (chapter 4), or construct categorizes that form the basis for scoring or ranking past worker behaviour (Rahman, 2021). As exemplified by the socio-professional categories in France, this marks a break from classifications of labour that have long been a central function of the rational state (Scott, 1998). Bourdieu (2014, p.9) even recognized the 'production and canonization of social classifications' as an essential function of modern statehood. In other words, the classification of workers and their services is another example of platform firms embracing a function previously left to state bureaucracy (Lehdonvirta, 2022). The limits of the state analogy are clear. Theoretically, workers and employers deliberately choose to enter a labour market and only do so when transactions leave them better off (Swedberg, 2010). In practice, however, platforms have become essential infrastructure for many workers (Plantin et al., 2018). They are fundamental to those who depend on them for subsistence (or staffing), and might have invested heavily in platform-specific social capital (Wood et al., 2019a). In their pursuit of profits, platform

firms thus have the power to create 'classification situations' with potentially stratifying effects on people's life chances (Fourcade & Healy, 2013, p. 560).

Simultaneously, the type of individuals who categorize and classify labour have changed. As I illustrated via the example of headhunters who co-construct the competencies of an ideal candidate (Meriläinen et al., 2015), for-profit companies routinely categorize work and workers as intermediaries in conventional as well as internal labour markets. Senior management takes decisions on internal job titles and the corresponding promotional ladder (Barnett et al., 2000; Strang & Baron, 1990) or breaks down the labour process for better control (Thévenot, 1984). However, the employees of platform firms tasked with the categorization and classification of labour are predominantly of a new kind. They are 'software engineers and data scientists' (Stark & Pais, 2020, p. 62). These workers have been argued to resemble a new type of occupational class (Dorschel, 2022; Stark & Pais, 2020) distinct from previous experts or managers. While research has focused on the categorical practices involved in developing machine learning applications (Bechmann & Bowker, 2019; Kotliar, 2020) and the datafication of human behaviour (Alaimo & Kallinikos, 2017; Flyverbom & Murray, 2018; Slota et al., 2020), it is less clear how these new knowledge workers differ from previous generations of managers. For example, Dorschel (2022) used interviews to uncover that while this new class still follows an ideal of an 'entrepreneurial self', it also cares about issues of inequality and diversity.

How: From 'kategoria' to proprietary classifications

In digital market-settings, platform firms rely on automated classification to intermediate labour market processes at scale. Automated and dynamic classification is typically 'backed by [proprietary] algorithmic techniques' that make invisible the

underlying social conventions, history, and practices that produce a given hierarchy (Diaz-Bone, 2017; Fourcade & Healy, 2017, p. 10). While statistical models used to run with a relatively modest number of variables such as gender or age and estimated results based on comparatively small samples, machine learning models ‘typically [work] with hundreds and in some cases tens of thousands of variables and sample sizes of millions or billions’ (Mackenzie, 2015, p. 434). Categories are dynamically formed, processed, and fed into the socio-technical infrastructure of the platform via code and ‘invisible algorithms’ (Hogan, 2015, p. 103) to curate, sort, and rank workers and projects alike (Cheney-Lippold, 2011; Kornberger et al., 2017). It can be argued that via algorithmic categorization knowledge is constructed differently from from community-based and expert-based classifications (Alaimo & Kallinikos, 2021; Cheney-Lippold, 2017; Wood & Lehdonvirta, 2022). Thereby,

‘the basis upon which people are being scored, rated and evaluated is less predictable, or even knowable, to most of those who rely on it’ (Fourcade & Healy, 2017, p. 11).

Platform firms thus strategically render the underlying conventions and practices of classifying labour invisible for the users of their services (Diaz-Bone, 2017). Disconnecting categorization and classification from the social runs against the origins of the term ‘category’. The ‘Greek term *kategoria* [was] connected with judgment rendered in the public arena’ (Desrosières, 1998, p. 238). This raises the immediate question as to what happens to the social order of markets once the basis for quantified comparisons—the underlying practices of categorization and calculation—are removed from the public arena (Diaz-Bone, 2017).

In online markets, platform firms’ ability to alter classifications, and thus the basis for evaluation, unilaterally and *ad-hoc* introduces a layer of uncertainty (Beckert, 2019). This is true for freelancers as those being evaluated, and employers as those using

classifications without knowing the underlying assumptions. Such shifts in how work and workers are classified is related to scholarship on algorithmic management and control (Bucher et al., 2020; Rahman, 2021; Rahman & Valentine, 2021; Ramizo, 2022; Wood et al., 2019a). Studying the case of *upwork.com*, Rahman (2021) likens the opaqueness of algorithmic evaluation, specifically based on reputation scores, to an 'invisible cage'. According to him, workers respond with either experimenting or withdrawal, but either way find it hard to learn and improve from this type of feedback. Wood et al. (2019a) point out that it is only through this type of algorithmic control that trust is established and non-locational transactions are made possible, but equally implies that workers can only achieve marketplace bargaining power through in-demand skill sets or a positive platform reputation.

That said, evidence from studying algorithms in other contexts serves as a reminder that even superficially autonomous machine learning models rely on human classificatory work, in this case on behalf of the platform firm (Bechmann & Bowker, 2019; Kotliar, 2020). The opportunity for contribution thus does not lie in another extension of work on algorithmic management, but instead to dig deeper into underlying practices of categorization and classification which are foundational to algorithmic management and the whole socio-technical infrastructure that enables remote gig work.

What: From 'outside-in' categories to platform-specific evaluation

Last, *on what basis* workers are classified has changed online. In conventional labour markets, 'class situations' are not directly reducible to their individual behaviour but 'flow from the distribution of property, skills, and other resources people bring to the market' (Fourcade & Healy, 2017, p. 22).

What differentiates online markets is that distinctions are instead increasingly made based on data collected on platform-specific actions and behaviours (Alaimo & Kallinikos, 2017; Fourcade & Healy, 2017). In combination with their automated construction, categories no longer have a universal meaning but can be reduced to 'empirical assessments of prejudice and/or patterns that work, according to a particular confidence percentage, at a particular moment and by a particular set of rules' (Cheney-Lippold, 2017, p. 88f).

However, researchers have argued that individuals, in this case workers, may accumulate a new form of digital capital that originates in their own behaviour and traces left online, and allows platform firms to extract more value (Fourcade & Healy, 2017; Sadowski, 2019). In other words, a worker's class is based on data collected on individuals' performance and behaviour within the market, as defined and encoded by platform firms (Alaimo & Kallinikos, 2017; Flyverbom & Murray, 2018), rather than outside of it (Fourcade & Healy, 2017). Signals constructed by platform firms on this basis, from workers' reputation scores to their track record of completed projects, significantly shape the success of workers online (Lehdonvirta et al., 2019). For example, submitting reviews to inexperienced workers, ideally of a detailed nature, helps overcoming barriers to market entry (Pallais, 2014).

Similarly, classifications of work are less based on occupational identities but constructed at the level of individual skills. Komljenovic (2019), for example, makes the case that *linkedin.com* moves the focus from official credentials to skills as signs of employability, explicitly using their intermediary position. In response to a platform-mediated workspace that flattens social interaction into a largely symbolic 'evaluative infrastructure' (Kornberger et al., 2017; Wood & Lehdonvirta, 2022), workers require new skills specific to competing in such an environment (Cedefop, 2020; Sutherland et

al., 2020). Many workers report to counter the commodification of their labour power to on-demand skill delivery, that is their dis-embeddedness in Polanyi's terms, with local embeddedness in ongoing social relations, as in Granovetter's terms (Wood et al., 2019b). More generally, labour platforms are 'laboratories' which foster the re-combination of skills in novel bundles outside traditional occupational structures (Stephany, 2021). On the one hand, this raises questions on the viability of such a granular classification on global platforms. Measuring and conceptualising *skill* is in no way straightforward (Attewell, 1990; Spenner, 1990; Vallas, 1990), even more so once a classification system is to span a global community. On the other hand, once workers are evaluated and matched at the skill-level, it is unclear how, if at all, workers with similar characteristics will coalesce outside the platform. This question fits in with debates on the loosening occupational structures and coalescence from as early as the 1990s (Abbott, 1991).

Both developments remain somewhat constrained. The shift towards skills and platform-specific signals by no means implies the end of formal education or occupational status. In our study on online freelancer skill development, 65% of the 1,002 freelancers surveyed had at least a bachelor's degree, and 77% had more than three years of work experience prior to joining the platform (Cedefop, 2020). In the same project, we found qualitative evidence that formal education and prior work experience provided the foundations in the technical skills offered online, the basic competencies to participate in platform work to begin with (e.g., self-regulatory behaviour, English language proficiency), and knowledge on how to be successful in a professional environment (e.g., communication skills). Similarly, scholars have argued that cultural and symbolic capital of the Global North, for example in the form of educational certificates or behavioural norms, still play a significant role on global

labour markets (Demirel et al., 2020), and digital capital might be highly correlated with success in conventional labour markets (Fourcade & Healy, 2017).

2.7 A research agenda emerges

The discussions of these three shifts paint a picture that is somewhat removed from the social practices and contexts of the classified workers. I do not mean to imply that the cited authors would agree that ‘classification situations’ (Fourcade & Healy, 2013, p. 560) are removed from social practices *per se*. Most would agree that the construction of platform infrastructure is embedded in the practices and cultural context of the employees of platform firms. As a consequence, the resulting classification systems will work better for some than others (Star, 1990). For example, comparison of job boards to newspaper advertisements showed that transforming the format of job presentation has led to convergence and standardization making it harder for candidates with non-quantifiable characteristics or unusual CVs (Marchal et al., 2007). Most scholars also agree that digital classes and the new forms of ‘übercapital’ on which basis workers are assigned to them are influenced by individuals’ circumstances beyond the platform (Fourcade & Healy, 2017, p. 17ff; Sadowski, 2019). However, questions remain on how platform firms put classificatory tools into practice, how the resulting classification systems impact labour market dynamics, and intervene with workers’ everyday work practices (Cansoy et al., 2020; Fourcade & Healy, 2017). In this sense, the picture presented in the scholarly debate arguably remains somewhat distant from the practices and contexts of the workers.

Reducing the distance to workers’ practices and context

My research question—*how and to what effect are work and workers classified in online labour markets*—can be further specified to address some of the distance of

current scholarly debate from workers' practices and contexts. As a first step, more research is necessary to understand how platform firms in practice categorize and classify labour to construct and manage online markets:

How do platform firms classify work and workers in online labour markets?

Answering this question, will require the study of social practices of platform firms' employees (Kelkar, 2018; Kotliar, 2020), for example software engineers that build the digital infrastructure (Bechmann & Bowker, 2019). In chapter 3, I take an alternative approach and denaturalize classifications of work and workers based on what is visible at the level of the platform interface (Ash et al., 2018; Bowker & Star, 2000a) or as experienced by the individuals who are classified (Bowker & Star, 2000a; Seberger & Bowker, 2021). This approach shifts attention to the struggle at the level of the interface where the power 'naturally resides with platform owners, [who] constantly have to balance users' demands with business interests' (van Dijck, 2013, p. 210). Platform interfaces and the underlying classification systems have the power to shape how organizations and humans work (Kelkar, 2018). They are 'part and parcel of a power struggle between users, employers/employees and platform owners to steer online information and behaviour' (van Dijck, 2013, p. 212) and thus demand our attention.

Second, it is unclear whose interests are privileged or ignored in the classification systems codified in online labour platforms:

Whose interests do these classification systems privilege or ignore?

Classification systems do not work equally well for all. Star et al. (Star et al., 1998, sec. 7) remind us

'that no one scheme has yet worked for everyone, [although] some [...] work reasonably well for many people at particular times. [...] There are] "clear and present differences" between people who are very comfortable within some world of information

[...] and those who are intimidated, confused, and limited by their relationships to that same information.'

Individuals who are difficult to categorize and fit multiple categories tend to suffer negative consequences (Hannan, 2010; Zuckerman, 1999; Zuckerman et al., 2003). Using data from a peer-to-peer crowdsourcing platform, Leung and Sharkey (2014) demonstrate that individuals who span categories and therefore do not fall within one clear market category are valued less. This lower valuation is not a consequence of differences in quality but caused by customers' perceptions insofar as they find it difficult to attribute category-spanners to any categorical standard. In online freelancing, workers experience vastly heterogeneous outcomes (Schor, 2020). In chapter 3, I thus foreground whether the adopted classification systems of labour hide or accentuate competencies of some types of workers over others, and whether platform firms thus co-construct differences in outcomes. The above question acknowledges the politics of categories (Suchman, 1993), as well as the dynamic and social nature of labour qualities negotiated by the involved actors (Beckert & Musselin, 2013; Callon et al., 2002). In chapter 4, for example, I investigate how a specific type of market device (Muniesa et al., 2007) shapes hiring online. Since platforms regularly attract thousands of freelancers of uncertain quality, it is inevitable that employers do not evaluate every single one but draw on such tools to make workers commensurable (Karpik, 2010).

Last, we do not know how and by whom classifications are performed or challenged:

How, and by whom, are these categorization systems performed or challenged?

Similar to MacKenzie's (2006) study of the performativity of finance theory on markets, classification systems shape and are shaped by the actions of market participants and their social interactions:

'New infrastructures do more than support work that is already being done. They change the very nature of what it is to do work, and what work will count as legitimate' (Bowker & Star, 2000a, p. 239).

By explicitly including informal categorical practices into the scope of my thesis, I acknowledge that classifications of labour are constructed formally by platform firms and informally by their users. All stakeholders have own vested interests. The users are workers and employers alike who are implicitly hypothesized to draw on local knowledge and shadow classifications like codes, signals, and other heuristics to categorize each other and the services on offer. My research in the subsequent chapters, especially chapter 5, takes actors' 'agency and creativity [seriously] while maintaining the view that action is endogenous to structure' (Overdeest, 2011, p. 534). Answers to this question will add to a growing body of literature on how users (Barach et al., 2019; Ramizo, 2022) and workers (Anwar & Graham, 2020; J. Y. Chen, 2018b; Rahman, 2021; Veen et al., 2020) exert agency within or even resist platform-based control. For example, while platform recommendations nudge employers towards presented workers because they are interpreted as a sign of quality (Barach et al., 2020), there is evidence that clients limit their use of such recommendations to secure their independence from the platform (Barach et al., 2019).

Making the invisible visible

'Information infrastructure is a tricky thing to analyse' because it tends to become invisible, especially if it functions reasonably well (Bowker & Star, 2000a, p. 33). Luckily, several authors cited in this review offer guidance on how to make the invisible visible. One salient point of entry are the shared similarities of classification systems and infrastructure, that is their 'materiality' and 'ubiquity' (Bowker & Star, 2000a, p. 36ff). A focus on materiality allows us to foreground the '*properties* of boundaries such

as permeability, salience, durability, and visibility' (Lamont & Molnár, 2002, p. 186). Ubiquity is closely related to investigating the scope of a category or classification, that is the extent to which someone's life chances depend on the assignment to a particular category or class (Domina et al., 2017). Such qualities often become visible during moments of breakdown (Star, 1999), or when contemplating residual categories and deviations from what is considered normal (Star & Bowker, 2007).

There lies value in following a pragmatic approach to foreground the hidden work that has gone into the construction of classification infrastructures. Metaphors like the 'statistical chain' (Desrosières & Thévenot, 1979, p. 49) refocus the human classificatory efforts which are fundamental to quantified value judgments, for example in the form of statistics (Espeland & Sauder, 2007; Thévenot, 1984) or algorithms based on artificial intelligence (Bechmann & Bowker, 2019; Kotliar, 2020). That said, our attention shall not end with the constructors of classifications. Work on classifications must also illuminate how formal systems are used by practitioners, how they are performed and challenged by those classified, and how they are interpreted by those using the systems for their own ends (Fourcade & Healy, 2017; Lamont & Molnár, 2002). By concentrating on the human element, the underlying politics of categories encoded in the platform infrastructure reappear (Bowker & Star, 2000a, pp. 44ff, 319; Suchman, 1993). Classification systems are said to 'move in space, time, and process' (Bowker & Star, 2000a, p. 42). As a result, 'classification struggles' between social groups get obscured over time as history is indetermined and continuously updated (Bourdieu, 1984/2010, p. 481ff; Bowker & Star, 2000a). It is thus an important task of the researcher to 'recover[the] multivocality' of the classification system (Bowker & Star, 2000a, p. 41).

3. Explaining heterogeneous outcomes in platform work: A categorical approach

Abstract

This chapter investigates why remote gig workers experience diverse labour market outcomes. Drawing on qualitative data including an interface walk-through and worker interviews across two freelancing platforms, I find that labour platforms rely on explicit and implicit classifications of work and workers to construct and order their marketplaces. Thereby, they effectively place workers into four distinct market categories: workers who are *global competitors*, *platform superstars*, workers who are *(effectively) excluded*, and *industry professionals*. Workers in these categories vary categorically in the clients they serve, how they are evaluated, and who ultimately succeeds. In the remote gig economy, heterogeneous market outcomes can thus neither be reduced to a continuous variable of success, nor solely explained by the discrete differences between workers' circumstances. Instead, I argue that platform firms actively shape and institutionalize categorical variations in workers' experiences and market outcomes. As platform firms perpetually categorize, classify, and value their users, I propose the sociology of classification as an overlooked theoretical lens onto how online markets work.

3.1 Introduction

Millions of workers earn some or all of their livelihood in the gig economy (Kässi et al., 2021; Pesole et al., 2018). Also known as platform work, gig work includes locational services such as ride hailing or food delivery (Rosenblat & Stark, 2016; Veen et al., 2020) as well as remote online labour ranging from data labelling to programming (Irani, 2015; Wood et al., 2019a). After more than a decade of research on platforms that intermediate such gig work, scholars have identified workers' diverse market outcomes as a defining feature of this new way of organizing employment relations (Vallas & Schor, 2020).

For some workers, gig work can be a success story. One of my respondents, Conor, joined a labour platform early and made his first five dollars by videotaping a client's message in the snow wearing nothing but shorts. From these humble beginnings, he has since grown his digital reputation and skill set to launch a successful career as a voiceover artist earning most of his income on the platform (14F, Creative & Multimedia, North America). Other workers tell a more precarious story. Olga signed-up to a labour platform out of necessity as her local labour market failed her. She relies on platform work for all her income and has been left frustrated by low wages, disrespectful client behaviour, and the inability to secure long-term projects (08U, Marketing & Sales, Europe). Other workers fit into neither of these polar narratives of success or precarity. Workers might fail to break into an online market entirely (Newlands & Lutz, 2020), have already withdrawn from active use based on negative experiences with a platform (Rahman, 2021), or rate their experiences based on the fulfilment of more complex motivations (Cansoy et al., 2020) including non-financial aspects such as skill development or user testing (02F, Software Dev & Technology,

Europe). These observations raise the question how such diversity in labour market outcomes can be theoretically explained.

In the literature, it is possible to identify at least two plausible explanations for outcome heterogeneity in the gig economy. One research stream argues that the gig economy works better for some workers than others because the workforce itself is extremely diverse. In other words, this explanation refers to categorical differences in workers' *inputs*, that is all their inherent qualities, motivations, and circumstances (Dunn, 2020; Kuhn & Maleki, 2017; Schor, 2020). The gig workforce is heterogeneous because platform mediation allows 'the firm [to retreat] from controlling hours, scheduling, and the labour process' (Schor et al., 2020, p. 834). For example, differences in economic dependence on gig work explain categorical differences in labour market outcomes such as temporal flexibility (Lehdonvirta, 2018), 'satisfaction, autonomy, and earnings' (Schor et al., 2020, p. 833). Put simply, if a worker depends on gig work to pay her bills, she will experience gig work and its related risks differently than someone who only uses it to supplement her income.

Another research stream explains outcome heterogeneity by placing more emphasis on the role of platforms in structuring how gig workers' *outputs* are measured and accumulate. This approach foregrounds how platforms encode, measure, collect, and use metrics of workers' platform-specific performance to govern their marketplaces. As a result, differences in labour market outcomes are no longer conceptualized as categorical but calculable in continuous metrics such as the number of projects completed or a reputation score that are mediated by individual ability (Lehdonvirta et al., 2019; Pallais, 2014; Wood et al., 2019a).

This chapter contributes to this debate by proposing the sociology of classification as an overlooked analytical lens to theorize diversity of outcomes in platform work. My work is motivated by the observation that platform firms also construct consequential boundaries that categorize and classify workers (Fourcade & Healy, 2017). Examples of such acts of categorization include decisions on who gets access to a marketplace (Gawer, 2020), the definition of what counts as online labour (Pongratz, 2018), or the attachment of quality labels to workers' profiles (chapter 4). Such practices are neither captured by reference to workers' *inputs* nor the platform firms' construction of continuous metrics measuring their *outputs*. Yet, it has been established in previous research, ranging from the use of credit scores (Fourcade & Healy, 2013; Kiviat, 2017) to the categorization of workers in labour markets (Leung, 2014; Zuckerman et al., 2003), that being placed into distinct categories or classes impacts individuals' life chances. I therefore ask how labour platforms categorize work and classify workers, and if their practices produce heterogeneity in individuals' market outcomes.

To answer these questions, I collected qualitative data during more than three years as a registered client on two globally operating online freelancing platforms, *upwork.com* and *fiverr.com*. Online freelancers offer remote knowledge work to employers on a per-project basis, mostly via labour platforms (Kuek et al., 2015). Such services can involve a variety of tasks such as administrative support, graphic design, software development, or even digital tarot reading. Primarily based on walk-throughs of the interfaces of these two platforms (Light et al., 2018) and in-depth worker interviews (n=28), I find that both labour platforms meaningfully categorize work and classify workers along the entire labour process. As marketplace organizers (Ahrne et al., 2015; Kirchner & Schüßler, 2019), they classify labour to the effect of making online markets intelligible, but also ensuring exchange quality and profitable behaviour.

Through their use of classificatory practices and devices, platforms effectively co-construct four classes of remote gig workers. I term these classes *global competitors*, *platform superstars*, *industry professionals*, and those *effectively excluded*. The workers in these segments vary in terms of their day-to-day experiences, in the ways clients evaluate them, and ultimately their success online. I thus make the case that variations in market outcomes are neither fully explained by individuals' heterogeneous circumstances nor adequately captured by reducing them to cumulative effects of continuous output metrics such as platform reputation. Instead, I propose that platform firms play an active role in placing workers into discrete market categories that matter.

3.2 Heterogeneous outcomes in platform work

Platforms like *upwork.com* and *fiverr.com* are theoretically interesting because they organize employment relations between workers and employers in novel ways (Kirchner & Schüßler, 2019; Kornberger et al., 2017; Vallas & Schor, 2020; Wood & Lehdonvirta, 2021). They give rise to online labour markets by digitally intermediating supply and demand for remote services (Ramizo & Lehdonvirta, 2022). This chapter starts from the observation that such digital intermediation does not work equally well for everyone. Workers report vast differences in market outcomes, including pay, precarity, autonomy, and job satisfaction (Demirel et al., 2020; Ravenelle, 2019; Schor, 2020; Schor et al., 2020). In the literature, one can arguably identify two research streams that explain variety of outcomes by either referring to the heterogeneity of the gig economy workforce itself (*'inputs'*) or by emphasizing the role played by labour platforms in algorithmically measuring and controlling workers' performance (*'outputs'*).

Inputs matter: Workforce heterogeneity explains diverse outcomes

In the first research stream ('inputs'), scholars argue that workforce heterogeneity explains diverse outcomes. Given the ease of access to gig work due to the flexibility it affords to workers around location, time, and type of contracts (Spreitzer et al., 2017), 'workforce heterogeneity may [in fact] be one of the most distinctive structural attributes' of such work arrangements (Vallas & Schor, 2020, p. 16.9). Workers' 'motivations, characteristics, and intentions' (Dunn, 2020, p. 247) vary on the same platform as well as between types of gig work (Hoang et al., 2020). In a separate study (chapter 4), I surveyed 723 Europe-based online freelancers who had previously completed at least one project on either *upwork.com* or *fiverr.com*. Despite having controlled for some geographical differences, workers still differed from one another significantly. About a quarter of respondents used these freelancing platforms as their primary source of income. Others only supplemented their finances while still holding a full-time job (20%), studying (16%), or being a homemaker (2%). About 60% had spent less than one workday on these platforms in the past week, while more than 13% had worked four days or more. The argument goes that these and other categorical differences which workers bring as '*inputs*' to the platform are a significant mediator of workers' market outcomes. In an ethnographic study of gig workers, Ravenelle (2019), for example, found that not all workers struggle and suffer precarity. Still, successful workers tend to have common class advantages that come with more education, less financial dependency, and the freedom to opt for less arduous forms of platform work. First and foremost, economic circumstances matter. Workers' success and satisfaction with platform work is determined by the level of dependence on a particular platform, that is whether a worker relies on platform work as a primary source of income or

merely for supplementary income (Dunn, 2020; Kuhn & Maleki, 2017; Lehdonvirta, 2018; Schor et al., 2020). Schor et al. (2020) find that across different types of platforms those who were not financially dependent on platform work experienced higher per hour earnings, job satisfaction, and better overall working conditions. This finding counters the generalized imagery of platform workers in perpetual precarious employment (Schor, 2020, chapter 2). Dunn (2020, p. 237f) similarly argues that an essential theme in explaining gig workers' experiences is whether their participation is 'voluntary or involuntary.' The level of dependency also predicts whether a worker supports collective action (Wood et al., 2021). Dependency is not only shaped by the financial context but more holistically by someone's entire labour market situation. It makes a difference whether a worker joins the gig economy in a time of transition to another white-collar job or out of economic despair (Dunn, 2020; Manriquez, 2019). Similarly, workers' experiences vary with the level of demand for the specific bundle of skills they supply to the market (Stephany, 2021). Workers with highly regarded skill sets may freely chose to enter (and exit) labour platforms at their terms (McDonald et al., 2019; Spreitzer et al., 2017).

Non-financial characteristics and circumstances likewise shape workers' outcomes. Working from a developing region, being female, or being a worker who (to a degree) prioritizes social goals over financial outcomes are all categorical distinctions that influence experiences categorically. For example, while remote workers from the Global South can generally offer services at lower rates, their cost advantage is offset as many clients value forms of symbolic, cultural, and social capital typically held by workers in the Global North (Demirel et al., 2020). Perceptions of someone's gender similarly shape success online (Brooke, 2021). For example, remote female workers are on average more likely to be hired than male applicants due to being perceived as

more trustworthy (Chan & Wang, 2018). However, female workers bill lower hourly wages (Foong et al., 2018) and are only half as likely to be hired for jobs stereotypically considered as completed by males such as software development (Galperin, 2019). Workers also differ in their preferences, for instance around temporal flexibility (Piasna & Drahokoupil, 2021) and behavioural modes (Cansoy et al., 2020). The authors of the latter study argue that although all remote workers are financially motivated, they nevertheless fall into one of three behavioural types. Some workers optimize their outcomes by strategizing based on and adhering to a 'lens of idealized rational action' (Cansoy et al., 2020, p. 147) (*economicus*), while others include (and sometimes prioritize) social considerations in their decision-making (*socialis*). A third group of workers satisfies their financial goals without much strategizing either way (*instrumentalis*).

This research stream ('inputs') has not only been essential in foregrounding categorical differences in workers' experiences. It also recognizes differences between platforms as a second, important axis of differentiation for explaining workers' experiences (Ravenelle, 2019; Schor et al., 2020). On one hand, platform characteristics influence which type of platform work attracts which type of worker (Dunn, 2020). On the other hand, different types of platforms will try to promote different types of behaviours using devices such as 'response rates, popularity metrics, elite status and curated ordering of entities for sale' (Cansoy et al., 2020, p. 159). However, while platforms and their diverse means of control matter, the focus is clearly placed on how these effects are always 'mediated by workers' market situations' (Schor et al., 2020, p. 834).

Output matters: Platforms construct continuous metrics of success

In a second research stream ('outputs'), a more powerful and uniform role is ascribed to labour platforms in structuring employment relations and workers' outcomes (Wood & Lehdonvirta, 2021). The simplified argument is that labour platforms construct, encode, collect, aggregate, and selectively publish metrics on individual-level worker behaviour. These metrics accumulate to a form of digital capital (Bourdieu, 1986; Fourcade & Healy, 2017; Sadowski, 2019) which positions workers' along a continuous spectrum from precarity to success.

In this approach, platform firms are seen as powerful organizers of their online marketplaces (Ahrne et al., 2015; Aspers & Darr, 2022; Kirchner & Schüßler, 2019) who rely on a set of socio-technical devices to manage the risks of remote employment. Platforms 'co-opt' workers and their labour power through the information infrastructure they provide (Watkins & Stark, 2018, p. 66). Through the quantification of worker performance and client feedback as continuous metrics and scores, labour platforms seek to reduce employer uncertainty in remote contracting (Lehdonvirta et al., 2019). For example, reputation as a form of social status (Fine, 2019) is traditionally regulated through community-based mechanisms such as behavioural norms (Zuckerman et al., 2003) or trust within professional networks (Granovetter, 1985). Platform firms, however, 'displace this social regulation [...] with their own regime of software code and organization practice' (Wood & Lehdonvirta, 2022, p. 13). Such flattening of social capital into symbolic form is a general tendency of practices subsumed under the term algorithmic management (Rosenblat & Stark, 2016; Stark & Pais, 2020; Wood et al., 2019a). Algorithmic management is used to 'direct workers by *restricting* and *recommending*, evaluate workers by *recording* and *rating*, and discipline workers by

replacing and rewarding' (Kellogg et al., 2020, p. 372). Translated to the example of online reputation, platform firms *record* workers' past performance such as the number of completed projects (Wood et al., 2019a) and algorithmically *rate* them based on client input on dimensions including technical ability, availability, reliability, communication, and level of customer service (Rahman, 2021).

While all quantification relies on categorical work at a fundamental level (Espeland & Stevens, 2008; Mennicken & Espeland, 2019), the use of performance metrics and reputation scores implies a continuous conceptualization of success. As platforms construct and make use of a network of interconnected evaluative devices (Kornberger et al., 2017), they make gig workers calculable and commensurable (Callon, 1998b; Espeland & Stevens, 1998). In this view, workers' success in a platform-mediated work environment largely depends on their own bargaining power primarily determined by their 'skills and platform reputation' (Wood et al., 2019a, p. 70). Workers' experiences are no longer separated by categorical boundaries but placed along continuous scales of achievement. Platform firms record and publish workers' number of completed projects, summarize and quantify their past feedback in reputation scores, as well as rely on more abstract forms of 'übercapital' (Fourcade & Healy, 2017, p. 17ff) to influence their visibility in automated search results and platform-based recommendations (Horton, 2017). These metrics are part of the 'signalling environment' (Lehdonvirta et al., 2019, p. 572ff) constructed and mediated by platform firms, and over time define a worker's trajectory and overall experience in the market. Even as scholars highlight how signals affect workers differently—for example if individuals have no prior work experience (Kässi & Lehdonvirta, 2022; Pallais, 2014), are from developing contexts (Agrawal et al., 2016; Lehdonvirta et al., 2019), or live in

rural areas (Braesemann et al., 2020)—effect sizes remain conceptualized as differences in degree.

The case for a categorical approach to explaining heterogeneity

Instead, I propose to take seriously the categorical practices of platform firms. After all, the organization of digital markets also involves many boundary decisions of discrete form. In fact, platform firms perpetually categorize, classify, and value individuals who use their services (Cheney-Lippold, 2017; Diaz-Bone, 2017; Fourcade & Healy, 2017; Jürgenmeyer & Krenn, 2016). Algorithmic management, for example, as defined above (Kellogg et al., 2020), also includes *rewarding* specific groups of workers with quality labels (Schörpf et al., 2017), *recommending* certain workers or services to employers (Horton, 2017), *restricting* access to some people (Gawer, 2020), or *replacing* workers who unsuccessfully bid on projects (Jarrahi et al., 2020). Such ‘classification situations’, when people are placed into discrete categories or classes, impact their life chances on and beyond the platform (Fourcade & Healy, 2013, p. 560).

The centrality of categorization and classification to constructing and maintaining digital marketplaces becomes visible once platforms are described in infrastructural terms.²³ Traditionally reserved for material things such as bridges or roads, platforms as infrastructure are an ‘assemblage’ (Kelkar, 2018, p. 2632) of technical (e.g., platform interface, algorithms), social (e.g., terms of service, classification systems, legal environment), and individually human (e.g., worker routines and practices) elements (Edwards, 2019; Kelkar, 2018). Kornberger et al. (2017, p. 79) argue that platform firms can distribute control while keeping power centralized only because of

²³ Here the concept of ‘infrastructure’ is used in a related but not equivalent form to chapter 1. As used in this chapter, it provides a metaphor for how platforms work. In chapter 1, it was used to describe the ubiquity of platforms in society.

an 'evaluative infrastructure' of 'rankings, ratings, reviews, and audits'. Platforms are one example of how society invests in 'thinking infrastructures' that 'structure attention, shape decision-making and guide cognition' (Bowker et al., 2019, p. 1). While platform firms limit their investment in capital and employees, they deploy resources to construct socio-technical devices that intermediate user relationships (Gawer, 2020).

Bowker and colleagues (Bowker et al., 2019), for example, compare classificatory tools such as recommender algorithms to what Thévenot (1984) called investment in forms. Thévenot argued that the management of labour fundamentally relies on such investments in forms including the introduction of theoretical concepts like *lean management*, the use of organizational charts, the formalization of process categories, or the construction of metrics to measure workers' output. Similarly, the construction of digital marketplaces fundamentally relies on 'concepts, classifications, categorizations, commensurations, and evaluations' (Bowker et al., 2019, p. 1). Bowker and Star (2000a, p. 47) dedicated much attention to the consequences of such categories, classifications, and standards as 'scaffolding in the conduct of modern life'. They showed how systems of classifications are an essential foundation to 'boundary infrastructures' (Bowker & Star, 2000a, pp. 313–314) like information systems that allow for communication across communities of practice separated in space and time.

In this chapter, I conceptualize categories and classifications as social institutions that structure our lives (Berger & Luckmann, 1966/1991; Douglas, 1986). As humans, we rely on concepts and categories as part of human cognition (Hannan et al., 2019). Only by drawing distinctions and rendering our continuous experiences discrete we can make sense of the world (Zerubavel, 1991). Irrespective how natural they might appear, such boundaries are always social and contested (Bourdieu, 1984/2010; Durkheim, 1963/2010). The adoption of a category always valorises one perspective

at the expense of multiple others (Bowker & Star, 2000a). In the economic realm, categories constitute markets, digitized or not, by making them intelligible and calculable for workers, employers, and intermediaries alike (Callon, 1998b; Carruthers & Stinchcombe, 1999). In organized settings like digital marketplaces, they are the output of costly 'investments in forms', formal and informal 'coding operations' as 'sets of conventions which govern "regulated" human interactions (Thévenot, 1984, p. 1). While they enable exchange via common market categories and standards, classifications of labour are always also judgments of worth (Boltanski & Thévenot, 2006), co-construct employer expectations (Zuckerman et al., 2003), and form the basis for commensuration of workers (Power, 2004; Ranganathan & Benson, 2020). In conventional labour markets, categories and classifications of labour often has distributional effects (chapter 2). After all, class formation and by extension individuals' life chances are closely intertwined with people's employment relations (Erikson et al., 1979; Weber, 1922/2021; Weeden & Grusky, 2005). In this study, I therefore ask: *How do platform firms categorize work and classify workers? Do these practices produce heterogeneity in workers' market outcomes?*

3.3 Methods

To address these questions, I collected data across two globally operating online freelancing platforms, *upwork.com* and *fiverr.com*. My primary methods of data collection were interface walk-throughs (Light et al., 2018) and in-depth interviews with workers active on at least one of these labour platforms.

As such, my analysis was limited to the codified and observable classifications at the level of the interface and as experienced by workers. I thus only cover a subset of the invisible practices that underpin digitized classification systems (Bowker & Star, 2000a,

p. 320ff). In an ideal set-up, I would have also collected data on the informal and to users generally invisible categorical practices of platform designers (Kelkar, 2018; Kotliar, 2020). Unfortunately, I was unable to get access to either of these platforms, mainly due to resource limitations and because platform firms tend to consider their socio-technical infrastructure proprietary. In their 2021 annual report (p. 3), Upwork, for example, lists the ‘combination of the latest technology’ such as their ‘feedback system’, a ‘proprietary database [that] maintains detailed and dynamic information, including skills provided by talent, feedback, and success indicators of talent and clients’, as well as ‘machine learning algorithms’ as competitive advantages. As a result, my data does not allow me to comment on the underlying motivations of the platform firm and its workforce. Instead, I can draw inferences from an outside-in perspective that describe the effect of certain classifications on workers.

Data collection on two platforms had the advantage that any theoretical generalizations extend to both cases (Yin, 2013). Upwork and Fiverr are alike in that they are both for-profit companies that primarily generate revenue from intermediating remote, per-project work arrangements between workers and employers. Although they are globally active firms, more than two thirds of their clients are from English-speaking countries²⁴. They are both market leaders and direct competitors whose marketplaces cater to a broad audience and spectrum of remote services. However, the platforms differ in how they structure online labour. Fiverr centres its marketplace around concrete service offerings, so-called gigs, which are offered by millions of workers. Fiverr considers itself a standardized e-commerce marketplace like Amazon, where clients browse services that are bundled as products. Upwork has positioned itself as

²⁴ Upwork Annual Report (2020); Fiverr F-20 (2020)

a 'work marketplace' that caters to a future in which 'independent talent [contributes] at the heart of every business.'²⁵ It sees itself as a hybrid model between traditional staffing firms and 'platform-first' service models like Fiverr: 'Platform when you want it – people when you don't' (Upwork, 2021).²⁶ Therefore, Upwork strategically centres on workers and their skills rather than off-the-shelf services. Workers either apply for projects posted by employers or are invited to participate directly based on their profile.

A walk-through of the interface

The decision to 'walk through' both marketplaces rests on the premise that some boundary decisions by platform providers become visible at the level of the interface (Gawer, 2020). The study of classification systems is challenging as they tend to become invisible once they are functional and familiar (Bowker & Star, 2000a, p. 33). As noted above, for-profit platform firms have an additional incentive to make their categorical work proprietary and to evade scrutiny. Thus, I combined a walkthrough method of digital applications (Light et al., 2018) with proven methodological themes of 'infrastructure inversion' (Bowker, 1994). Such inversions are an attempt to provide researchers with 'new eyes [...] for restoring the deleted and desiccated narratives' of classification infrastructures and the human practices which sustain it (Bowker & Star, 2000a, p. 37). During data collection and analysis, I paid specific attention to residual categories, the presentation and feel of classifications as observable or described by informants, developments over time, and experiences of conflict (Bowker & Star, 2000a). Following Bowker and Star (2000a), my goal was to make visible the ubiquity and materiality of classification infrastructures, recover aspects of their otherwise

²⁵ [Upwork investor presentation](#) (2021: last accessed on November 2, 2021)

²⁶ [Upwork investor presentation](#) (2021, p. 47: last accessed on November 2, 2021)

invisible history, and the politics (Suchman, 1993) that went into their construction. To structure data collection and analysis, I also used Bechmann and Bowker's (2019) process of uncovering human knowledge production in work processes sustaining artificial intelligence. Based on a set of secondary in-depth interview transcripts (n=41) with Europe-based remote gig workers on *upwork.com* and *fiverr.com* and official documentation published by both platforms (e.g., their terms of service, SEC filings, official community guidelines), I first defined the labour process of remote gig work as generalized over both platforms. Implicitly, I thus treated both platforms as 'digital-based points of production' (Gandini, 2019, p. 1051). My interface walk-through and its documentation followed this standard labour process from sign-up to completing a project. Throughout, I took detailed notes of 'classification situations' (Fourcade & Healy, 2013, p. 560) workers experienced, the socio-technical devices involved, and the inferred human categorical work at their core.

As noted above, the interface walk-through was informed and contextualized (Light et al., 2018) by a selection of secondary interview transcripts. These transcripts were part of a larger research project on skill development and matching in the remote gig economy (Cedefop, 2020). All 41 workers were active on either *upwork.com* or *fiverr.com*, and interviews lasted 49 minutes on average. The sampling frame included workers who had completed at least one project on either platform and currently lived in one of six European countries (Finland, Germany, Italy, Romania, Spain, UK). The interviews primarily covered informal practices and skills needed to be successful in the remote gig economy, which made them a valuable resource for inferring a generalized labour process of remote gig work, as visible in Table 8 (cf. appendix A.2). I further contextualized my walk-through by collecting official documentation published

by the platforms and relevant newspaper articles as well as by doing digital archival work to capture developments over time (*archive.org*).

In-depth worker interviews

Following my interface walk-throughs, I conducted in-depth interviews with a second set of workers (n=28) using video-conferencing software or phone calls. The average interview lasted just over one hour. Workers were remunerated for their time in accordance with online freelancing culture and the terms of service of the platforms. Participants' consent was recorded via a pre-interview survey which also collected information on participants' socio-demographic background and platform use.

Interviews served a dual purpose. First, participants acted as informants on breakdowns of the classification infrastructure (Star & Ruhleder, 1996), and moments of 'hyper-functionality' (Seberger & Bowker, 2021), whenever the classification infrastructure worked as intended but was experienced in an alienating way. Second, they provided feedback on the impact of being classified on their own experience and life chances as platform workers. Most informants were contacted through the platforms by inviting them to participate in this research project. To reduce reliance on search and recommender algorithms, which are sustained by classificatory work under investigation, I identified a proportion of workers via other channels including official discussion forums, *reddit.com*, and *twitter.com*.

I followed a theoretical sampling strategy whereby I iteratively balanced the mix of workers by platform, gender, and the subsequently observed classes of workers (Foley et al., 2021). In the end, half of the workers I interviewed were female, 15 workers worked on *fiverr.com*, and 13 on *upwork.com*. I interviewed 5 workers that I later identified as belonging to the class of (*effectively*) *excluded workers*, 9 *platform*

superstars, and 7 workers in each of the other two worker categories. I stopped data collection when I reached theoretical saturation insofar as learnings per class of worker with each additional interview were increasingly marginal. With 28 interviews I am within the range described as most productive for grounded theory research (Marshall et al., 2013). If at all, my sample errs on the side of having sampled a subset of rather successful online freelancers. In particular, I failed to include any voices that were fully excluded from the platform, that is those workers that wanted to but never made it onto the platform. Given my research design, the only viable path for inclusion would have been via snowballing or through online forums. Unfortunately, no such opportunity presented itself during data collection.

Analysis and integration

Data collection and analysis unfolded sequentially. Interview transcripts, walk-through notes, and contextual documents were analysed following a grounded theory approach (Corbin & Strauss, 1990). First, a set of interview transcripts of workers active on *upwork.com* and *fiverr.com* (n=41) was used to generalize a labour process across platforms. On that basis, the interface walk-through was structured. The detailed notes taken during the latter were openly coded for themes indicative of any centralized categorical practices by the platform firm. Then, I conducted, transcribed, and continuously coded further worker interviews (n=28) in an iterative process. I integrated and merged initial codes from all previous stages of analysis into higher-level codes (Charmaz, 2006). I thereby identified four classes of workers: *global competitors*, *platform superstars*, *industry professionals*, and *workers effectively excluded* from the platform. Going forward, these classes of workers were used as cases of analysis. At this stage, I focused on potential relationships between higher-level codes, categories

in the language of Corbin & Strauss (1990). I specifically focused on how classification systems constructed by the platforms might impact dynamics between worker classes.

3.4 Four classes of online labour

Treating both freelancing platforms as ‘digital-based point of production’ (Gandini, 2019, p. 1051), I created a generalized labour process across both target platforms from sign-up to project completion. I find that both platform firms rely on automated and manual classificatory devices throughout this labour process. A detailed overview of each phase and the corresponding classifications of labour can be found in appendix A.2, and specifically in Table 8. Select examples of classifications of labour include the vetting process of new profiles and the distinction of workers into those accepted and those rejected on *upwork.com*, the categorization of what services normatively constitute online labour (e.g., the production of pornographic content is not allowed by either platform), the attachment of quality labels to workers’ profiles (chapter 4), the categorization of worker behaviour and subsequent recording of personal productivity metrics, and the classification of what dimensions of performance are measured as part of clients’ feedback form.

I find that workers experience the centralized classification systems constructed by the platform firms as sites of struggle that directly impact their livelihoods. They explain how even small changes at the classificatory level can have significant economic consequences:

‘Last year, [...] I changed my [gig] category from ‘product e-commerce business’ to ‘web development’ [...] I [used to make] 2 or 3 [thousand USD] in a month. But then I changed my category and [...] wasn’t getting orders anymore. [...] It] killed me off for months [...] I think there are some glitches in the algorithm. If you change categories

or tags, something happens, and you just never get back on track.’ (21F, Marketing & Sales, North America)

In sum, I find that categorical work by platform firms partially explains discrete variations in workers’ outcomes in online labour markets. By constructing a centralized classification infrastructure, platform firms effectively place workers in four distinct market categories. Three of these classes actively participate in exchange. I call them *global competitors*, *platform superstars*, and *industry professionals*. The fourth class is comprised of workers (*effectively*) *excluded* from participation altogether. Subsequently, I present my findings per identified class and ordered by theoretical novelty. For each category, I present one illustrative worker example, induce general characteristics of the class, and emphasize which classificatory tools matter most in shaping workers’ everyday work practices.

Global competitors

Global competitors are workers who managed to break into an online labour market, both full- or part-time. They primarily compete for clients based on price and the provision of in-demand services. Of those actively engaged, *global competitors* comprise the largest digital class.

Olga, briefly mentioned in the introduction to this chapter, serves as an illustrative example. She is a freelancer based in a small town in Eastern Europe who joined *upwork.com* prior to the Covid-19 pandemic as an alternative way of finding work. The local job market was ‘not very bright [and] the salaries [...] a disaster.’ She explained how she nevertheless suffers from the pressures of global competition online:

‘We all work for money. [...] but i]t’s crazy, because if you ask for \$9-10 [for a simple job] it is impossible [...] because all these Indians and especially people from Philippines [...] want \$3.’ (08U, Marketing & Sales, Europe)

Global competitors are confronted with the full force of a globalized market because they largely compete based on price. Without platform reputation in form of reviews or a sizeable number of completed projects, their only other means of attracting clients early on is to identify specialized and less competitive market niches. Olga explains:

'The first thing I did, because an [experienced] freelancer, very successful and top-rated, told me: "First, define your skills. Define what you can do that others cannot. Because if you want to do a data entry job, this is something that everybody can do. You cannot compete with anybody.'" (08U, Marketing & Sales, Europe)

This class of workers comes closest to Fiverr's initial vision of on-demand service provision. Most workers in this category experience some form of precarity as their services are interchangeable (van Doorn, 2017). Olga describes, for example, how she spent considerable amounts of unpaid time to learn how the platform works:

'Initially, I didn't know what I can do, I didn't know what I'm good at. I didn't know how to market myself, and I needed time to explore the platform. It takes some time for sure. It can be two months depending on how smart and experienced you are. I'm not that much. So, it took me— let's say some time— to create a better profile, to understand the market.' (08U, Marketing & Sales, Europe)

Olga experiences platform work as distressing because she would prefer a full-time job over project-based work. She also described how she is limited in her agency towards clients and got upset due to false promises made by some of her potential clients. She summarizes her experiences in platform work as such:

'Some people like Upwork, and some people don't like it. I believe it is some sort of opportunity. It helped me in a moment when I didn't have work or money. That is what I like. But there is also this ethical problem, a lot of people that exploit. I had many interviews that led to nothing because these guys don't care.' (08U, Marketing & Sales, Europe)

From Olga's experiences, it is possible to generalize some characteristics of this class of workers. Individuals become *global competitors* once they break into the labour

market, that is managed to attract visibility within the classification infrastructure constructed by platform firms and succeeded in securing a project. However, rather than reducing all workers in this category to such a lens of precarity, it appears to be Olga's dependence on platform work that explains her struggles (Schor et al., 2020). Other workers like Katja, a young mother with a full-time job outside the platform, use freelancing as supplementary income (17F, Marketing & Sales, Asia). Her services are still largely evaluated by price, but she experiences the pressures of the market as less pertinent. In fact, she outsources parts of the service delivery. She managed to attract initial demand for her services by specialising on in-demand gigs which helped her to continuously improve within the classificatory logics of the platform. Another freelancer followed a similar path to transition from global competitor to platform superstar:

'I started to focus on social media [a few] years ago [... as] this area [was] getting more [...] important for overseas clients. [...] I [couldn't] only focus on translation because translators face very tough competition because many people will [choose to translate] at the beginning.' (12U, Marketing & Sales, Asia)

For global competitors, automated classificatory tools play the biggest role, including their reputation score, the number of reviews received, and their positioning in the search interface. These are their means of standing out, attracting clients, and accumulating platform reputation. On the flip side, they are especially vulnerable to changes to this infrastructure. Another worker described how the assignment of workers to service categories was centrally adjusted which affected his income:

'Initially, [my] gigs were in Programming and Tech. Then after some time, I was notified by the Fiverr system that my gigs have been moved to their [new] Data category. [...] As a result,] there has been a reduction of orders and the task due to the new categories that the system has placed my gigs in.' (19F, Software Dev & Technology, Africa)

Manual categorical interventions by the platform firm are rare but can play a huge role for these types of workers:

'I kind of was giving up. But after [my] third client [...] I got picked to be featured [on the homepage]. After that my exposure was [huge]. I don't know whether it was random. [...] All of a sudden, a lady sent me an email saying that [I was] a rising talent and [they] find great potential in [my] gig. [I have been on there for] two months now.' (15F, Creative & Multimedia, Australia)

In general, workers in this class do not experience much agency towards the platform and feel restrained in their actions even towards clients. The latter is driven by their fear of how negative feedback, a turned down project offer, or a late reply might affect their platform reputation, the only upwards path towards becoming a *platform superstar*.

In general, platform firms' classificatory practices have a large influence on workers in this class. For example, workers are affected by the way a platform defines 'online labour'. Global competitors on Upwork tend to directly apply for projects and spend considerable amounts of time on this process. With more experience direct offers by clients start to come in:

'In the beginning, [...] I had to apply to a lot of [...] job posts. So, at that time, I was applying for those kinds of technologies that were well suited to my skills. But now, I don't usually apply. People like you invite me.' (01U, Software Dev & Technology, Asia)

They also experience other forms of control most immediately such as the automated monitoring for breaches of the rules of conduct:

'If I send you a message like, "pay me via PayPal" they will block you and block me, and I will lose everything, my job success, etc. They are very-very strict.' (06U, Marketing & Sales, Middle East)

In sum, the classificatory practices that matters most to workers in this group are the automated systems that determine their visibility. Workers thus try to take advantage of automated tests, aim to receive automated quality labels, and feel the largest pressure to comply with behavioural rules set by the platform. They try to optimize and

experiment within the standardized classification infrastructure and aim to rise in the hierarchy of the market by improving their metrics of past performance.

Platform superstars

Conor, who I mentioned in the introduction, is an example of a *platform superstar*. Superstars managed to rise in the ‘evaluative infrastructure’ (Kornberger et al., 2017) of the platform. Relative to their peers, *platform superstars* extract most economic value from the platform and often derive a large share of their income from platform work. On average, they have completed the highest number of projects in their service categories, and have accumulated the largest amount of ‘übercapital’ (Fourcade & Healy, 2017, p. 17ff) as measured by the automated classification infrastructure of the platform. Many of these workers were early adopters of platform work:

‘In 2014 [when I joined Fiverr], the Internet was a very different place. Even the concept of a platform like Fiverr was a really novel idea. Just the idea of people generating income out of... out of what? There is no employer? What is this? So that kind of grabbed me! So that’s probably what attracted me to Fiverr!’ (14F, Creative & Multimedia, North America)

‘It was easier for me to stand out. We often neglect opportunity, timing, [and] privilege. I [sometimes] forget [...] what the platform was like back then and what it is right now. [... I am unsure] if I could be successful [...] in the marketplace [today].’ (20F, Creative & Multimedia, Europe)

Some of these workers, like Conor, started off very small:

‘When I first started on Fiverr, I was doing... I can’t remember. It was something like 250 words for \$5 [...] That was the whole scaling. [...] I was really just doing very dirt-cheap work.’ (14F, Creative & Multimedia, North America)

‘[My profile] evolved tremendously. [...] started at one dollar [per hour...and] am now at 30, it is amazing. But that is eight years ago.’ (03U, Professional Services, Africa)

Today, Conor has accumulated more than 1,000 reviews and earns most of his income from *fiverr.com*. He explained that his clients have changed with his increased pricing and professionalization. Workers in this class have risen through the classification infrastructure of the platform. One platform superstar describes her rise to becoming pro-verified by Fiverr:

'I got the invitation to apply. [to become pro-verified]. And I had already made it through Level 1, Level 2, and Top-Rated seller. [...] So, I applied to get pro-verified [...] and now Fiverr is going to push my profile, I can charge way more, and that has made a great impact on my business' (27F, Writing & Translation, Asia).

Platform superstars extract most economic value because they have accumulated the largest amount of platform-specific experience and thus profit from status effects over time. Some *platform superstars* exclusively offer their services in one specific category. In relation to their competitors, they accumulate status through the number of projects completed, positive reviews, platform-specific badges, and the subsequent visibility in form of search results and recommendations by the platform:

'In 2016, Fiverr is already a popular website. But I was the first one [to offer] guitar transcription services. [...] I had no competitors. If I am being generous with myself, I am the pioneer of the service. [...] By 2017, 2018, orders started to increase [...] until now. [...] I don't actually do anything. [...] It is only the Fiverr algorithm and the search engine that do it.' (23F, Creative & Multimedia, Asia)

Still, there is a notable quality dimension to their success. *Platform superstars* have perfected the skills needed to succeed in gig work:

'You need to be laser-focused. You need to learn something that people still don't know about. [...] You need to be the first to claim a whitespace. At the same time, people [...] leave out a bunch of stuff like soft skills.' (20F, Creative & Multimedia, Europe)

As a result, their power dynamic with clients and the platform changes:

'Back in the day, Fiverr didn't know who [I] was and they didn't [...] care. Right now, I have a [...] close relationship with most of the team in Israel because [...] they

frequently reach out for feedback, asking questions, having me involved in whatever' (20F, Creative & Multimedia, Europe).

(Effectively) excluded workers

Workers are *effectively excluded* from online labour markets if they are either unable to get access to the platform or cannot attract sufficient visibility or demand to generate any labour market attachment. They are unable to extract any or any significant economic value from labour platforms.

By making a methodological focus on boundaries, a focus is placed on workers who are residual to the classification systems constructed by platform firms, or even entirely excluded from them (Bowker & Star, 2000a). In online labour markets, contrary to platform work in general (Hoang et al., 2020), online freelancers on average have a higher level of education (Cedefop, 2020; Pesole, 2021) and a more privileged social class background than a comparable population (Martindale & Lehdonvirta, 2021). In other words, workers with structural disadvantages are less likely to be active in remote freelancing marketplaces (Dunn, 2020; Newlands & Lutz, 2020). For example, one interviewee from Africa described how his account got suspended temporarily because his credit card did not accept international payments needed to purchase the platform-specific credits needed to approach clients on *upwork.com* (10U, Writing & Translation, Africa). Beyond inequalities of access to labour platforms due to lack of hardware or skills (Lutz, 2019), I find that platform firms' categorical practices actively exclude workers from participating in their labour market.

Exclusion can be total. In these instances, platform firms 'erect[...] virtual borders' (Lehdonvirta, 2022, p. 89). They create digital boundaries that determine who and what services are allowed on the platform. Upwork, for example, reserves the right to regulate access to their marketplace based on the submitted worker profile:

'Upwork has already [...] become very strict on approving new profiles. [...]' (09U, Software Dev & Technology, Asia)

'After signing-up, your profile might not get accepted because they have enough freelancers for that niche already.' (10U, Writing & Translation, Africa)

For example, Aylin, a freelancer based in Kazakhstan, told me how she was originally not accepted to *upwork.com*, and how she ended up being successful on a second try:

I registered for Upwork but wasn't successful. They rejected me. [Before I tried for a second time,] I created a website and bought a company email from Google to look more professional. I even registered myself as an agency, as if I had a team [...] and we were already active offline. [All that] so they knew it's a solid business, that new buyers will come to Upwork because of me. [This way,] I was successful. (17F, Marketing & Sales, Asia)

While Fiverr does not restrict access in a similar fashion, both platforms decided to exclude Russia-based workers from selling their services in response to the Russian invasion of Ukraine.²⁷ Equally, both firms specify what categories of services may be offered. They define the boundary of what counts as online labour and what types of activities are excluded. While some services are outlawed for legal reasons, for example selling the fabrication of positive reviews on other digital marketplaces or ghost-writing academic output, others like offering any kind of pornographic content are not permitted as a pure normative and categorical choice. Similarly, platform firms retain the power to disconnect a profile for violations of their terms of service:

If you violate Fiverr's Terms of Service you get expelled... [or if] you couldn't meet one of the verification requirements, ...you act fraudulent, [for example...] you accepted payment and then you deliver an empty document..., [or] if you take a client outside the platform and receive payment. (10U, Writing & Translation, Africa)

²⁷ See statements by either company here: <https://blog.fiverr.com/post/fiverr-suspends-business-in-russia> (Fiverr, 2022), <https://community.upwork.com/t5/FAQ-Suspended-Operations-in/qa-p/UpworkHelpsqanda-board> (Upwork, 2022).

Beyond such clear-cut cases of exclusion, those who successfully managed to sign-up and enter a digital marketplace can still be *effectively excluded* from participation. Lin, for example, is an unemployed woman in her thirties based in an Asian metropolis. Despite holding an undergraduate degree and having secured an unusual, location-based project through the platform early-on, Lin:

‘gradually realized, it [wasn’t] like I was dreaming [and] I cannot rely on these platforms [for subsistence].’ (11U, Marketing & Sales, Asia)

In other words, those *effectively excluded* from remote gig work simply fail to partake once they are on the platform. Even if a worker attracts a first project, the lack of in-demand skills or characteristics that result in visibility within the classification systems of the platform, workers cannot rely on online labour markets as a reliable source of income.

The categorical choices by platform firms have an impact on the dynamics experienced by workers. For example, the decision to require specific documentation for sign-up or the requirement to broadcast one’s location can have unintended effects. One worker explained how he chose to cover his true location for fear of being discriminated against on the platform:

‘Fraudsters [... have] given us [Nigerians...] a very bad identity. [...We] struggle to make it, even if [we] are very good. [...] I have experienced that [signing up as if based in] the UK, there’s a tax [form] issue. In the US, a W-9 issue. [Pretending to be working from] Canada is a better, [feasible] option [to hide my true location] on Upwork’ (10U, Writing & Translation, Africa).

Another informant (16F, Marketing & Sales, Africa) had so far failed to match demand with an adequate skill set. Instead, he relied on strategies like advertising languages or skills beyond his ability and copying ‘gigs’ from other freelancers to attract at least some visibility through ‘categorical work’ (chapter 5). His behaviour negatively affected

his rating. Others stay at the margins because platform work simply is not attractive enough compared to other opportunities (05U, Creative & Multimedia, South America). In a vicious circle, the sporadic withdrawal from the platform further negatively impacts platform-specific reputation as the classificatory infrastructure values consistent availability. Altogether, effectively excluded workers simply experience that the demands of the current evaluative logics of the platform do not work for them, they fail to stand out the given classificatory systems, never recover from a bad review, or simply do not have the necessary in-demand skills.

In sum, platform firms effectively exclude workers from their platforms in two main ways. First, they have the power to prevent individuals from accessing the market altogether at the outside boundary of the market. Such decisions can be taken strategically and knowingly. Upwork for example states on their website:

'We receive over 10,000 applications daily, and we try to keep a balance between freelancers and projects available. Because we want you to find jobs and succeed, if our marketplace doesn't currently have opportunities for your combination of skills and experience, we won't accept your application at that time.'²⁸

Workers are evaluated based on their bundle of skills and experience and potentially included into the category of the *effectively excluded*. However, as demonstrated by my findings above, labour platforms also fully exclude people based on their normative choices around what constitutes desirable 'online labour' and through the legal requirements they set. Once workers manage to sign-up to a platform, platform firms contribute to their effective exclusion by the choices made in constructing the underlying classification systems. For example, by awarding quality labels based on platform-specific experience, new workers will find it relatively harder to attract

²⁸ <https://support.upwork.com/hc/en-us/articles/214180797-Application-to-Join-Upwork-Declined> (last accessed on January 2, 2023)

attention. In other words, new workers are evaluated in comparison to their more successful peers within their area of specialization. As such, being *effectively excluded* is an interaction of the demands of the centralized platform infrastructure, a workers' inability to demonstrate or actual lack of in-demand skills, and employers' demands.

Industry professionals

While I previously described how platform superstars rise in the hierarchy of a market through accumulation of largely automated forms of symbolic capital such as the number of projects completed or their reputation score (Wood & Lehdonvirta, 2022), platform firms have started to provide those who I call *industry professionals* a manual gateway to enter online labour markets.

As the result from efforts by platform firms to associate online freelancing with the provision of in-demand skills, large companies have started to increasingly rely on online labour. Between March 31 in 2020 and 2021, Upwork had about 50% of Fortune 100 companies as clients (Upwork Investor Day Presentation, 2021). *Industry professionals* have emerged as a new class of workers on both marketplaces to address the demand for online workers with high professional standards:

'Outsourcing until "Fiverr Pro" was mostly used by small to medium businesses; and maybe personals some. [...] Fiverr Pro is something that offers enterprises enterprise-level of services.' (02F, Software Dev & Technology, Europe)

This class of workers is characterized by having extensive work experience, reputable client or education credentials outside the remote gig economy, or a sought-after skill set currently lacking on the platform.

Liliana, for example, is a freelancer with a vast amount of experience in graphic design:

I have a lot of experience because I have been working in advertising and graphic design for more than 10 years. Before I started to do freelancing work, I worked a lot with advertising agencies. [...] I have an education from a classical art school [as well as] in computer graphics. (13U, Creative & Multimedia, Europe)

For her, the remote gig economy is an extension to an already profession career outside the platform. She described how Upwork administrators reached out to her without having yet attracted any work on the platform:

When I didn't have any contracts or reviews, anything. [A] manager from Upwork chatted with me and told me they wanted to interview [me] for the expert-vetted label. [...] she told me that [...] they saw my portfolio and want to discuss [it...] They gave me this label without any contracts just because of my experience. (13U, Creative & Multimedia, Europe)

In the interview itself, they discussed her career and especially Liliana's past clients:

They just ask you about yourself [and] the clients who you have worked with. Because if you have a list of very major brands, it [matters]. As far as I know, each manager from Upwork communicates with [major brands] and [connect them with] different freelancers. It is the reason why they look for the best and construct lists of expert-vetted [freelancers who they] can recommend to major brands. (13U, Creative & Multimedia, Europe)

In other words, to capture the market for workers with high professional standards, especially demanded by corporate clients of labour platforms, Upwork and Fiverr both started to specifically categorize *industry professionals* to give them easier access to their marketplaces. Thus, platforms manually and selectively subvert the automated classificatory logics that gave rise to the class of *platform superstars*. It can be inferred that platforms view in-demand professionals as a strategically desirable class of workers. To grant more visibility on the marketplace, platforms manually curate them through active marketing and in-person interviews:

'[An employee of Fiverr] published a post and he told everyone on this private [Facebook] group [for IT experts about] these pro[fe]ssional categories. [...The person] told everyone on the group that if someone is interested, he can help to make it happen.' (18F, Software Dev & Technology, Middle East)

Some workers reported that they even received extra training to allow for a smooth introduction to remote gig work and the standards set by the platform firm:

I could tell that some people in my onboarding class came from a 20-year corporate career. Another guy was a voice actor and must have done well in that field. I definitely had the feeling that it was legit and Fiverr was highly selective with who they included. I was definitely very proud to be considered into that category. (27F, Writing & Translation, Asia)

Even in cases where *industry professionals* are not manually curated by the platform itself, they take advantage of the centralized classification infrastructure to transfer valuable signals from outside onto the platform. Put differently, clients evaluate workers in this class based on experiences prior to platform work, either assessed by the platform or as visible in the platform interface:

'There's some people who will just contact me when they see the name [of a known professional service firm] and there was like two or three clients that have worked with [this professional service firm before]. So, it gives people confidence.' (21F, Marketing & Sales, North America)

The directionality of platform superstars and industry professionals runs in opposite directions. On the one hand, *superstars* build their brand on the platform to then expand beyond it (e.g., interviews 4U, 14F, 20F, 27F, 28F). On the other, *industry professionals* tend to have built a career in conventional labour markets and view online labour markets as an interesting extension to their career. Interviewed workers in this class described online labour with an entrepreneurial spirit. They use labour platforms for

'stay[ing] on top of the learning curve about industry standards [...] that you can then apply into your regular day-to-day work.' (02F, Software Dev & Technology, Europe)

'setting up my own company [utilizing Upwork...] because I am literally flat out [busy with projects] all the time.' (07U, Professional Services Europe)

'using this platform [...] to create different gigs, different titles, and different pricing models and basically test the demand because Fiverr is a place where people [...] have the actual willingness to pay for something. So, it's a good place for me to test different ideas and conversion rates.' (18F, Software Dev & Technology, Middle East)

Due to their ability to earn income off the platform, they experience high levels of agency in relation to clients:

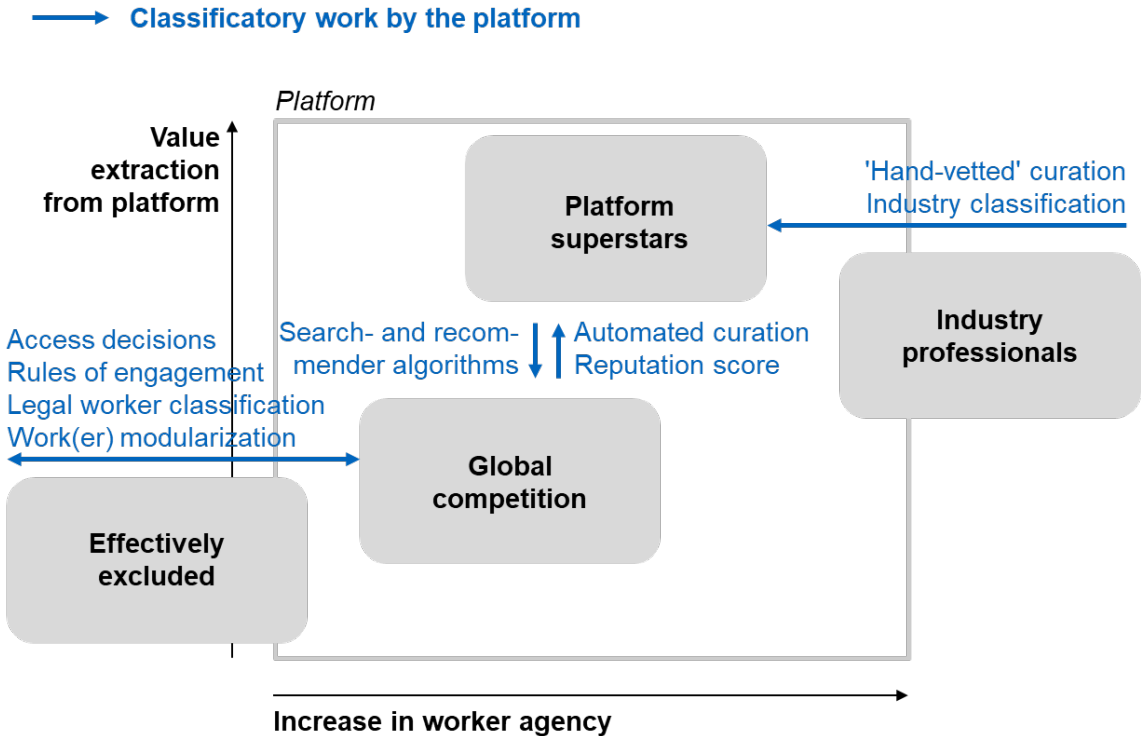
'Yes, I screen the clowns. [laughs] [...] Of course, I screen them. [...] I am in the lucky possession now that even if I just get a little personal warning bell going off, I don't take them on.' (07U, Professional Services, Europe)

Their economic value extraction on average lies below that of *platform superstars* because they pursue most of their professional goals outside the boundaries of the platform. In other words, while they on average demand higher hourly wages than superstars, they spend less time on the platform. Only a small proportion of their income is derived from platform work which makes them less dependent on a particular platform. Hence, their employment relationship with the platform is characterized by less subordination towards the platform firm and heightened agency towards clients (Wood & Lehdonvirta, 2021). Through manual quality labels based on conventional hiring techniques such as interviews, both classes might converge into an overarching class of platform-certified, freelancing experts in their respective market categories.

In sum, my findings are illustrated in Figure 6. It visualizes how much economic value an average worker in each class extracts from platform work relative to workers in other classes (y-axis). It also shows the reported levels of agency towards the platform as well as clients (x-axis). Last, it lists classificatory devices which matter most for

dynamics between these digital classes. It illustrates how the experiences and market outcomes of workers effectively excluded from labour platforms and industry professionals are largely shaped by platform firms' manual categorical practices at the boundary of their marketplaces. The everyday work lives of global competitors and platform superstars, however, are predominantly influenced by the automated classification systems that allow platform firms to operate their marketplaces at scale.

Figure 6. Illustration of dynamics between four classes of online freelancers



While platform superstars are largely evaluated based on their accumulation of platform-specific, symbolic capital, industry professionals are able to transfer their educational and professional credentials from outside onto the platform. Global competitors mostly compete on price although some manage to identify in-demand market niches that give them some leverage and a path to become a superstar themselves. Workers who are effectively excluded are often not even visible to clients

and instead evaluated by the platform firm based on the perceived lack of skills and experiences. Such evaluation occurs either manually by platform administrators, or indirectly through the classification systems constructed by them or underlying automated systems such as recommender or search algorithms.

3.5 Discussion

In this chapter, I investigated whether differences in individuals' experiences as remote gig workers are shaped by the centralized categorical practices of platform firms. My review of the literature showed that one group of scholars conceptualizes output heterogeneity as categorical but reducible to workers' diverse circumstances and motivations ('inputs') (e.g., Dunn, 2020; Ravenelle, 2019; Schor et al., 2020). Another group of scholars theorizes such differences in labour market outcomes as continuous and primarily influenced by the cumulative effects of platform-constructed metrics measuring workers' 'outputs' (e.g., Lehdonvirta et al., 2019; Pallais, 2014; Wood et al., 2019a). Instead, my work foregrounds the categorical practices of Upwork and Fiverr as visible in the digital interfaces of their platforms (Light et al., 2018) and experienced by the classified workers (Lamont & Swidler, 2014).

Based on the collected data, I find that platform firms 'invest in' (Thévenot, 1984) a range of explicit and implicit categories of work and classifications of workers to construct and organize their online markets (Ahrne et al., 2015; Kirchner & Schüßler, 2019). Resultant 'classification situations' (Fourcade & Healy, 2013, p. 560) are observable along the entire labour process from sign-up to project completion. The centralized classification systems—from taxonomies of work to worker hierarchies expressed via quality labels (chapter 4)—are defined and codified by the employees of these for-profit firms. The resultant boundaries are socially constructed but

'simultaneously real since action can be based on [them]' (Desrosières, 1998, p. 12). They are an essential part of the socio-technical infrastructure of labour platforms (Aspers & Darr, 2022; Kornberger et al., 2017). Platform firms have the classificatory power to 'freeze a certain state of the power relations' (Bourdieu, 1984/2010, p. 482) of their triangular employment relations with workers and employers into the digital interface, algorithms, and back end of their platforms. This way, they classify labour to the effects of making their exchanges intelligible, ordering them hierarchically, and enforcing normative standards in line with their strategic interests (chapter 2). In short, they actively shape and institutionalize differences between categories of workers.

In fact, I observe four discrete classes of workers that are mediated by but not fully reducible to workforce heterogeneity alone. I identify these classes as *global competitors*, *platform superstars*, *workers (effectively) excluded*, and *industry professionals*. Workers in each class differ in how they are evaluated by clients, how their employment relations with these clients and the platform are structured, and ultimately how successful they are in an online market. In relation to my initial research question, this chapter therefore identifies platform firms' categorical practices and their subsequent use of classificatory devices as a previously overlooked force in explaining some of the variation in workers' market outcomes. While my findings support the view that labour market outcomes are mediated by categorical differences in workers' characteristics such as financial dependency (Schor et al., 2020), geography (Demirel et al., 2020), or behavioural attitudes (Cansoy et al., 2020), I argue that classificatory practices by platform firms have an effect beyond such 'inputs'. Categorical choices appear to be in alignment with strategic considerations, constrained by technological limits, and in flux over time. Theorizing output heterogeneity as co-constructed by the

categorical boundaries created by platform firms thus also differs from research that conceptualized such differences along a continuous spectrum.

The extent of their centralized decision-making power has earned platform firms comparisons to nation states (Lehdonvirta, 2022; Parker, 2016; Schörpf et al., 2017). The classificatory power of platform firms offers another such parallel. For the ‘rational state’, classifications of labour are ‘simplifications’, standardized abstractions of a complex reality designed to inform governance, exert control over citizens, and allow for state interventions that impact their constituents (Scott, 1998, p. 76f). For example, being classified as unemployed defines a worker’s claims before the law (Salais, 1986, as cited in Diaz-Bone, 2018) and institutional licensing secures professional monopolies like those enjoyed by doctors or lawyers (Habinek & Haveman, 2019). State classifications hold prescriptive power by becoming ‘salient points’ and commonplace in social discourse, but simultaneously remain constraint by people’s efforts to interpret and contest their own classification (Boltanski & Thévenot, 1983, p. 674f). While classificatory power of platform firms is confined to their digital marketplaces (but ironically applies across national borders), it evidently has material impacts for workers who rely on a specific platform for subsistence or who are actively excluded from it. Like states, they therefore do not only describe but actively constitute the world of work (Abbott, 1989) and ‘contribute to the existence of classes’ in society as a whole (Bourdieu, 1984/2010, p. 480).

Platform firms actively place workers into four digital classes

The identification of four classes of remote gig workers matters for its explanatory value in describing diverse experiences in the remote gig economy. Rather than generalizing across the entire population of gig workers (Schor et al., 2020), such novel distinctions

allow us to get closer to the studied phenomenon (Aspers & Corte, 2019) and develop a better understanding of platform work. For example, the triangular employment relations between workers, platforms, and clients is widely considered to be characterized by 'subordinated agency', entrepreneurial autonomy towards clients but a lack of voice *vis a vis* the platform as well as control over fees and how competition is structured on these marketplaces (Gegenhuber et al., 2020; Wood & Lehdonvirta, 2021, p. 1). However, it is unclear to what extent workers *effectively excluded* (and even some *global competitors*) really experience agency towards clients. Similarly, platform firms are more constrained in their actions, for example around fees, when dealing with users who view labour platforms as a dispensable extension to their successful careers in conventional labour markets (*industry professionals*) or who strategically move long-term clients off the platform once enough trust has been established (*platform superstars*). Thus, workers in these classes reported a heightened sense of agency towards platform firms which reached out to them for input and offered them new avenues for interaction such as on-boarding courses, personal points of contact, and in one case even offline events.

Global competitors embody much of the imagery evoked by scholars conceptualizing platforms in terms of algorithmic control (Rahman, 2021; Wood et al., 2019a) or precarity (Kalleberg & Vallas, 2017; Ravenelle, 2019). These are workers who compete in a globalized labour market largely based on price or scarcity surrounding their bundle of skills (Graham & Anwar, 2019). As expected, their satisfaction with platform work correlates with their financial dependence on it (Schor et al., 2020) as well as other sources of heterogeneity like gender or geography. *Platform superstars* have equally been identified in other studies (Demirel et al., 2020; Ravenelle, 2019). They have often joined a platform early on and over time built up significant platform-

specific reputation in their areas of expertise. Their success aligns with accounts who foreground the importance of the accumulation of platform reputation as captured by continuous metrics in the form of job success scores or number of projects completed (Kornberger et al., 2017; Rahman, 2021). While some of our respondents pointed to actual differences in kind to global competitors, for example their level of service delivery or educational background, many acknowledged that timing and a cumulation of status within the centralized classification infrastructure played a significant part in their success. As platform firms manually attach quality labels to workers' profiles to identify the supposedly best performers in their marketplaces (chapter 4), winner-take-all dynamics are likely to increase (Rosen, 1981). While platform superstars tend to be actively pursued by employers, the broad mass of global competitors is left to compete for projects that are not filled this way, a more general trend observable in talent recruiting (McDonald et al., 2019).

The remaining two classes of workers, those *effectively excluded* and *industry professionals*, mark the most novel distinctions made based on analysing platform work through the analytical lens of categorization. Research on classification systems traditionally seeks to identify those who are excluded from or assigned to residual categories (Star & Bowker, 2007). This methodological starting point was essential in distinguishing those who remain fully or effectively excluded from online labour markets. On the one hand, platform firms may exclude workers *completely* via centralized categorical practices including taking access decisions (Gawer, 2020; Lehdonvirta, 2022, pp. 88–90), defining what types of services and behaviours they legally permit on their marketplaces (Schörpf et al., 2017), and setting technical requirements (Newlands & Lutz, 2020). On the other, workers can be *effectively* excluded by centralized classification systems, for example by not receiving any or

sufficient client visibility on the market. No information system works equally well for all types of work and workers (Bowker & Star, 2000a). Paradoxically, although this group is likely the biggest in size given that more than 90% of worker profiles on online labour platforms are estimated to be inactive (Kässi et al., 2021), research designs—the one in this study included—often fail to sufficiently include these voices located in the grey zones of platform work. For once, it is difficult to include such voices because the nature of invisibility experienced by workers is heterogeneous (Gruszka & Böhm, 2020). Second, it is not easy to identify and reach people who have failed at getting access to a platform or have since deactivated their profiles. Potential ways forward could be the identification of interview partners via snowballing techniques or complaints in independent community forums such as *reddit.com*.

The class of *industry professionals* highlights most clearly how platform firms actively intervene in the categorization of labour supply. Both platform firms in my sample took a strategic decision to manually intervene in the automated classificatory infrastructure that ordered their marketplaces (Kornberger et al., 2017). To pave them an entry route to platform work and appease larger and higher value clients, platforms manually curated in-demand professionals. This innovation marks another step in classificatory history that has seen platform firms move from crude categorizations of services offered and no reputation systems in the early days to complex and largely automated classification systems only to now realize that some manual curation is strategically desirable to structure labour demand and supply (Figure 20, cf. appendix A.2). It exemplifies how platform work is characterized by heterogeneity as ‘variation across people, platforms, and time’ (Schor, 2020, p. 43). The relatively new class of *industry professionals* is theoretically significant because it experiences more agency and less subordination towards the platform (Wood & Lehdonvirta, 2021). Because these

workers often did not have to go through the same struggles as *global competitors* to build up their online reputation, they are less likely to experience platform infrastructure as an 'invisible cage' (Rahman, 2021). In addition, they more often cite non-financial motivations (Cansoy et al., 2020; Dunn, 2020) for engaging in platform work including skill development and the testing of ideas for entrepreneurship.

Digital boundaries matter beyond the platform

Platform firms' categorical practices also have implications beyond digital marketplaces. For workers, classifications that characterized their employment relations traditionally hold stratifying potential beyond labour markets as such (Fourcade & Healy, 2013). In general, the commodification of workers has long been a tactic to limit workers ability to collectively organize. On the one hand, the categorization of workers as bundles of skills and a collection of performance metrics is likely to inhibit their ability to organize effectively and form a social class beyond the platform (Wood et al., 2018). On the other hand, there are first instances of worker resistance at the individual and collective level (Anwar & Graham, 2020; Cameron & Rahman, 2021; Gegenhuber et al., 2020; Wood et al., 2021; Wood & Lehdonvirta, 2021). Theories of classification are helpful in providing a framework that connects classifications of labour as sites of struggle that range from the level at the interface to legal struggles concerning workers' classification before the law (Cherry, 2016).

Beyond workers, my findings add to the debate on heterogeneity of platforms and the platform firms that organize them (Gawer, 2020; Schor, 2020). Workers reported that their initial decisions which platform to join are influenced by how platform firms categorize online labour (Pongratz, 2018) and the resulting everyday practices that follow from such definitions. While some workers preferred to actively apply for jobs, a

process only possible on *upwork.com*, others favoured the services-as-a-product approach on *fiverr.com*. Just like individuals, firms thus face classificatory struggles at an industry-level to further their strategic objectives, first and foremost the generation of profits for shareholders (Srnicek, 2017). To improve their market position, platform firms actively engage in the social construction of industry categories and competition (Beckert, 2009; Durand & Khaire, 2017; Porac et al., 1995). They categorize online labour as a specific type of work to attract workers and clients alike (Pongratz, 2018) and impact how they are perceived in public discourse (Gillespie, 2010; Pujadas & Curto-Millet, 2019). As public companies, they are subject to a 'categorical imperative', the social obligation to follow role conforming behaviour deemed appropriate for their corporate type (Zuckerman, 1999). The alternative is to face punishment by their respective audiences: workers, employers, governments, and investors.

Finally, my findings allow reflections on how processes of categorization and classification change in digitized market-settings. Most information systems that enable remote work, whether organized through online markets or within hierarchies, are privately owned. Corporate ownership of infrastructures which are integral to society is likely to give rise to conflicts (Plantin et al., 2018). One salient point to consider is to what degree the future of work is shaped by platform firms who, knowingly or not, codify certain normative values within the technologies they build (Abbott, 1989). My findings showed that platform firms standardize how remote labour is categorized and broken down, how it is conducted, and what behaviours are deemed normatively acceptable (Zelizer, 2010) and are thus positively rewarded on a global scale. Since classifications as a form of judgment device are rooted in context and culture (Kharchenkova & Velthuis, 2018), it warrants our attention that the categorical choices, conventions, and agenda of a select few impact the (working) lives of many,

while being largely hidden from public scrutiny (Diaz-Bone, 2017). By moving the needle from categorization to classification, those in charge formalize categories, define hierarchies between them, and prescribe a specific social order. Research on classifications thus denaturalizes them and for a short while prevents them to stay invisible in the background. This form of research offers a pathway to uncovering those who are 'othered' (Star, 1990) and structurally disadvantaged by such systems and their powerful architects (D'Ignazio & Klein, 2020). After all, 'each category valorises some point of view and silences another' (Bowker & Star, 2000a, p. 5).

3.6 Future research

In this chapter, I theorized worker heterogeneity based on data collected at the level of the interface and through the experiences of remote gig workers. This approach builds on a long tradition of making visible the mundane practices and conventions sustaining ubiquitous, yet often overlooked classification systems (Bowker & Star, 2000a; Desrosières, 1998; Thévenot, 1984). Still, my research design is limited insofar as it does not include data on the informal categorical practices and social context of platform administrators (Kelkar, 2018) or how clients incorporate centralized classification systems into their evaluation of workers and their hiring decisions (Horton, 2017; Leung, 2017). By limiting my analysis to the centralized platform infrastructure, I also exclude any informal categorical practices by the classified workers (chapter 5). Second, it is unclear to what extent my findings are generalizable. In chapter 4, I study if quality labelling, as one example of worker categorization by platform firms, influences workers' success online for a larger sample of remote gig workers. Third, I fail to account for the heterogeneity of platforms beyond those intermediating remote knowledge work (Schor et al., 2020). Further research will need

to compare the identified classificatory tools in this specific context to other types of gig work such as microwork or location-dependent platform work. Uber, for example, has been the prime case to study how algorithmic management shapes workers' experiences (Rosenblat & Stark, 2016) and resistance against the resultant socio-technical infrastructure (Englert et al., 2020). Yet, little attention has been paid to the categorical practices of the firm. In a notable exception, scholars show how Uber perpetually redraws the lines of its own ontology on a policy level (Pujadas & Curto-Millet, 2019) just like freelancing platforms shape what constitutes online labour.

4. Platform-certified: How worker quality is constructed online

Abstract

This chapter studies why online labour platforms attach quality labels to workers' profiles. Drawing on interview, survey, and profile data from remote knowledge workers active across two digital marketplaces, I find that those who have been awarded a quality label experience greater labour market attachment and success. Rather than explaining the phenomenon by reference to signalling theory or algorithmic management, I argue that quality labelling is an act of market categorization which actively co-constructs a worker's qualities at the hiring stage. As market devices, quality labels are a political tool for platform firms to make workers and their services commensurable and to provide employers with a basis for their hiring decision. For workers, labelling as qualification does not only have distributional effects but also impacts their autonomy by foregrounding another obstacle to reputation portability.

4.1 Introduction

Why do online labour platforms attach quality labels to workers' profiles? Online labour platforms are websites that serve as a marketplace to match buyers and sellers of remote knowledge work, such as software development and graphic design. The firms who run these marketplaces attach labels such as being 'pro-verified' or a 'rising talent' to the profiles of some workers. In the platform economy literature, one leading theory is that such quality labels function as signals which reduce employer uncertainty (Kässi & Lehdonvirta, 2022; Lehdonvirta et al., 2019; Pallais, 2014). Another popular approach theorizes quality labels as tools of 'algorithmic management' insofar as they are only attached to profiles of workers who comply with the platform firm's policies (Rahman, 2021; Stark & Pais, 2020; Wood et al., 2019a). Such labelling requires examination because prior research has suggested that classifications of labour have the potential to impact who succeeds or fails on a platform (chapter 3), thus affecting the livelihood of millions of workers worldwide (Kässi et al., 2021).

I challenge the views that quality uncertainty in online labour markets is predominantly a signalling or management problem. Instead, I draw on work from economic sociologists who conceptualize uncertainty as something more fundamental which concerns the constitution of quality itself (Beckert, 2009; Callon et al., 2002, 2007). In this view, worker quality is the outcome of qualification, a negotiation between workers, employers, and platform firms at a specific point in time (Callon et al., 2002). It is not a purely intrinsic trait simply to be uncovered but also a function of factors external to the worker, for example hiring practises or client needs (Beckert & Musselin, 2013; Eymard-Duvernay & Marchal, 1997). Thus, certificates issued by platform firms are a 'market device' (Callon et al., 2007) or 'judgment device' (Karpik, 2010) which help employers qualify potential hires (Aspers & Beckert, 2011). It matters how these

devices 'are tinkered with, adjusted and calibrated' as it impacts 'the ways in which persons and things are translated into calculative and calculable beings' (Muniesa et al., 2007, p. 5). I argue that platform firms, as organizers of marketplaces for services (Ahrne et al., 2015; Kirchner & Schüßler, 2019), do not just uncover and label workers' qualities during the hiring stage but actively constitute them and the resultant hierarchies of labour supply. Labelling moves from being a mere problem of information asymmetry between sellers and buyers to the theoretical intersection of how workers are categorized, made commensurate, and assigned value by platform firms and their efforts to organize the order of digital marketplaces (Beckert & Musselin, 2013; Nedzhvetskaya & Fligstein, 2020). A failure to account for this fundamental dimension of platform power would imply that research misses an opportunity to question inequalities in the digital economy and hold those who decide on what qualities matter accountable (D'Ignazio & Klein, 2020).

My findings are based on a mixed-methods research design. As primary data source, I relied on interviews with 39 workers to learn about the process of qualification and its effects. As a secondary data source, I collected survey responses and scraped profile data of another 448 freelancers. For this dataset, I fit regression models to test for an association between quality labels awarded by platform firms and workers' success on the platform. A mixed-methods design was used to weigh two distinct epistemological conceptualizations of worker quality, offset methodological limitations, and approach the phenomenon at various levels of abstraction (Bryman, 2006).

In the following, I begin by juxtaposing signalling theory and algorithmic management as ways to conceptualize quality labelling by platform firms. Then, I problematize both accounts and suggest theories of qualification (Callon et al., 2002) and categorization (Beckert & Musselin, 2013) as a viable alternative. Based on this analytical entry point,

I separate labelling into two distinct processes: automated and manual labelling. I present evidence on the positive impact of quality labels on individual workers' labour market attachment and success. However, some of the workers' experiences neither signalling theory nor algorithmic management can contend with. Instead, I present them as evidence for how platform firms also actively co-construct quality at the hiring stage. They construct market categories that matter, and act as gatekeepers to them. Findings are integrated to discuss the underlying social mechanism and its impacts on and off the platform.

4.2 Literature review

Online labour markets are characterized by a triangular relationship between the platform, workers, and their clients (Schörpf et al., 2017; Vallas & Schor, 2020). Platform firms organize digital marketplaces as a new type of intermediary by constructing, owning, and governing the underlying digital platform infrastructure (Kirchner & Schüßler, 2019). Quality labels are one part of this infrastructure constructed and awarded centrally by platform firms (Aspers & Darr, 2022; Kornberger et al., 2017). In the literature on online labour platforms, there are two leading theories on how to theorize the observation that platform firms attach quality labels to workers' profiles. The process is either conceptualized as a means of signalling quality in the hiring process (theory 1) or algorithmically managing workers thereafter (theory 2).

Theory 1: Quality labels are signals that reduce employer uncertainty

A common way to make sense of quality labels awarded by platform firms is signalling theory. A core assumption of signalling theory is that markets are characterized by information asymmetries between sellers and buyers which lead to uncertainty and

socially undesirable outcomes (Akerlof, 1970). By reference to the used-car market, Akerlof (1970) demonstrated how asymmetric information risks market collapse where only sellers of low-quality 'lemons' remain incentivized to transact. In labour markets, high-quality workers thus attempt to signal their desirable type to capture value for themselves (Spence, 1973), just as employers have an incentive to screen for these better quality workers (Stiglitz, 1975). Both signalling and screening increase the transaction costs associated with hiring talent. After all, obtaining a higher education degree or internships are costly. Given the global and distributed nature of online labour markets, uncertainty is exacerbated by anonymity, cultural differences, and the absence of hierarchical control. Prospective employers do not know the quality of workers ('hidden information') or their behaviour after contracting ('hidden actions') (Pavlou et al., 2007, p. 106). For example, remote employers take hiring decisions without full transparency on whether a worker's skill set matches their needs or whether their transaction partner will engage in hazardous behaviour such as outsourcing the job to subcontractors. Thus, digital platforms are institutions which can reduce some of the transaction costs associated with individual-level outsourcing by constructing signalling environments for workers and employers (Lehdonvirta et al., 2019).

In labour markets, one typical means of signalling quality is obtaining an academic qualification awarded by a recognized higher education provider. However, once workers managed to break into an online labour platform, their ability to signal quality rests on markers beyond traditional education (Cedefop, 2020). Some rely on 'alternative credentials' (Kato et al., 2020) such as micro-credentials. These are commonly defined as skill-specific certificates which are awarded by private companies as the outcome of short and often automated courses (Kässi & Lehdonvirta, 2022; Wheelahan & Moodie, 2022). In one study, micro-credentials reduced employer

uncertainty and increased workers' income per project by more than USD 30 (Kässi & Lehdonvirta, 2022). The effect was 1.5 larger for workers without a verifiable work history on the platform, although it did not increase the likelihood of being hired for the first time. Quality labels attached to workers' profiles by platform firms are thus viewed as another form of such 'alternative credentials' (Kato et al., 2020).

On platforms, such alternative credentials are situated in a rich information infrastructure available to employers. Signals of worker quality can be unverified (e.g., worker description, self-reported skills), mediated (e.g., rating scores, micro-credentials), or constructed (e.g., performance data) by the platform provider, the latter being the most effective in increasing wage rates (Lehdonvirta et al., 2019). Quality labels are another form of platform-constructed signals such as platform recommendations (Horton, 2017), money-back guarantees for the services of certain workers offered by the platform (Barach et al., 2020), or standardized information on past performance (Agrawal et al., 2016; Barach & Horton, 2021; Lehdonvirta et al., 2019). On platforms, mediated signals are those which are only to some degree verifiable by the platform firm, for example client feedback or reputation scores (Lehdonvirta et al., 2019; Pallais, 2014). In an early study of one labour platform, oDesk.com, the author showed that detailed feedback helped inexperienced workers with labour market integration. Two months after receiving their first feedback, the average inexperienced worker's earnings had tripled (Pallais, 2014). Similarly, higher reputation ratings are significantly associated with a higher probability to win an output-based, fixed-price project (Lin et al., 2018). Examples of unverified signals include the skill advertised by the workers (Anderson, 2017) or listed language proficiency (Lehdonvirta et al., 2019).

To explain quality labelling with signalling theory has its limitations. First, there are limits to the process of signalling itself, even if we assume that worker quality is an intrinsic trait to be uncovered. Third-party certifiers, like platform firms, might have strategic reasons to alter the precision (e.g., aggregation of data) and bias (e.g., over-optimism) of available information (Dranove & Zhe, 2010). Similarly, employers interpret signals in unintended ways. For example, in the absence of sufficient other information employers in digital marketplaces rely on heuristics to judge a worker's fit. They take hiring decisions influenced by workers' gender (Chan & Wang, 2018; Galperin, 2019), geography (Agrawal et al., 2016; Graham et al., 2017), or affiliation to intermediary agencies (Stanton & Thomas, 2016). Second, and more importantly, signalling theory assumes that workers have intrinsic qualities which can be uncovered once enough information is made available to the employer. However, this assumption is contested. For example, it has been demonstrated that people change their behaviour following or in line with various forms of labelling (Espeland & Sauder, 2007; Rahman, 2021; Rietveld et al., 2021). Consequently, signalling theory is likely at best a partial account of why platform companies attach quality labels to workers' profiles. Its epistemological starting point assumes worker quality to be something intrinsic and discoverable and thus cannot explain these changes in worker behaviour.

Theory 2: Quality labels are a means to algorithmically manage workers

Another way to make sense of quality labels awarded to online freelancers is to view them as a form of digital control. The term algorithmic management was originally used to name

'software algorithms that assume managerial functions and surrounding institutional devices that support algorithms [...] to allow companies to oversee myriads of workers in an optimized manner at a large scale' (Lee et al., 2015, p. 1603)

Since then, the term algorithmic control has come to refer 'to the use of computerized technologies to (partially) automate processes of decision-making and control' (Bucher et al., 2020, p. 3). On online labour platforms, such control can take many forms such as screen captures, monitoring of key strokes, matching algorithms, rankings, automated detection of breaches of the terms of service, or platform-based reputation systems (Wood et al., 2019a). The latter has been described as an 'invisible cage' whose opaque evaluation mechanisms make it difficult for workers to respond (Rahman, 2021). The goal of creating an 'evaluative infrastructure' in the form of 'rankings, ratings, reviews, and audits [is] to establish orders of worth' (Kornberger et al., 2017, p. 79). Rather than more hierarchical command structures, algorithmic management allows platforms to 'co-opt' workers into certain behaviours (Stark & Pais, 2020). While maintaining a strategically advantageous narrative of 'freedom or flexibility', platform firms retain the power to 'incentivize, homogenize, and generally control how workers behave' (Rosenblat & Stark, 2016, p. 3777).

While algorithmic control is never complete and leaves room for worker agency and resistance (Anwar & Graham, 2020; Ferrari & Graham, 2021), it allows employers to exercise some level of control over workers by managing them from afar. It thus alleviates some of employers' concerns about how to address the indeterminacy of labour power in remote settings. By indeterminacy of labour power I refer to the inability to contractually fix labour power before contracting (Smith, 2006) and the subsequent challenge for employers to get the most out of the hired worker, for example through managerial oversight (Woodcock, 2020). In addition, algorithmic control also reduces

the risk of 'hidden actions' by freelancers such as billing more hours than justified (Pavlou et al., 2007, p. 106).

However, rewards and sanctions are not only a managerial tool for employers active but a means of governance for platform firms (Chen et al., 2022). Especially if fully automated, the award of quality labels can be an important part of the socio-technical infrastructure of a digital marketplace (Aspers & Darr, 2022). After all, 'algorithmic bureaucracy' is essential to the organization of marketplaces (Kirchner & Schüßler, 2019, p. 142; Schörpf et al., 2017), for example by increasing visibility or aligning workers' incentives with those of the platform (Gerber & Krzywdzinski, 2019). In the context of microfinancing, for example, Rietveld et al. (2021) illustrated that platform firms rely on labelling for 'market orchestration', that is to further their own strategies by influencing the actions and performance of select sub-groups of their platform sides. On a platform for care work, practitioners were labelled a 'CarePro' as a reward for past behaviour both relevant to their line of work (e.g. a history of high reviews, scheduling flexibility, verification checks) and economically beneficially to the platform firm (e.g. availability, responsiveness) (Ticona & Mateescu, 2018). Employed in this way, automatically awarded quality labels contrast with the opaqueness of other applications of algorithmic management (Bucher et al., 2020; Rahman, 2021). Instead, they tend to be prescriptive, associated with an effort to quantify performance (Power, 2004), and reward desirable behaviour like

'completing a certain amount of projects, earning a certain amount of money, receiving reviews and also 'strategic' achievements like bidding on a number of projects, quickly answering to the client or logging in every day over a period of time' (Schörpf et al., 2017, p. 50).

Qualification and the construction of quality

In contrast to signalling theory, scholars of algorithmic management foreground the constitutive dimension of labelling. If workers are classified on certain principles and this classification impacts their labour market success, we can expect them to adapt their behaviour in response (Bowker & Star, 2000a). However, algorithmic management is a theoretical concept that describes a new form of labour control after contracting. It falls short, in explaining how worker quality is also constructed as part of the hiring process. What, in other words, is the social process 'of establishing what qualifies as quality' before a contract is agreed (Aspers & Beckert, 2011, p. 14)?

While microeconomic models of asymmetric information are simplified by assuming stable preferences, the formation of demand has been problematized as the 'value problem' of exchange under uncertainty (Beckert, 2009, p. 253ff). In this view, quality is 'attributed, stabilized, objectified, and arranged' through 'processes of qualification' (Callon et al., 2002, p. 199). The qualities of a service are the temporary outcome of its 'intrinsic' characteristics and an 'extrinsic' dimension that comes down to the buyer's evaluation and judgment shaped by a negotiation with the seller, as well as other intermediaries and decision devices (Callon et al., 2002, p. 199). Such coordination and qualification between actors require a reliable and predictable social order to markets which has been attributed to various social phenomena such as institutions (Fligstein, 2002), networks (Granovetter, 1995), conventions (Biggart & Beamish, 2003; De Larquier & Rieucau, 2019), commensuration (Espeland & Sauder, 2007; Espeland & Stevens, 1998), or market devices (Callon et al., 2007; Karpik, 2010).

In the following, I thus problematize the views which reduce quality labels awarded by platform firms to a mere problem of signalling or managerial oversight. I seek a third

response to the research question: *Why do online labour platforms, or more precisely the firms that provide them, attach quality labels to workers' profiles?*

4.3 Research design

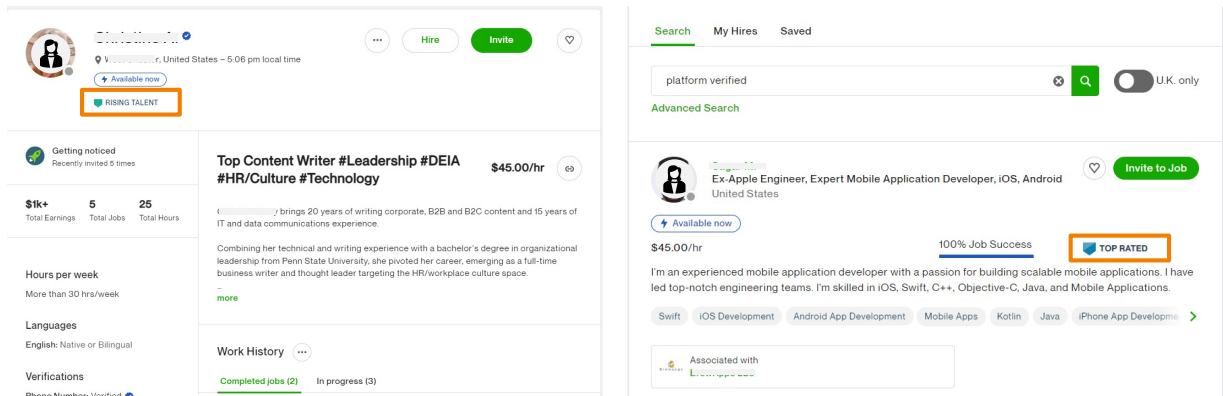
To answer this question, an ideal research design would have collected data in collaboration with a platform, for example interviewing their upper management and engineers on their motivations behind attaching quality labels to workers' profiles. Since I did not have access to a platform firm directly, I opted for an alternative, second-best design. Across two leading online freelancing platforms, *upwork.com* and *fiverr.com*, I collected two types of worker input: in-depth interviews and survey responses combined with workers' platform profile data. By empirically approaching the phenomenon this way, I effectively answer a slightly altered research question: To what effect do platform firms award quality labels to workers' profiles? While I therefore do not have access to proprietary information on the thought process of employees of platform firms, interviewing and surveying workers helps to emphasize the social impact of labelling, the main motivation behind this research.

I chose *upwork.com* and *fiverr.com* as sites of research because they both represent globally operating marketplaces that match supply and demand for remote knowledge work. Quality labels feature prominently on both websites and workers can earn 'talent badges' or reach new 'levels' and 'pro-verification'. Such labels are highly visible on workers' profiles and employers can even apply them as filters in the search interfaces available to them (Figure 7, Figure 8). Historically, labels evolved from badges workers could pay for, like the 'Select Professional' package on *elance.com*,²⁹ to something

²⁹ In 2013, oDesk and Elance announced their merger that was later rebranded as Upwork.

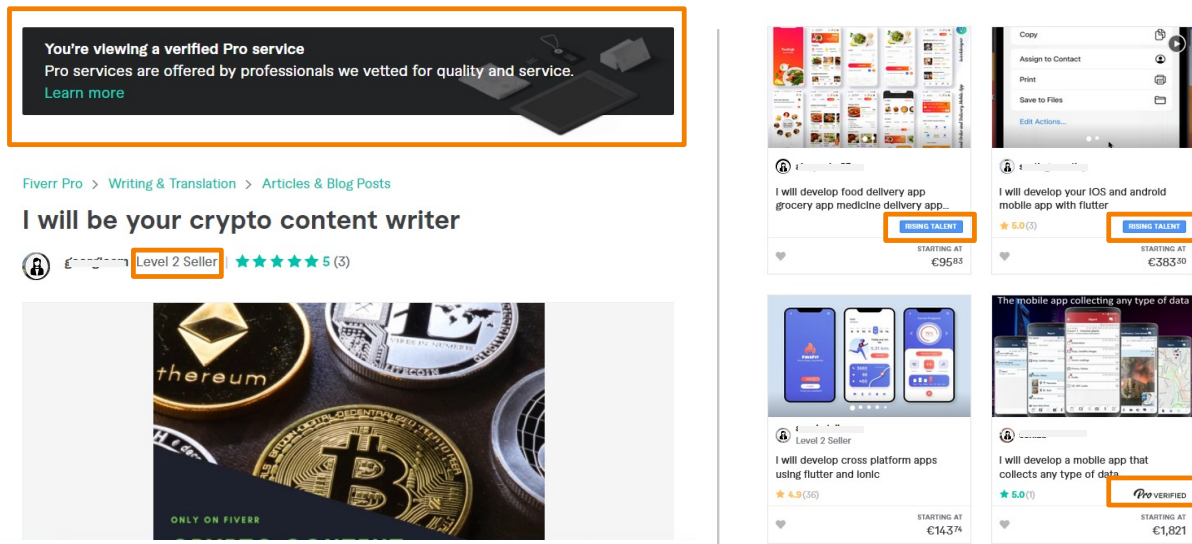
awarded based on platform-specific metrics like positive client feedback. In 2017 and 2020, Fiverr and Upwork additionally started to manually label the so-called top one percent of talent on their platforms.

Figure 7. Quality labels on upwork.com



Note. Highlights included by the author. Workers' names and pictures anonymized. Worker profile on the left, and search interface on the right.

Figure 8. Quality labels on fiverr.com



Note. Highlights included by the author. Workers' names and pictures anonymized. Gig profile on the left, and search interface on the right.

Qualitative approach: In-depth worker interviews

My primary method of data collection were in-depth interviews with two samples of workers. The first sample (n=11) was a subset of a larger collection of interviews (n=40) funded by the *European Centre for the Development of Vocational Training of the European Union, Cedefop* (Cedefop, 2020). The Europe-based workers had all completed at least one project on the target platforms. They were asked about skills matching on labour platforms, and I only included transcripts in which quality labels were discussed (n=11). The insights generated from these transcripts primarily informed survey development, what data points to scrape from worker profiles, and the development of an interview questionnaire for the second sample. Workers in the second sample (n=28) were interviewed with an explicit focus on practices of classification by platform firms including efforts to label worker quality. Interviews were conducted digitally via Zoom and lasted on average just below 58 minutes. As is required by online labour platforms and typical in research on online freelancing (e.g., Stephany et al., 2020; Wood et al., 2019a), I compensated workers for their time. I communicated to participants to consider this as a sign of appreciation for their time rather than payment for a job.

One advantage of interviewing was that it allowed me to theoretically curate a sample of workers that enabled meaningful comparisons between groups, for example hand-vetted experts, experienced, and inexperienced workers (Lamont & Swidler, 2014). I ensured that interviewees included workers without a label (22%), promising talents (11%), experienced workers (22%), top-rated workers (22%), and manually curated experts (22%). I further kept ratios for gender, specialization, and main platform roughly equal. Of the workers in the second sample, 48% were older than 30 years, most worked from Asia (37%), and about half earned most income through platform

work (48%). Transcripts of both samples were coded iteratively, broadly following a grounded theory approach (Corbin & Strauss, 1990). Initial codes were integrated and merged into higher-level categories (Charmaz, 2006), as visible in Figure 10.

Quantitative approach: A European worker survey

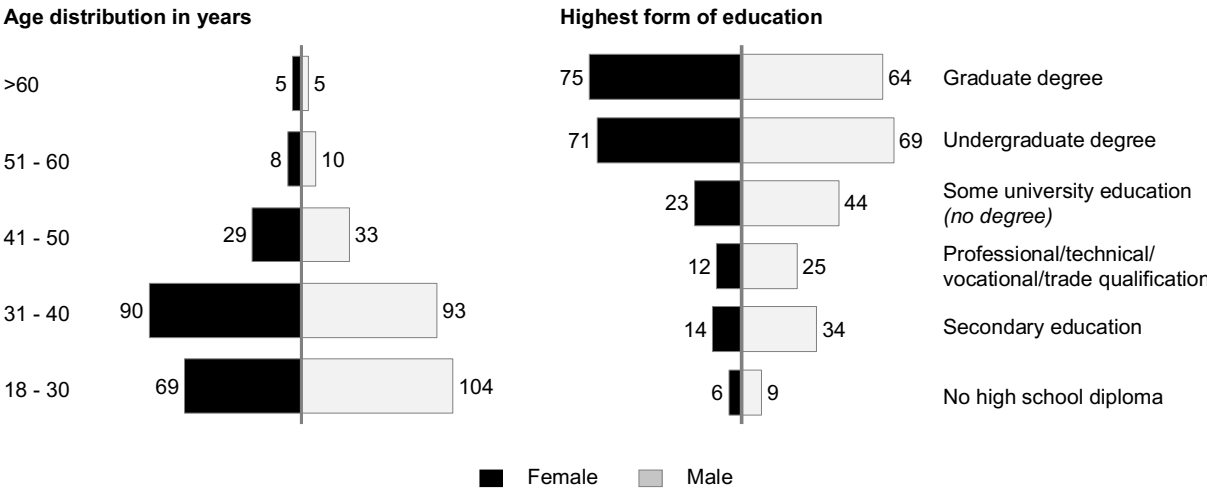
Quantitative analysis was based on a sub-sample of 448 workers across both platforms. The original survey comprised 723 workers and was also funded by Cedefop (Cedefop, 2020; Margaryan et al., 2022). In the analysed sub-sample, workers consented to having their profile information scraped to supplement survey responses and were still active at the time of scraping. Profile information were recorded on two points in time, roughly one-and-a-half years apart. Workers had completed at least one project and were based in Finland (n=54), Germany (n=68), Italy (n=91), Romania (n=56), Spain (n=60), and the UK (n=119). The selection of countries ensured variability in national labour markets with unemployment rates ranging from 3.8% in Germany to 15.5% in Spain (2020).

One platform collaborated by collecting responses (n=177) from a random sample of eligible workers with an undisclosed response rate. The second platform declined collaboration and equal-quota sampling was chosen as a second-best, non-random sampling alternative (n=271). While keeping quotas for gender and country of residence approximately constant, workers were invited to participate in the survey with a 52% response rate. To reduce reliance on the search algorithm of the platform, the page and rank of a worker to be invited was randomly selected. Despite these efforts, generalisability of my findings might still be limited beyond this specific subset of workers. Survey data tends to suffer from self-selection (Bethlehem, 2010), especially due to topical and economic interests of the respondents (Lehdonvirta et al.,

2021). For example, successful and well-paid workers had higher opportunity costs to engage in the survey (Margaryan et al., 2022) which would imply that my sample is skewed towards lower-paid workers.

That said, against the backdrop of a 'lack of [...] consistent statistics [...] on the number of platform workers, their characteristics and their types of jobs and tasks' (O'Farrell & Montagnier, 2020, p. 130), sample characteristics align with what is known about gig work in Europe (Pesole et al., 2018) or the US (Hoang et al., 2020). Most respondents in the sample are 40 years or younger (80%), hold a university degree (61%), and do not use online freelancing as a primary source of income (73%) (Figure 9). My sample thus reflects that online freelancer on average represent a privileged group compared to the average population. Many workers fail to sign-up to platforms because of digital inequalities like lacking technological access or digital literacy (Lutz, 2019; Newlands & Lutz, 2020), or not having the right skill set to get their profile approved (chapter 3). Thus, workers with profiles on online labour platforms tend to be better educated (Cedefop, 2020; Pesole et al., 2018) and come from a more privileged class background (Martindale & Lehdonvirta, 2021). This observation is often obscured by grouping online freelancers with other labour-exchange platforms including so-called microwork on platforms like Amazon Mechanical Turk (Irani, 2015), and locationally-bound services like ride sharing or food delivery (Hoang et al., 2020).

Figure 9. Age distribution and educational attainment of respondents by gender



Note. Three respondents did not identify as either female or male.

In addition to the socio-economic and platform-specific information collected through the survey, I scraped performance metrics for each respondent on two points in time, t_0 and t_1 . On average, the point of data collection were 552 days apart. The relevant metrics are summarized in Table 2. To understand varying levels of employment over time, I constructed two dependent variables, employment (E) and platform activity (PA). Platform activity is approximated by the annualized number of additional client reviews received over a period $t_1 - t_0$, as reported in Table 2, relative to the platform-specific mean. If available, I chose the maximum annualized value from additional client reviews received, earned income and hours worked in the period.³⁰ Employment is a binary variable which indicates whether a worker found employment on the platform over the period $t_1 - t_0$. A worker was deemed as unemployed when the

³⁰ For one platform, such supplementary data was available for said period. We selected the maximum value for relative success as measured by reviews received, income earned (both relative to the platform average), and hours worked (as share of 1513 hours worked, i.e. the 2020 average of the European Union). Annual hours worked in the European Union were taken from the OECD database: OECD (2022), Hours worked (indicator). doi: 10.1787/47be1c78-en (last accessed on 10 March 2022).

account was no longer active, the worker page had been set to private by the platform due to inactivity, or a lack of platform activity, $PA = 0$. In other words, there were no additional reviews, hours or income added to the profile over the period $t_1 - t_0$.

Table 2. Summary statistics of worker metrics

	n	mean	min	max
<i>Platform success (annualized values for $t_1 - t_0$)</i>				
Additional reviews received [no.]	448	34	0	1380
Additional hours worked [no.]	271	204	0	2676
Additional income earned [USD]	271	4712	0	57937
<i>Performance metrics at t_0</i>				
Normalized success score [0:1]	448	0.93	0	1
Reviews [no.]	448	240	1	19355
Awarded quality label [%]	448	0.52	0	1
Hourly wage [USD]	448	27	3	195

Why a mixed-method design is helpful

My goal was to triangulate findings from both methods to yield a ‘negotiated account’ of worker labelling by platform firms (Bryman, 2007, p. 21). My reasons for putting quantitative and qualitative methods into conversation were twofold. First, it allowed the study of quality labels from two conceptions of quality. While quantitative analysis comes from an epistemological starting point more suitable to economic conceptions of worker quality, qualitative analysis of worker interviews affords the study of processes of qualification. Second, a mixed-method design offsets weaknesses of the other method (Bryman, 2006). On the one hand, interviews go beyond merely discussing workers’ behaviours but collect data on ‘representations, classification systems, boundary work, identity, imagined realities and cultural ideals, as well as emotional states’ experienced by respondents (Lamont & Swidler, 2014, p. 157). The

insights complement data collected through the survey and scraped worker profiles by providing context and critical interpretation of constructed variables (Neff et al., 2017). On the other hand, regression analysis of survey and profile data put my work into conversation with the literature on signalling (Agrawal et al., 2016; Kässi & Lehdonvirta, 2022; Lehdonvirta et al., 2019; Pallais, 2014) and offered an opportunity to test hypotheses for a larger sample of workers.

4.4 Findings

The focus of my analysis were quality labels attached to workers profiles. These are distinct from other practices employed by platform firms such as segmenting employers (interview 01U), verifying identities (interview 10U), or confirming the completion of automated assessments of a specific skill (set) via micro-credentials (Kässi & Lehdonvirta, 2022).

Automated and manual quality labelling

Qualitative findings. There are two processes through which platform firms award quality labels to workers. I will denote them automated labelling and manual labelling.

Automated labelling attaches quality labels to workers' profiles largely algorithmically as a reward for platform-specific, past behaviour. On *upwork.com* and *fiverr.com*, these labels are respectively coined 'talent badges' which highlight 'proven talent and expertise'³¹ or 'seller levels' which incorporate information on workers' 'monthly performance' including 'superb service, high buyer satisfaction, and on-time delivery'.³² Workers noted that these labels combine metrics of platform-specific experience and

³¹ Screenshot of an official description of talent badges on *upwork.com* (March 28, 2022).

³² Screenshot of an official description of seller levels on *fiverr.com* (August 22, 2022).

quantifiable behaviour compliant with platform interests. Examples of the former include reputation scores, generated revenues, time since sign-up, and on one platform the value of individual projects over a set time horizon. Metrics for compliant behaviour include the level of profile completion, average response time, accurate availability settings, on-time service delivery, and a record of compliance with the terms of service of a marketplace (Table 3). Labels are thus awarded to workers based on a mix of publicly available information (e.g., reputation scores) and for the employer previously unknown, individual-level performance data (e.g., response rates). Navigating these metrics is one example of ‘corrdwork-specific skills’ (Margaryan et al., 2022, p. 9) essential to success online. Especially respondents with platform experience could recall the targets needed for receiving a better label:

‘For a Level 2 [badge], you must have earned \$2000 cumulatively. You need to be rated above 4.7 within the last 60 days [and] completed at least 50 orders. [O]ne has to avoid bad ratings [and] the completion rate of the orders has to be above 90%.’ (19F; Software Dev & Technology; Africa)

Manual labelling is a complementary vetting process by platform firms which also allows the evaluation of qualities demonstrated off the platform, for example a proven track record of in-demand skills, work with reputable clients or a high-quality portfolio:

‘Fiverr Pro is a top sort of seller [for whom Fiverr] has [verified] the quality of work. [...] You submit an online application [with] examples of your work. [...] That’s where people make a lot of money, [...] [even] the co-creator of the Apple logo [...]’ (37F; Sales & Marketing; Europe)

Becoming more selective about who joins a platform side is a common trait of platforms as they mature (Gawer, 2020). While automated labelling results in an algorithmically constructed hierarchy of workers based on data collected on the platform, manual labelling affords new workers, especially professionals with in-demand expertise, a path towards market entry:

'[A] manager from Upwork chatted with me [about] the expert-vetted label. I [told] her: 'This is very strange because I really don't use the platform, I just have a profile. I don't have any clients.' [...] But she told me that it doesn't matter because they saw my portfolio and want to discuss [becoming expert-vetted].' (13U; Creative & Multimedia; Europe)

Information is verified either based on past output or worker interviews conducted by a representative of the platform firm:

'Basically, it gets down to having a proven way to demonstrate that you know what you are doing. That includes referencing companies you worked for [and] providing some examples [of your work]. They're going to check that deeply.' (02F; Software Dev & Technology; Europe)

Workers are considered for such expert-vetting not only because of their portfolio but also in-demand expertise and serving premium clients (interview 02F), their past success on the platform (interviews 20U, 09U, and 27F), as well as social contacts outside the platform (interview 18F). Workers on *upwork.com* were unable to proactively apply for manual labelling. Fiverr allowed applications but awarded its 'pro-verified' status only by skill type as opposed to the entire worker profile. On both platforms, manual labelling was available for workers active in software development and technology as well as creative and multimedia. According to the Online Labour Index 2020, these are the two largest occupational categories comprising more than 60% of labour demand in 2022 (Stephany et al., 2021). Further, manual labelling was available for writing, translation, and digital marketing services on *fiverr.com*, and sales and marketing on *upwork.com*. In spring 2022, Fiverr estimated to have manually labelled 'tens of thousands of quality sellers' over six months.³³

³³ Quotation from online article 'Fiverr International Ltd. (FVRR) CEO Micha Kaufman on Q1 2022 Results – Earnings Call transcript' (Seeking Alpha, May 11, 2022)

Table 3. Overview of requirements for the award of quality labels by platform

Hierarchy Labelling	Upwork Requirements	Fiverr Requirements
General workforce	New workers or workers without relevant experience on and off the platform	
Promising talent Hybrid	<p>Rising Talent</p> <p><i>General factors:</i> Signs of prior experience, skills, and education</p> <p><i>Platform-specific factors:</i></p> <ul style="list-style-type: none"> ▪ Early positive demand for services (e.g., client feedback, successful bids) ▪ Professional behaviour (e.g., on-time delivery, submitted proposals to relevant projects) ▪ Adherence to norms (e.g., completed profile, no violations of terms of service) 	<p>Rising Talent:¹ Temporary and manually awarded label 'based on quality & potential' of a worker via information displayed on ('portfolio, profile, and services') and off ('digital presence', 'verified background and skills') the platform</p>
Platform experience levels Automated	<p>'Top Rated': Top 10-12% of workers</p> <ul style="list-style-type: none"> ▪ Compliance with platform rules (terms of service, profile completion, availability settings) ▪ Activity and experience (first project >3 months ago, \$1k annual earnings, client interactions in past 3 months) ▪ Quality (current Job Success Score $\geq 90\%$ or 'Rising Talent' badge and for 'at least 13 of the last 16 weeks') <p>'Top Rated Plus': Top 3% incl. long-term or high-value projects over last 12 months</p> <ul style="list-style-type: none"> ▪ High quality (Top Rated) ▪ High earnings (>10K\$) ▪ Large contract (5K–20K\$) 	<p>Three levels available: Level 1, Level 2 and Top Rated</p> <ul style="list-style-type: none"> ▪ Active for 60, 120 and 180 days ▪ Earnings are a minimum of \$400, \$2,000, or >\$20,000 ▪ Client feedback ≥ 4.7 (over past 60 days) ▪ Completed $\geq 10, 50, 100$ orders (all time) ▪ >90% scores for response, completion, and on-time delivery rates (over 60 days) ▪ No warnings received over 30 days ▪ Level 1 and 2 are awarded automatically while the award of and the demotion from top-rated status occur manually
Hand-vetted experts Manual	<p>Expert-Vetted: By invitation only and awarded to top 1% of workers who 'have gone through a thorough pre-screening process that evaluates technical expertise and soft skills.'</p>	<p>Pro-verified¹: Manual vetting process includes information on professional experience, educational background, work process, social network, and portfolio.</p>

Notes. (1) On fiverr.com, a 'rising talent' and 'pro-verified' labels are awarded to a specific service offering ('gig'). Strictly speaking, it does not refer to the entire worker. In practice, however, this distinction is not immediately clear to the employer which is why I included them in my analysis.

Quantitative evidence. Automated and manual labelling are widespread in my survey sample. At time t_0 , half of the Europe-based workers surveyed (53%) had a quality label attached to their profile (Table 2). About 18 months later, that number had risen to 60% of remaining workers. In other words, workers who stay active on the platform rise in the hierarchy of labour supply. On one platform, the prevalence of hand-vetted experts in the sample rose from 2 to 3%. I observed the same trend for platform-specific experience levels where the share of ‘top-rated’ and ‘experienced’ freelancers rose from 6 to 8% and 34 to 46%, respectively. The share of active workers without a label sank from 47 to 16%. Continued activity in digital marketplaces appears to go hand in hand with adherence to platform-defined standards of quality. Overall, the prevalence of quality labels in our sample should be interpreted as an upper bound. By excluding workers without prior platform experience, our sample of European freelancers is more privileged than the average worker. Entering a marketplace by attracting a first client is arguably the hardest step to launch a freelancing career (Pallais, 2014). Only an estimated 8.6% of registered users on online labour platforms have been hired at least once (Kässi et al., 2021). Hence, the range of workers who end up receiving a quality label is likely to be in the low double-digits with prevalence increasing to 50-60% only for active freelancers.³⁴

Platform labels matter for workers

Qualitative evidence. For workers, quality labelling matters for labour market success. Most (but not all) respondents concurred that quality labels changed their professional trajectory. Reduced employer uncertainty about their abilities led to better

³⁴ This has methodological implications for sizing online labour markets. Since criteria for badges are partially transparent, scraping curated worker profiles could be a means for estimating the number of workers with a sizeable income on these platforms.

and more work. A lawyer on Upwork, for example, suggested that being top-rated helps to instil confidence in clients:

'[Being top-rated is] something that's useful to me. [...] when I do interviews with clients, they're normally not asking: "Look, can you really do this?"' (07U; Professional Services; Europe)

One pro-verified seller on Fiverr stated that manual labelling identifies experts on the platform:

'On Fiverr, it wasn't transparent before [who was an expert] until the 'Pro' feature was introduced.' (12F; Creative & Multimedia; Europe)

It is unclear, whether heterogeneity in outcomes was due to actual differences in quality between those with and without a label, or the associated accumulation of status. Early adopters, for example, continue to reap the benefits of their early success also because their status is re-enforced through quality labels:

'In 2016, [...] I was the first [...] to offer that kind of [music-related] service. [...] I had no competitors. If I am being generous with myself, I am the pioneer of the service. [...] So] no, [I did not actively work towards being top-rated], it just accumulated.' (23F; Creative & Multimedia; Asia)

All in all, this evidence supports the view that employers rely on quality labels as signals to reduce their uncertainty about worker quality (Agrawal et al., 2016; Horton, 2017; Kässi & Lehdonvirta, 2022; Lehdonvirta et al., 2019). In line with signalling theory (Spence, 1973), most respondents were equally aware of the value and costs of retaining a quality label. One worker explained how he thinks through whether retaining a specific label is profitable:

'The value that [Upwork] give[s] after [a few months on the platform] decreases. The only reason I could think of why you would like to stay is [to] maintain \$10,000 revenue for the last 12 months, [so] that you can [keep] your Top-Rated Plus status. You

basically [...] pay them around \$1,000 a year for Top-Rated Plus, that's the cost [in fees].' (24U; Software Dev & Technology; Asia)

On top of the benefits of reduced employer uncertainty, workers are further incentivised with reduced platform fees, manual matching support by platform firms, some ability to remove client feedback, more control over service offerings, better customer service, and administrative benefits such as faster earnings withdrawal.

Quantitative evidence. Regression analysis of data on European online freelancers supports the view that employers take note of quality labels and rely on them for hiring decisions. Based on the signalling literature, I hypothesized that:

H1: Quality labels are positively associated with the probability of employment (E).

H2: Quality labels are positively associated with the level of economic activity (PA).

To test hypothesis H1, I estimated three binary logistic regression models to predict the probability of a freelancer being gainfully employed on the platform between t_0 and t_1 (Table 4).³⁵ To test hypothesis H2, based on the sub-sample for all workers with any registered economic activity between t_0 and t_1 ($n=332$), I fit three multiple regression models to predict the level of platform activity in the next year for all workers who were employed (Table 5). I produced my results in a stepwise fashion to control for the robustness of my results. The independent variables used for both regressions were *badge* (having been awarded a badge at t_0), *reviews* (the number of reviews at t_0) and *score* (the normalized job success score at t_0). Platform-specific controls included a dummy variable to account for platform-specific differences³⁶, as well as measures for platform experience, platform dependence (measured as a share of total income

³⁵ A correlation matrix is included in appendix A.3 (Table 9).

³⁶ In the collaboration agreement with one of the platforms, it was agreed that no platform-specific results would be shown. Hence, the dummy is simply named Platform A, signifying one of the two platforms.

earned on the platform), and the hourly wage on the platform. Further controls included gender, education, and age. Log-transformations account for non-linearity, as small shares of workers tend to capture a large share of the value in online markets.

Table 4. Logistic regression models to predict economic activity between t_0 and t_1

Independent variables	Model 1 Exp(β) (SE[β])	Model 2 Exp(β) (SE[β])	Model 3 Exp(β) (SE[β])
<i>Platform-mediated signals</i>			
Badge/certificate	3.367*** (0.270)	2.575*** (0.286)	2.705*** (0.289)
Number of reviews (ln)	1.612*** (0.110)	2.231*** (0.150)	2.301*** (0.154)
Success score	0.999 (0.005)	1.000 (0.005)	0.999 (0.005)
<i>Platform controls</i>			
Platform A dummy		3.777*** (0.339)	3.677*** (0.356)
Platform experience		0.886 (0.065)	0.854* (0.068)
Platform dependence		1.168 (0.268)	1.167 (0.273)
Hourly wage (ln)		0.743 (0.212)	0.672 (0.222)
<i>Socio-demographic controls</i>			
Male			1.762* (0.273)
University graduate			0.733 (0.284)
Age			1.033* (0.016)
Constant	0.412 (0.473)	0.923 (0.816)	0.787* (0.923)
Model Chi-squared	69.574*** (df=3)	86.544*** (df=7)	97.237*** (df=10)
Nagelkerke R ²	0.217	0.265	0.294
No. of observations	448	448	448

Note. ***: $p < .001$; **: $p < .01$; *: $p < .05$

I observe significant levels of positive association between quality levels and probability as well as scope of employment. The odds of being employed in the following year are 2.71 times higher for workers with a badge than for workers without a badge (Table 4). In comparison, increasing the number of reviews a worker had collected at t_0 by 1 percentage point raised the odds of a worker being employed in the following year by 0.8%.³⁷ Hence, the observed effect of a badge is comparable to increasing the number of reviews at t_0 almost by factor 3 (a 187.5% increase). The project success score was not significantly associated with being employed in the following year. It is worth noting that I do not claim any causal effects since my data did not allow for a necessary difference in differences econometric setup. Instead, I use these correlational results as additional data to support my qualitative findings for a larger group of workers.

The positive association between workers' success in online labour markets and being awarded a platform-constructed badge similarly holds for the level of workers' economic activity. A platform-generated badge on a worker's profile at t_0 is associated with 116 percent increase in platform activity.³⁸ In other words, having a badge was associated with workers more than doubling their activity on the platform over a one-year period (Table 5). In comparison, all other things equal, a one percent increase in reviews at t_0 , is associated with a 0.73% increase in platform activity over the following one-year period.

³⁷ A one percentage change in the log-transformed IV implies a $100 * (1.01^B - 1)$ percentage change in the likelihood of employment, with $B = 0.833$.

³⁸ Having a badge is associated with a $100 * (e^B - 1)$ percentage change in the dependent variable.

Table 5. Multiple regression models to predict level of economic activity (ln[PA])

Independent variables	Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)
<i>Platform-mediated signals</i>			
Badge/certificate	1.13*** (0.18)	0.76*** (0.16)	0.77*** (0.16)
Number of reviews (ln)	0.15* (0.06)	0.72*** (0.08)	0.73*** (0.08)
Success score	-0.01 (0.06)	-0.01* (0.00)	-0.01* (0.00)
<i>Platform controls</i>			
Platform A dummy		2.32*** (0.22)	2.30*** (0.23)
Platform experience (ln)		-0.19*** (0.04)	-0.21*** (0.04)
Platform dependence		0.40** (0.15)	0.40** (0.15)
Hourly wage (ln)		0.09 (0.12)	0.05 (0.12)
<i>Socio-demographic controls</i>			
Male			0.06 (0.15)
University graduate			-0.25 (0.16)
Age			0.02* (0.01)
Constant	-1.11* (0.45)	-4.23*** (0.56)	-4.41*** (0.59)
Model F	18.66*** (df=3)	29.8*** (df=7)	21.75*** (df=10)
Adjusted R ²	0.13	0.37	0.40
No. of observations	339	335	332

Note. ***: $p < .001$; **: $p < .01$; *: $p < .05$

While platform dependence is intuitively associated with an increase in activity, years of experience on the platform is negatively associated with activity. The result could be driven by the fact that more experienced freelancers tend to work longer, better paid

projects. As a result, they might complete fewer projects but at a higher value per project. Since the independent variables are correlated, after all badges are conditional on the job success score and number of reviews, I used variance inflation factors (VIF) to test for multicollinearity. VIF for all variables lie well below the threshold of VIF=10 generally considered acceptable (Cohen et al., 2013, chapter 10).

Qualifying online labour

Qualitative evidence. While signalling theory assumes that manual and automated labelling uncover intrinsic differences in workers' qualities, I find evidence that curation by platform firms also shapes said worker quality. On one hand, labelling rewards behaviour in alignment with platform interests and thus co-opts workers into adherence (Stark & Pais, 2020). Automated labelling, in particular, rests on mostly transparent, quantifiable metrics which are deemed desirable such as availability, on-time delivery, or maintaining an up-to-date profile. In response, workers explained that performance metrics underlying automated labelling changed their incentives and, consequently, their behaviour:

'[The metrics] affect me. I always think that there is a benchmark I need to keep up with. For example, my inbox response rates. [...] I'm just always on my inbox.' (25F; Writing & Translation; Asia)

'Yeah, [I took the English spelling tests] to complete my profile. It's nothing. I mean, it's so easy. It's just to make sure that the profile gets 100% completed which is one of the criteria for being a top-rated freelancer.' (45U; Writing & Translation; Asia)

This type of automated labelling of behaviour valued by platform firms may indeed be theorized as a form of algorithmic management (Rahman, 2021; Stark & Pais, 2020; Wood et al., 2019a).

However, my findings indicate that labelling is not only a tool to manage workers and change their behaviour, but also reflects choices by the platform firm about which qualities to reward and foreground at the hiring stage. By labelling, platform firms influence what qualities are valued, displayed on a profile, and ultimately made available to and used by employers in their decision making. In other words, platform firms partake in the qualification of workers, the process which establishes what qualities matter for an employer active in the marketplace. While quality labels are mediated by workers' intrinsic abilities and characteristics, I find evidence that what is considered a high-quality worker also depends on factors external to the worker.

First, what qualities are valued in the form of quality labels changes with temporary strategic platform interests. One female lawyer described how she 'levelled-up' in the hierarchy of labour supply without changing her behaviour at all:

'I didn't do anything [differently] to get 'Top Rated'. [...Previously] Upwork's algorithm didn't take into account [longer, ongoing projects. Upwork] was there for piece work only and [I did not get any feedback] because they didn't have the functionality. [As] soon as they changed the algorithm, I became 'Top Rated'.' (07U; Professional Services; Europe)

Instead of better performance, the platform firm changed what types of workers were valued, accounted for technologically, and thus highlighted as high quality to employers.

Second, worker qualification is shaped by data availability and measurement constraints. One expert-vetted freelancer described the limits of algorithmic qualification as follows:

'[Platforms] don't know how to judge talent [...]. They can only tell, using data [...] that a machine understands, [...] if you're efficient as a seller and if your buyers are satisfied. And if you take out the exit survey [and] public review, then there's not much left other

than: How quickly did I respond? How easy was it for the buyer to be converted when they landed on my gig?’ (20F; Creative & Multimedia; Europe)

As online freelancing comprises much knowledge work, it is unclear whether there is an actual link between being a good fit for a specific employer and measurable metrics like availability or on-time deliveries. In fact, some metrics such as a certain level of income earned on the platform over a given period might be a quality valued by the platform firm more than an indication of quality to future employers.

Third, while standardizing the measurement of certain qualities makes categorization and commensuration of workers via labels possible, it can have unintended consequences as such socially constructed and distinct boundaries are a strategic choice to discount individual context (Timmermans & Epstein, 2010). For example, even successful respondents shared stories about having been demoted, that is having lost a previously awarded label. Reasons ranged from intellectual property violations (Interview 20F) and failure to deliver services on-time (Interview 25F, 28F) to a lack of responsiveness due to being on holiday (interview 26F) or a series of cancelled projects (interview 27F). In all cases, workers acknowledged a failure to comply with some platform standard, but most criticized the limitations of a one-size-fits-all system unable to acknowledge circumstances outside their control like illness, spikes in demand, or client negligence which did not reflect their abilities as professionals.

Fourth, quality labels do not communicate their specific histories (Bowker & Star, 2000a). One worker, for example, described how the symbolic capital associated with quality labels allowed him to re-skill from being an administrative assistant to being a data scientist:

'Even when I changed my profile [from being an assistant], I maintained top-rated status on Upwork. [... Clients] still see me as top-rated, the feedback that I have got from other people, and [...] that helps them to trust me with my new [specialization].' (03U; Professional Services; Africa)

In this case, the worker would still appear as top-rated in employers' searches for a data scientist, even though labelling originally occurred for his data entry work. Altogether, the influence of platform interests and data availability, as well as the lack of context and transparency over the history of classification foreground how external factors rather than inherent abilities impact the award of quality labels. Automated labelling in particular highlights certain metrics, behaviours, and underlying qualities which are not only convenient for managing workers, but also shape what competencies matter when employers take hiring decisions on online labour platforms.

The constitutive character of quality labels becomes even more apparent in the process of manually labelling in-demand professionals. I find that platform firms effectively re-categorized the supply side of their marketplaces on a set of qualities that includes but is no longer limited to metrics of past behaviour on the platform. Those privileged enough to become manually labelled described it as a step change in terms of quality and quantity of employment:

'Fiverr Pro was a good opportunity to offer freelancing at a totally different level [... Rather than] outsourcing [...] used by small to medium businesses and maybe some [individuals, it] is something that offers enterprises enterprise-level services. [There was a] change in the way of how freelancing is perceived by the [...] clients.' (02F; Software Dev & Technology; Europe)

Manually labelled workers gained access to a new segment of enterprise clients. One designer re-lived his introduction to expert-vetted status as follows:

'[Fiverr Pro launched] at 10pm on a Tuesday. I sold a \$10,000 gig 48 hours later. With just a couple of messages. It was crazy because I was accustomed to a completely

different thing on Fiverr, anything over \$500 was laughed at [by clients].’ (20F; Creative & Multimedia, Europe)

Being expert-vetted not only provides access but the cultural and normative legitimation as professionals who may demand higher prices and serve clients of more status (V. A. R. Zelizer, 1979). At the same time, I did not find evidence that the quality of delivery of manually labelled respondents changed in response to having such a label attached to their profile:

‘Fiverr changed their algorithm at one point [...] and I saw a decrease in sales and traffic. [...] I remember thinking: “Something has got to change here!” [...] Pro Verification was a real saving grace for me [...] because now Fiverr is push[ing] my profile, I can charge way more, and [it had] a really great impact on my business, for sure.’ (27F; Marketing & Sales; North America)

In other words, good workers end up on either side of the boundaries drawn by platforms to distinguish groups of workers based on their abilities. One expert-vetted IT specialist explained how he routinely directs clients to other freelancers in his networks.

‘There are good [freelancers] outside the pro-categories, especially for clients [who] are having problems with [their] budget.’ (02F; Software Dev & Tech; Europe)

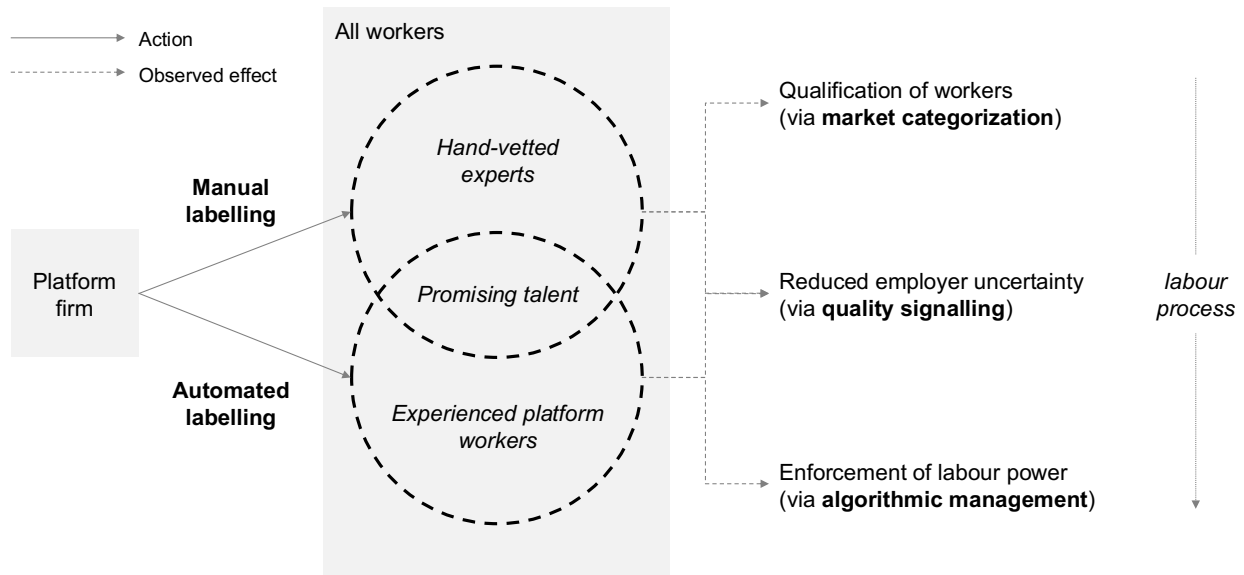
Workers made the point that manually labelling experts and the subsequent re-drawing of market categories on the supply side changed market dynamics by making platforms attractive to in-demand professionals as well as enterprise clients alike:

‘I [just] facilitated a project for [a large firm] via Fiverr. That means the agency involved actually thought Fiverr was a good idea. [...] It means [...] the ‘Pro’ feature is starting to pay off. People are considering Fiverr as a viable solution for top-tier product.’ (20F; Creative & Multimedia; Europe)

Overall, these findings can be summarized in a model of how platform firms label worker quality (Figure 10). While signalling theory and algorithmic management both

explain important aspects of the phenomenon, they fail to account for how platform firms categorize workers active in their marketplaces and thus qualify workers and their services already at the hiring stage.

Figure 10. Process-based overview of how labour platforms label worker quality

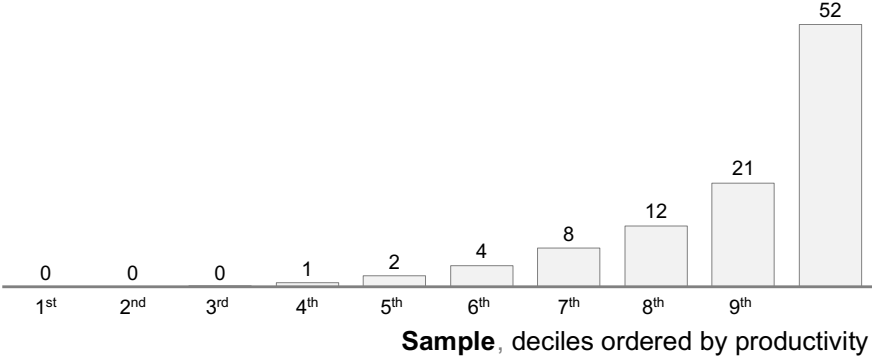


Winners and losers of platform-led qualification

Quantitative evidence. Acts of classification are always hierarchical and thus normative (Bowker & Star, 2000a). It is thus paramount to foreground them at times to question how they impact individuals' lives. My findings suggest that especially expert-vetting via manual labelling has serious implications for how value is distributed in online labour markets. Although platforms communicate expert-vetting as applicable only to the top 1% of talent, its impact on the distribution of market value is not to be underestimated. After all, digital markets follow winner-takes-all dynamics (Rosen, 1981). In our survey sample, a small share of workers accounted for most of the economic activity over the observed period (Figure 11). Less than three percent of all respondents (n=13) account for one quarter of observed economic activity. About nine

percent of all workers (n=41) added about half the economic value (Figure 11). In other words, even a small group of manually labelled experts may capture a large share of market value due to more frequent and higher value employment.

Figure 11. Share of economic activity by workers ordered by productivity for t1-t0



Note. Share of added value measured as *Platform Activity*, the annualized number of additional client reviews received, hours worked, or income earned in the period $t_0 - t_1$.

Qualitative evidence. As labelling evidently risks further stratification of workers, I conclude my findings section by discussing who wins or loses from curation. Most workers are not labelled by the platform, as they fail to attract even one project (Kässi et al., 2021). They might be new, have not managed to break into the market, or failed to play by the rules of the platform firm by not completing their profiles, offering services that are over-supplied, or using the platform only on occasion. If employers take notice of quality labels as suggested by the data, the task of breaking into digital marketplaces without being awarded a quality label becomes even more challenging. For example, some Upwork clients pre-specify that their projects are only open to workers with certain quality labels:

‘Clients post the job announcement, and you apply for the job. And most of the time, they require [you] to have a certain certification level.’ (46F; Creative & Multimedia; Europe)

Some workers are highlighted as 'rising talents' which offers visibility to some who not yet qualify for other labels but demonstrate potential, for example by offering in-demand services. Their label flows from a hybrid process that includes automated and manual elements. Becoming a rising talent is thus more unpredictable for workers:

'I don't know whether it was random. I really don't know. All of a sudden, [I was] sent an email saying: "You are a Rising Talent and we find great potential in your gig."' (15F; Creative & Multimedia; Australia)

'I created another profile for a friend of mine, and his directly went to [...] Rising Talent. I was really annoyed. I did both of [our] profiles, and I'm not [a] Rising Talent. I changed mine [in response], but it didn't matter. I didn't become a Rising Star [even though] his profile is almost the same as mine.' (04U; Professional Services; Asia)

Due to the perceived randomness, it is difficult to identify who might profit. There is some evidence that workers who abide by platform rules, for example by fully completing their profile, and offer in-demand services are afforded this form of temporary visibility.

Next, there are various levels of experiences such as 'Level 1', 'Level 2', 'Top Rated' on *fiverr.com* or 'Top Rated' and 'Top Rated Plus' on *upwork.com*. In contrast to other forms of algorithmic management like reputation scores, these labels require a degree of transparency. As activity on the platform is being rewarded, for example responsiveness or the generated financial output, labels benefit workers who spend more time on the marketplace and derive a higher share of their income from them:

'Upwork is not my main source of getting contracts. [Hence,] since I'm not using it that much, I do not have any of those budgets [necessary to receive a badge].' (10U; Content Writing; Africa)

This puts pressure on workers who originally joined for non-financial reasons such as flexible working hours:

'In my case, I have to answer quickly. But this month, I don't want to do any work here and don't answer many people. [...] But it is the only requirement that Fiverr is asking from me for Level 1 [...] Fiverr wants all my time. But I won't [accept] that. I [manage] my own time. [...] We have a life. Go outside. Enjoy life.' (26F; Statistics; South America)

While labels restricts worker agency for some, it has the potential to improve power relation with clients and the platform for workers who are more active:

'Fiverr would be always on the side of the client, but right now, they're more considerate of the sellers, as well. But maybe it is due to my level now.' (17F; Marketing & Sales; Asia)

Overall, automated labelling appears to benefit workers whose preferred user behaviour is in alignment with platform interests (Cansoy et al., 2020). These workers spend a considerable amount of time on the platform, earn regular income, and have gained some initial momentum.

Manual labelling establishes a new group of freelancers at the top of the worker hierarchy:

'[There's a] split in the marketplace [between expert-vetted workers and the rest] and the gap is increasing between the two categories.' (20F; Creative & Multimedia; Europe)

This new professional group comprises of experienced freelancers as well as skilled professionals who newly joined or were even specifically invited by the platform firm:

'There is this [...] professional group on Facebook where different [IT] experts [...] are invited [to]. There are many people that I know from real life. [...] One of them [has relations to the platform firm...] and he told everyone on this private group [about expert-vetting] and that he can help to make it happen. [...] Then, I just sent a message to this guy and said: 'Hi, I applied.' And after one week, I got approved.' (18F; Software Dev & Technology, Asia)

Manual expert-vetting enables those professionals to subvert the algorithmic hierarchy rooted in past platform success (chapter 3). Instead, they enter the marketplace as labelled and more visible experts. That is, workers successful in conventional labour markets can translate their status and social capital there into symbolic 'übercapital' (Fourcade & Healy, 2017, p. 10) online:

'Friends who own businesses [often] want to know how to make it on these platforms. [...] I hope to see Fiverr Pro continuing to open the door [these people].' (27F; Marketing & Sales; North America)

On the other side of the same coin, there are workers who do not receive an invitation to become manually vetted and will lose out because they end up on the wrong side of the boundary of this label. Irrespective of their position, most workers understood that any form of labelling by platform firms may be revoked or changed at any point in time:

'[Being pro-verified], I'm in a leveraged position which I understand and appreciate. [That said], I also understand that maybe I wake up tomorrow and the 'pro' badge is gone.' (20F; Marketing & Sales; Europe)

4.5 Discussion

My goal was to understand why labour platforms award quality labels to workers. From the literature review, I established that extant theoretical approaches conceptualize quality labels as means to either signalling intrinsic worker qualities to reduce employer uncertainty while hiring (Agrawal et al., 2016; Kässi & Lehdonvirta, 2022; Lehdonvirta et al., 2019; Pallais, 2014), or (algorithmically) managing worker behaviour remotely after contracting (Jarrahi & Sutherland, 2019; Kellogg et al., 2020; Rahman, 2021; Wood et al., 2019a). In contrast, my findings point towards a more fundamental effect of labelling by platform firms: the qualification of workers by means of market

categorization. Automated and manual labelling matter because they co-construct the competencies valued by employers during the hiring process. This explains why most workers mentioned positive effects from labelling on the scale and quality of their projects, something corroborated by my quantitative findings.

The social construction of worker quality

By now, it is well established that platform firms actively organize digital marketplaces (Ahrne et al., 2015; Aspers & Darr, 2022; Kirchner & Schüßler, 2019). Such organization relies on deciding on who may participate, the (partially algorithmic) rules of engagement, building an infrastructure to monitor and evaluate workers, the power to sanction, and the centralized decision-making power of platform firms (Gawer, 2020; Kirchner & Schüßler, 2019; Kornberger et al., 2017), including the ability to classify workers and their services (chapter 3). Along these lines, I argue that platform firms use quality labels to institutionalize market categories of workers that are in alignment with the motifs of their shareholders, that is increased profits and continuous growth (van Doorn & Chen, 2021). Labelling then is not only a means for platform firms to ‘orchestrate’ users and ensure *adequate* behaviour (Rietveld et al., 2021), but to shape the classifications of labour as part of the ‘decided’ social order of their marketplaces (Aspers & Darr, 2022, p. 824).

As a result, platform firms actively co-construct ‘what qualifies as [workers’] qualities’ (Aspers & Beckert, 2011, p. 14). They intermediate and intervene in the process of qualification between workers and prospective employers (Callon et al., 2002). They do so by orchestrating the process of recruitment which co-constructs the competencies by which employers evaluate prospective hires in the first place (Eymard-Duvernay & Marchal, 1997). Quality labels thus act as market devices which

make workers calculable and allow for commensuration, evaluation, and ultimately attachment by an employer (Aspers & Beckert, 2011; Callon et al., 2002, 2007). Extant theories fail to fully explain the phenomenon. Signalling theory cannot account for the constitutive character of platform curation. Theories of algorithmic management only explain the constitution of quality in the form of adapted behaviour in response to labelling after the contract has already been agreed to. It only concerns the management of workers rather than the hiring stage. In contrast, quality labels awarded by platform firms mediate the negotiation of workers' qualities by providing employers with a possible basis for decision making when evaluating workers and their services that are otherwise singular in nature (Karpik, 2010).

Theorizing labelling in this way helps us to uncover the social mechanism as to why quality labels impact workers' success in online labour markets. As comparisons between nation states and platform firms are common (Lehdonvirta, 2022; Parker, 2016, p. 158ff), occupational licensing offers a helpful frame for interpreting manual labelling. In 2020, 22.7 percent of all employed Americans held a license 'awarded by a government agency [conveying] a legal authority to work in an occupation' (U.S. Bureau of Labor Statistics, 2021). Just like labelling by platform firms, occupational licensing has distributional effects. In the US, it is associated with higher average wages at the individual (Kleiner & Krueger, 2013) and occupational level (Weeden, 2002), an effect mainly driven by reducing labour supply to those occupations. This supply-side mechanism is supplemented by increased demand, protection of monopoly access to service provision, and wage effects based on signalled quality (Weeden, 2002). A key debate remains whether licensing protects consumers by ensuring quality standards, or whether it only shields occupations such as doctors or lawyers from unwanted competition to seek material and symbolic gains (Kleiner,

2000). On labour platforms, this debate translates to whether quality labels convey new information to employers about inherent quality differences between workers, or instead propagate mere status effects to benefit certain social groups, similar to how educational degrees benefit middle- and upper-class children (Bourdieu, 1990) or the best-known researchers reap disproportionate rewards for their output (Merton, 1968).

My findings suggest that the social mechanism of how labelling impacts individual labour market outcomes is neither fully explained by quality nor status effects. At the hiring stage, rather than being mere signals of a worker's inherent ability (Lehdonvirta et al., 2019), labelling actively shapes what qualities are valued by employers. In this view, workers' qualities are the 'output of complex operations of qualification, of framing and reframing, of attachment and detachment' (Muniesa et al., 2007). As market devices, quality labels relate to different hiring conventions and thus co-construct competencies. For example, the move from automated labelling to a manual process also implies a shift away from hiring based on 'market dynamics', the selection of workers from a large pool of applicants based on price and platform-specific metrics. Employers who rely on manually awarded labels instead prioritize 'formal institutions', in form of certification by platforms firm as a trusted source of information, and 'interactions' as part of the co-construction of qualities via worker interviews in their hiring decisions (Eymard-Duvernay & Marchal, 1997). Workers' inherent levels of ability still matter as quality is not a socially construct but rather the outcome of social negotiation of intrinsic and extrinsic characteristics in a given context (Beckert & Musselin, 2013; Bourdieu, 1990). As new 'reference points' for employers and workers alike (Esposito & Stark, 2019), I found that (especially manually) labelled workers were able to charge more and experienced higher levels of trust by employers. Clearly, quality labels come with role expectations (Zuckerman, 1999). For example,

automated labelling rewards workers who are available and responsive 'on-demand' without much respect for differences in time zones or individual holidays. As a result, it has become a quality of successful online freelancers. In comparison, it might be more acceptable to not answer an email over the weekend or after hours in organizational work settings.

How qualification impacts workers

Automated and manual labelling are means of classifying workers based on their experience on and off the platform, which translate into differences in market outcomes (Fourcade & Healy, 2013). Like any classification system, platform curation highlights certain qualities over others (Bowker & Star, 2000a). By having the power to shape the categories which define a worker of high quality, platform firms construct not an 'average man' (Desrosières, 1998, p. 10) but the average worker. As platform work is characterized by heterogeneity (Cansoy et al., 2020), it is worth expanding on how various classes of workers are impacted by quality labelling (chapter 3). Just like occupational licensing institutionalizes professional boundaries (Abbott, 1988; Habinek & Haveman, 2019), quality labels are a way of institutionalizing different worker categories. As employers only need a set number of workers and competition in online labour markets is fierce, workers who were 'effectively excluded' (chapter 3) from a marketplace before will find it even harder to compete once quality labels are introduced. Their exclusion is implicitly sanctioned by their lack of quality labels. Similarly, worker who broke into the market but largely compete based on price will be negatively affected. On the one hand, these workers feel the most pressure to comply with metrics that approximate certain qualities and may lead to the award of a (new) quality label (Power, 2004) as automated labelling offers one of the few feasible chance for upwards mobility in the platform hierarchy. On the other hand, manual labelling is

likely to propagate status effects to the detriment of these ‘global competitors’ (chapter 3). As platform firms manually screen applicants, social differences and status beyond the platform, for example workers’ private networks, prestigious educational qualifications, or professional experiences, translate into symbolic capital on the digital marketplace. As a result, the ‘specific cultural and social practises’ (Demirel et al., 2020) of many global competitors, especially those situated outside the specific geography or social context of the workforce of the platform firm in charge, might be indirectly disadvantaged.

Like the state, platform firms thus act as gatekeepers to profitable categories such as being ‘pro-verified’ on *fiverr.com* or ‘hand-vetted’ on *upwork.com*. Theorizing quality labelling as qualification thus sheds light on the platform-mediated ‘institutionalization of expertise’ (Abbott, 1988) in a subset of professionals active on online labour platforms. In a way, we see what I call the *professionalization of online freelancing*. By professionalization of online freelancing, I mean the strategic decision of platform firms to alter the platform infrastructure to lock-in and newly integrate professionals with attractive skills and experience bundles (Stephany, 2021) to make online labour markets attractive for high value enterprise clients. The introduction of manually awarded quality labels therefore serves the purpose of maximizing a platform firm’s value extraction. In other words, hand-vetting talent resembles a re-categorization of labour supply (Beckert & Musselin, 2013) and a change to the order of online labour markets. Alas, some previously successful workers might end up on the wrong side of this categorical boundary (Piezunka et al., 2018). For example, interviews suggest that certain types of clients categorically only consider (or even get access to) the services of expert-vetted freelancers. Highly successful ‘platform superstars’ (chapter 3) who previously relied on their significant track record and automated labels now need to

struggle to receive a manually attached quality label to keep their competitive advantage. Even worse, they also might need to fend off new professionals who are suddenly able to enter the marketplace as their competitors. Evidently, heterogeneity in the platform economy does not only extend to its workforce and differences between platforms, but intra-platform developments over time (Schor, 2020). While manually labelled workers are well aware of the persistence of a level of subordination to the platform (Wood & Lehdonvirta, 2021), their relationship with these firms and clients nevertheless changes. For example, they report more access to representatives of the platform firm, more frequent points of interactions such as digital on-boarding sessions or informal opportunities for input, and additional leverage during dispute settlements. Only time will tell whether this new professional class of freelancers will amass enough significance to constrain the power of platform firms (Lehdonvirta, 2022), or at least become institutionalized as an occupational category (Thévenot, 1984) and active social group beyond the platform.

Beyond these economic impacts, quality labels matter for worker autonomy. The potential of alternative credentials to increase workers' autonomy is currently limited by the lack of portability to and recognition in other contexts (Hesse et al., 2022). Only 14% of survey respondents from the two platforms agreed or strongly agreed with the statement that they 'could easily switch to another platform without negatively impacting [their] income.' On the contrary, 64% disagreed or strongly disagreed with the statement which hints at so-called lock-in effects. Reputation portability is difficult because of a lack of economic incentives for platforms, the fluid nature of alternative credentials, technological hurdles of standardization, and concerns over data protection (Cedefop, 2020). These are only exacerbated by the finding that quality labels are market devices that co-construct workers' competencies in alignment with

context-specific business needs. Reputation portability then is not only a problem of numeric standardization but requires transparency on the context, history, and politics of platform-specific labels. Otherwise, portability of credentials constructed for the context of a specific platform risks so-called 'off-label use' as observed with credit scores (Rona-Tas, 2017). In the worst case, workers who are not labelled as being of high quality or are even demoted over time face what Rona-Tas calls 'error propagation' and 'enhanced performativity' rather than increased autonomy (Rona-Tas, 2017, p. 56). Thus, platforms are at times likened to laboratories for skill-based professional development (Cedefop, 2020; Stephany, 2021) in the sense that 'alternative credentials' (Kato et al., 2020) like micro-credentials (Kässi & Lehdonvirta, 2022), micro-internships (Cedefop, 2020), and platform-constructed quality labels are tested for application in the wider economy. For education policy we learn that the construction of quality labels is political as some qualities are always highlighted over others, there are multiple approaches to make a quality calculable, and workers react to the new incentives created by these market devices (Callon & Muniesa, 2005). My findings therefore underline the importance to involve multiple stakeholders when defining standards for micro-credentials, for example in the European Union (Commission, 2020), to make sure that as many of these politics are heard.

Limitations and future research

To my knowledge, this study is one of the first to empirically consider quality labels on labour platforms. Given its exploratory nature, future research should address its limitations. First, the generalizability of findings from the quantitative analysis might be limited due to partial reliance on non-random sampling (Lehdonvirta et al., 2021) and its focus on European workers with at least one completed project (Margaryan et al., 2022). Future studies should employ a more rigorous econometric design to test

whether manual and automated labelling differ in their impact on workers' trajectories, specify this impact (e.g., value and frequency of projects), and collect data from non-European contexts.

Second, while my methodological approach foregrounded workers' experiences, further research is needed on how clients incorporate labels into their decision-making processes (Barach & Horton, 2021; Rivera, 2020). For example, employers have been shown to rely on platform recommendations primarily during the screening stage of hiring to limit their dependence on external expertise (Barach et al., 2019). Research on platform firms and the organizational processes of user qualification and categorization is similarly scarce (Gawer, 2020; Kelkar, 2018).

Lastly, it could be fruitful to explore whether the professionalization of platform work through manual labelling transfers to other contexts such as locationally bound services or microwork. Such categorization of labour supply not only affects people's chances of being hired and the types of work they are eligible for on the platform but also their economic and social standing in society (Bureau & Marchal, 2009).

5. Completing the loop: How workers co-construct digital markets

Abstract

Millions of workers offer remote services via digital platforms. However, they are perpetually classified by the firms who organize such marketplaces. In this chapter, I study how centralized classification systems feature in workers' everyday practices. In the literature, workers' informal practices are largely conceptualized as reactions to a platform infrastructure imposed on them. Instead, I argue that workers are also complicit in co-constructing it. By reference to the experiences of workers across two online freelancing platforms, I foreground how classifications encoded into platform interfaces are necessarily incomplete. In fact, I argue that workers complete a classificatory loop across three stages: data entry, enacting boundaries with employers, and their wider application. Reflecting on these empirical results, I theorize informal categorical practices as *categorical work*, another form of so-called market work. It is needed to construct, maintain, and shape classification systems of labour that enable and order digital marketplaces.

5.1 Introduction

Workers who offer services such as logo design or software development remotely via labour platforms are perpetually classified by private platform providers. Examples of such digital boundaries are plentiful. Platform firms construct ‘virtual borders’ to regulate who gets access to their marketplaces (Gawer, 2020; Lehdonvirta, 2022, p. 89). They predefine which services workers are contractually allowed to provide and standardize what types of information may be displayed on an individual’s profile (Schörpf et al., 2017). To make the actions of singular workers commensurable for employers, they classify actions that are collected as data and then aggregated, for example as reputation scores (Kornberger et al., 2017; Lehdonvirta et al., 2019; Rahman, 2021). The subsequent ‘classification situations’, a term originally used to describe the class-like positions assigned to individuals by scoring agencies in credit markets, impact workers’ ‘life-chances and social identities’ (Fourcade & Healy, 2013, p. 560). As platform firms classify workers, they are responsible for some of the observed heterogeneity in these workers’ market outcomes (chapter 3). At the hiring stage, for instance, attaching quality labels to workers’ profiles not merely signals but actively shapes the qualities evaluated by employers (chapter 4). Despite the apparent consequential and pervasive nature of digital boundaries, little is known about whether workers are at odds with them, how they respond to being classified online (Cansoy et al., 2020; Fourcade & Healy, 2017), or interact with the broader, centralized infrastructure in their daily practice. In this chapter, I thus investigate the informal categorical practices employed by remote knowledge workers.

In the literature, it is possible to identify two approaches to conceptualize such informal practices. Both approaches share the implicit assumption that workers react to classification systems that are constructed and imposed on them by platform firms. To

simplify, I propose that informal categorical practices are theorized as either *economic optimization within* or *resistance against* a given digital infrastructure. The first lens ('economic optimization') highlights how informal categorical practices are part of workers' efforts to maximize rewards in platform-mediated workspaces. For example, workers break down their professional persona to categorize and market individual skills to make themselves amenable to digital marketplaces (Blyth et al., 2022). At least in theory, online freelancers enjoy considerable flexibility over scheduling, location, type of services offered, and to whom (Lehdonvirta, 2018; Vallas & Schor, 2020). In practice, however, platform workers are also constrained by the way employment relations in online freelancing are structured (Wood & Lehdonvirta, 2021). The second approach ('resistance') puts more emphasis on these constraints and makes sense of worker agency as the outcome of resistance against platform-based control. Informal categorical practices like workers disguising their true geography to avoid employer discrimination (Anwar & Graham, 2020) are explained as workers' reactions against being classified. In other words, workers' levels of autonomy depend on their ability to manage, resist, and subvert forms of platform-based control (Jarrahi & Sutherland, 2019; Rahman, 2021; Wood et al., 2019a).

Both alternatives ultimately theorize workers' informal categorical practices as reactive behaviour to the platform-mediated structures imposed on them. However, in the gig economy, platforms take a dual role of workplace and marketplace.³⁹ As both theoretical lenses focus on platforms as workplaces, they alas fail to appreciate how individuals may also contribute to the construction and maintenance of platforms as marketplaces. On the one hand, classifications are generally considered fundamental

³⁹ I would like to acknowledge that I first heard this helpful distinction being made by Dr. Greetje Corporaal (University of Oxford) in a discussion at the Platform Economy Seminar Series at the Oxford Internet Institute. See also Aspens and Darr (2022).

social institutions for constructing and ordering marketplaces (Beckert & Musselin, 2013; Fligstein, 2002). On the other, the informal practices of market participants have been shown to be a basic component of the socio-technical infrastructure of online marketplaces (Aspers & Darr, 2022). For example, workers re-embed commodified, on-demand employment relations into more complex social relationships to transcend an otherwise commodified relationship with employers (Alacovska et al., 2022).

Therefore, this chapter more generally asks how centralized classification systems feature in workers' everyday practices. Thereby, its scope goes beyond workers' mere reactions to such systems. I also examine how, if at all, workers' informal categorical practices co-construct online markets. Methodologically, I base my argument on the analysis of 28 primary, in-depth interviews and 41 secondary interview transcripts with workers active across two global online freelancing platforms. Both platforms intermediate supply and demand for remote, per-project knowledge work including a range of services from voiceovers to social media marketing, or web programming.

I argue that workers not only react to but are also complicit in co-constructing and enacting the categories and classifications which serve as social institutions essential to digital markets. My argument is based on two sets of empirical observations. To begin with, I find that when platform firms construct and encode categories of labour, the resultant boundaries are characterized by incompleteness. While all centralized and standardized classification systems necessarily leave room for interpretation in local contexts or applications (Bowker & Star, 2000a; Desrosières et al., 1983; Diaz-Bone, 2017), this incompleteness takes a decidedly circular form in online markets. In digital settings, the speed of the feedback loop between centrally constructed categories and workers' active data entry and their recorded online behaviour is increased. Some classificatory tools are automated and workers more generally

receive immediate feedback if and how their own categorical practices impact success online. In addition, the multiplicity of classificatory tools leads to the co-existence of partially contradictory hierarchies of worth (Stark, 2011). This fact leads to evaluative frictions which may give rise to further avenues for worker agency. In other words, I propose that we should conceptualize workers' informal categorical practices not as reactions in a linear chain of cause-and-effect, but as an integral part of a *classificatory loop*. As a direct implication, I thus foreground that workers' informal categorical practices are needed to complete this loop. First, workers co-construct the categories and classifications of labour by providing the necessary data (Doorn & Badger, 2020). Second, they enact the resultant boundaries in local and specific interactions with clients, something I liken to what is known as the *last mile delivery* (Bowker & Star, 2000a). Last, workers are complicit in participating in the classification of online labour, for example when they themselves classify platforms and clients, or adapt their behaviour to the institutional landscape of a given platform.

In light of this evidence, I repurpose Bowker and Star's concept of 'categorical work' (Bowker & Star, 2000a, pp. 310–311) to make sense of this form of worker agency. Originally, Bowker and Star used the term to conceptualize activities that manage differences in meanings within classification infrastructures. Such differences often stem from the idiosyncrasies of each distinct community that collaborate via such systems. To illustrate what they mean by categorical work, Bowker and Star give the example of the International Classification of Diseases and the case of abortion. While user A considers abortion a simple medical intervention, user B views it as illegal. User C who uses data from both communities might have difficulty interpreting differences in numbers of abortions reported without accounting for these invisible work practices hidden within the numbers.

Given my findings, I present the case that we should expand this narrow definition of what constitutes categorical work to span all activities along the ‘statistical chain’ (Desrosières et al., 1983, p. 79; Desrosières & Thévenot, 2002). Desrosières and Thévenot introduce this concept to emphasize how categories and classifications are social institutions that can never be fully imposed from the top. Instead, boundaries are re-interpreted by each actor and their individual politics along the chain of activities necessary to make categories work in practice (Boltanski & Thévenot, 1983; Diaz-Bone, 2017). In online labour markets, the platform firm constructs categories and encodes them into digital interfaces as so-called ‘investments in forms’ that order these markets (Bowker et al., 2019; Kirchner & Schüßler, 2019; Thévenot, 1984, p. 1). The subsequent collection and supply of data, the reconciliation of limits of socially constructed categories experienced by users, as well as their interpretation and application to concrete situations involves platform firms’ employees, workers, and employers alike.

I therefore suggest that categorical work is an underappreciated form of ‘marketization’ (Çalışkan & Callon, 2010, p. 2) or ‘market work’ in general (Aspers & Darr, 2022; Cochoy & Dubuisson-Quellier, 2013, p. 4; Garcia-Parpet, 2008) required to construct and sustain such economic structures online.

5.2 Literature review

In the platform economy literature, it is possible to pinpoint two ways of theorizing workers’ informal categorical practices. In both accounts, these practices are subsumed under the concept of worker agency and conceptualized in reaction to the structures of a platform-mediated workplace. In the following and at the risk of oversimplification, I summarize these accounts as theorizing worker agency as either

economic optimization within ('optimization') or *resistance against* ('resistance') the digital infrastructure imposed on them by platform firms.

Informal practices as reactions to the platform-mediated workplace

In the *optimization* literature, informal categorical practices are theorized as unpaid work that online freelancers engage in to improve their economic output within the socio-technical infrastructure of a given platform. Example activities include the identification of skills or services advertised in an environment that commodifies the labour process (Blyth et al., 2022; Wood et al., 2019b), classifying clients on limited information available to mitigate transaction risks (Anwar & Graham, 2020; Sutherland et al., 2020), and the re-categorization of the commodified worker-client relationship through building repeat relationships with employers (Alacovska et al., 2022). The focus of the *optimization* lens lies on how the employment relationship between workers and clients has changed as platforms expand workers' reach beyond the local economy and provide access to a larger pool of clients (Wood & Lehdonvirta, 2021). As one result of these developments, many online freelancers view themselves as self-employed. In a survey with Europe-based workers on *upwork.com* and *fiverr.com*, three out of four respondents agreed or strongly agreed to the statement 'I see myself as a freelancer' (chapter 4). In contrast to 'misclassified "independent contractors"' in location-based gig work like food delivery or ride-hailing (Howcroft & Bergvall-Kåreborn, 2019, p. 28), online freelancers do enjoy considerable autonomy when it comes to deciding on which platform to work for, what services to offer and at what prices, and their overall working conditions. While the extent of such agency depends on individual circumstances (Schor et al., 2020), they do on average score highly across important dimensions of autonomy (Pichault & McKeown, 2019). A worker's

ability to optimize economic success depends on her command of a set of literacies specific to gig work such as building a reputation, personal brand, client relationships, safety precautions against transaction risks, and productive work environments (Cedefop, 2020; Sutherland et al., 2020). In this reading, informal categorical practices are theorized as a means to maximize economic returns by managing one's digital persona, creatively taking advantage of platform affordances, and the self-motivated development and expansion of skills and services offered (Ashford et al., 2018; Blyth et al., 2022).

The second theoretical approach puts more emphasis on workers' *resistance* against digital infrastructure. In online freelancing, worker agency is constrained by the competitiveness of global labour markets (Graham & Anwar, 2019), systems of algorithmic control (Wood et al., 2019a), and the limitation of workers' voices and inputs to functional rather than platform-wide systemic issues such as fees (Gegenhuber et al., 2020). Wood and colleagues (2019a, p. 56), for example, juxtapose how algorithmic control in theory allows for more flexibility with its *de facto* results: poor quality of work especially for those who lack platform-specific reputation and face

'low pay, social isolation, [...] unsocial and irregular hours, overwork, sleep deprivation and exhaustion.'

The triangular employment relations of workers with the platform firm and clients is therefore characterized by subordination as well as agency (Wood & Lehdonvirta, 2021). The authors propose that the experience of self-employment towards clients is constrained by workers' subordination to platform firms who centralize power to organize their digital marketplaces (Kirchner & Schüßler, 2019), including the classification of workers and their services (chapter 3). According to the *resistance* literature, workers realize their agency by evading or resisting platform subordination.

Informal categorical practices are theorized as means to either escape or challenge the symbolic boundaries constructed by platform firms. Evasion rests on the assumption that platform-based control is never all encompassing. The classification of workers, for example via quality labels such as being ‘top-rated’ (chapter 4), is helpful in observing a judgment on a worker’s quality but not necessarily the activities that justify this categorization. Such information asymmetries are used by workers to resist platform control and to realize better market outcomes (Cameron & Rahman, 2021). In fact, many practices engaged in by remote workers remain hidden from employers and the platform, including the social and local networks which enable online freelancing for many workers, particularly in the Global South (Anwar & Graham, 2020; Wood et al., 2019b).

Resistance implies a more active role for workers. In this view, informal categorical practices are one of several ways to ‘appropriate’ algorithms (Jarrahi & Sutherland, 2019, p. 578 & 585). Workers are not mere recipients of ‘different automated features of the [...] platform’ but actively ‘make sense of’ them and learn how to work with or at times against them. For example, workers can bring about ‘fissures in algorithmic power’, defined as instances when algorithms no longer have their desired effect, by means of ‘manipulation, subversion, and disruption’ (Ferrari & Graham, 2021, p. 815). In the remote gig economy, respective informal practices include the evasion of geographical categorization by ‘buy[ing] highly rated pre-approved accounts with locations set for the [EU] and the [US]’ (Anwar & Graham, 2020, p. 1279), raising prices to reduce project requests in busy periods, or the formation of an internet-based community to establish normative guidelines for researchers using online labour markets (Salehi et al., 2015). Although workers are confronted with an ‘evaluative infrastructure’ whose conventions and workings are intentionally left opaque by

platform firms (Diaz-Bone, 2017; Kornberger et al., 2017, p. 80), they nevertheless react to being classified, hierarchically ordered, and evaluated. While some retreat from platform work, others experiment to subvert the opaque evaluations constructed by platform firms (Rahman, 2021).

Informal categorical practices as ‘marketization’

Both of these accounts fail to acknowledge an important dimension of workers’ informal categorical practices. The above views implicitly share the assumption that workers’ informal categorical practices are best theorized as *reactivity* (Espeland & Sauder, 2007) to a platform-mediated workplace. After all, there is a history of individuals and social groups who actively interpret social classifications (Boltanski & Thévenot, 1983). ‘Classification struggles’ that aim to take advantage of and even shape symbolic as well as social boundaries are indeed ‘a forgotten dimension of class struggle’ (Bourdieu, 1984/2010, p. 486). Theories of ‘optimization’ and ‘resistance’ thus surely explain an important element of informal practices in platform work. However, online labour platforms are not only workplaces but also marketplaces (Aspers & Darr, 2022). From economic sociology, we know that the construction of any market requires work and agency, so called ‘marketization’ (Çalışkan & Callon, 2010, p. 22):

‘For markets to emerge involves various framings (framing of goods, of agencies and of encounters), price-setting mechanisms, as well as issues of their design and implementation.’

Alas, both previously introduced theorizations fail to account for the potential role of workers’ informal categorical practices in such marketization. In other words, they do not discuss how, if at all, informal categorical practices contribute to the ‘social infrastructure’ that enables and sustains remote exchange (Aspers & Darr, 2022, p. 823), or acknowledge the necessary performative actions of stakeholders to enact

these economic structures (Callon, 1998a; MacKenzie, 2006). We already know that the social order of digital marketplaces is co-constructed, maintained, and challenged by the interdependent practices of their users (Aspers & Darr, 2022). In online freelancing platforms, examples of such activities include workers' struggles to reign in reputation insecurity, for example via unpaid labour (Wood & Lehdonvirta, 2022) or their relational work directed at clients and other workers to improve platform work or make it work at all (Alacovska et al., 2022; Tubaro, 2021; Wood et al., 2019b).

In this chapter, I thus adopt a standpoint rooted in economic sociology. I view categories and classifications as essential social institutions (Bowker & Star, 2000a; Douglas, 1986) for the construction and ordering of markets (Beckert & Musselin, 2013; Fligstein, 2002). In online labour markets, on the one hand, such platform infrastructure includes centralized classifications of labour resulting from a mix of manual, expert-based categorization, for instance via quality labels (chapter 4), and 'new formal and decontextualized techniques of data ordering' via algorithm-based technologies (Alaimo & Kallinikos, 2021, p. 1403). On the other, it is known that classification systems only succeed in enabling collaboration across communities with different practices and contexts through the informal work of its users (Bowker & Star, 2000a). As classification systems hide the invisible work that sustains, supports or subverts them (Bowker & Star, 2000a; Diaz-Bone, 2017; Star & Strauss, 1999), I set out to make this work visible by answering two research questions:

How do centralized classification systems of labour feature in workers' everyday work practices?

How, if at all, do workers' informal categorical practices co-construct online markets?

Thereby, I point my attention to the dual role of workers co-constructing and challenging the boundaries codified in the digital infrastructure of platform work.

5.3 Methods

To answer the above research questions, my study included a total of 69 synchronous, in-depth interviews with workers active across two leading online freelancing platforms, *upwork.com* and *fiverr.com*. Of these, I conducted 28 interviews specifically in the context of my project on categorization in online labour markets. The other 41 interview transcripts were the output of a broader research project on skill matching and development in the remote gig economy (Cedefop, 2020).⁴⁰

Since my research questions concern workers' everyday practices and their interactions with digital, symbolic boundaries, interviews provide a reasonable gateway to arrive at a theoretically insightful answer. As a method, interviews afford not only the identification of practices but can also facilitate data collection on a symbolic dimension such as 'classification systems [and] boundary work' (Lamont & Swidler, 2014, p. 157). Since my participants all earn money remotely over the internet, they were proficient in using software such as Skype, Zoom, or WhatsApp, and even considered it the most natural way to reach out to them (Cedefop, 2020). Digital interviewing also had the advantage that the final data set does justice to the global and distributed nature of online freelancing (Braesemann et al., 2022). All participants were remunerated as a token of appreciation of their time and effort. Such payments are custom in research on remote knowledge work (e.g., Rahman, 2021; Wood & Lehdonvirta, 2022).

Online freelancing platforms make for an insightful research site to study informal categorical practices in platform work. In comparison to platforms that facilitate the completion of microtasks such as data labelling or locational platform work such as ride-hailing, freelancing platforms afford an overall larger degree of autonomy to their

⁴⁰ A special thanks to Dr Laura Larke and Dr Siân Brooke who conducted these 41 interviews and gave me permission to use the transcripts as part of my research.

users (Howcroft & Bergvall-Kåreborn, 2019; Kuhn & Maleki, 2017). Although certain choices are constrained by the evaluative infrastructure of the platforms and the looming threat of sanctions, workers are on paper free to decide what services they offer, how much they charge per hour or project, what clients and projects they accept, and when they work. Since remote knowledge work can be complex, *upwork.com* and *fiverr.com* allow workers and clients to go beyond text-based communication once a contract has been formalized. Consequently, workers' informal categorical practices can be discussed in the context of their interactions with the platform interface as well as directly with other market participants, most notably their clients. While human labour that underlies artificial intelligence applications, including categorical work, is often made strategically invisible (Newlands, 2021), online freelancers and their interaction with AI-based (classificatory) technologies remain firmly in sight. My sampling frame was therefore online freelancing.

In practice, I limited data collection to two leading labour platforms, *upwork.com* and *fiverr.com*. Both platforms are sufficiently similar. They specialize in global, remote knowledge work and are predominantly used in English. They are market leaders in online freelancing with more than a decade experience.⁴¹ Both companies earn most revenue from fees charged for transactions, but also make money from subscription services as well as specific services such as purchasing platform-specific currencies (e.g., to be able to bid on more projects or promote their services). At the same time, their categorizations of what constitutes online labour offer some variation. On *fiverr.com*, workers create and promote pre-specified 'gigs', that is employers browse millions of services to pick from. On *upwork.com*, most projects are specified by the

⁴¹ Upwork is the result of a merger of two leading platforms at the time, *odesk.com* (2004) and *elance.com* (1998), completed in 2015. Fiverr was founded in 2010.

employers and workers can apply to be hired.⁴² As a result, data collection across these two platforms adds additional validity as theoretical generalization are at a minimum applicable across both observed cases (Yin, 2013).

Phase 1: Identifying the labour process and workers' informal skill set

I approached my research question in two phases. First, I familiarized myself with the labour process of remote gig work and the skills and informal practices necessary to be successful in such markets (n=41). Only thereafter, in a second phase, I built on this knowledge to make visible specific categorical practices and interactions with the centralized classification infrastructure (n=28). I opted for such an approach because categories, classification systems, and the practices that sustain them are elusive objects of investigation. They tend to move to the background and interaction with them often happen without much reflection (Bowker & Star, 2000a). As a researcher, I thus had to start at a certain level of familiarity with remote gig work to be able to produce a sufficiently detailed interview guide and subsequently conduct in-depth interviews to make freelancers' 'invisible work' (Star & Strauss, 1999, p. 9) visible.

The first phase thus included 41 transcripts of interviews with online freelancers on *upwork.com* (n=24) and *fiverr.com* (n=17). Interviews were conducted by two research assistants as part of a more general research project on skill development and matching in online freelancing funded by the European Centre for the Development of

⁴² In recent years, both platforms show signs of convergence. Upwork, for example, introduced a so-called 'Project Catalog' that resembles Fiverr's services-as-a-product approach. Similarly, most interviewees reported that more complex projects tend to be negotiated on a per-project basis. They are tailor-made for each client irrespective of the structure favored by the platform.

Vocational Training (Cedefop, 2020).⁴³ Interviewed workers were all based in one of six European countries (Finland, Germany, Italy, Romania, Spain, and the United Kingdom). The interviews covered the skills and informal practices necessary to succeed in online freelancing, and the workers' perspective on skills matching in online labour markets. The average length of each digital interview was about 48 minutes. Workers were contacted via private message over *linkedin.com* or the respective labour platform, either by posting a job for interviews or inviting participants directly to a hidden project (Cedefop, 2020).

The main output of this phase was a detailed question guide for the in-depth interviews in the second phase of research (Table 7). The interview guide followed a generalized labour process across both platforms from signing-up to creating a profile, searching for or advertising work, matching with clients, providing services, and finally completing projects. At the same time, I coded each transcript to identify a first set of informal categorical practices and interactions with the centralized classification infrastructure, as identified in chapter 3. Overall, this first phase was important to establish a level of familiarity with remote gig work. After all, using structured interviews for theory building requires sufficient knowledge on a phenomenon while still being unable to foresee the answers (McIntosh & Morse, 2015).

Phase 2: Studying workers' informal categorical practices

Based on this first phase, I then conducted 28 further in-depth interviews with remote knowledge workers. The data collection period extended from the end of 2020 to 2022 and thus overlapped with the global Covid-19 pandemic. While the influx of new

⁴³ The author of this chapter was also a research assistant of the project but collected the survey responses used for chapter 1, chapter 4, and chapter 6.

workers who looked to supplement their income and a temporary decline in demand made online freelancing more competitive in the short term (Stephany et al., 2020), the pandemic is unlikely to have skewed my findings on workers' informal categorical practices. The interviews on average lasted just over an hour. I reminded participants verbally and in writing (via the pre-interview survey that recorded their consent) that they participated in research and there were no right or wrong answers, despite being paid. All but two workers were hired and paid through the respective platforms. That said, only a share of workers (n=22) was identified through the search function on the respective platforms. Others were found in platform-owned community forums (n=2) or on other social media platforms like *twitter.com* or *reddit.com* (n=4). Thereby, I sought to decrease my reliance on the search algorithm of the respective platforms and their underlying classification of labour, while still being able to identify theoretically helpful perspectives. Table 6 provides an overview of the characteristics of workers interviewed for this second phase.

Table 6. Characteristics of workers interviewed in phase 2

Characteristics	Fiverr	Upwork
N	15	13
Female (%)	0.40	0.62
Average age	29	35
Higher education (%)*	0.80	0.92
Primary income (%)**	0.33	0.54
Working from a lower-income country (%)***	0.33	0.46
Most common services	Creative & Multimedia (4), Software Dev & Tech (4), Marketing & Sales (3)	Marketing & Sales (4), Software Dev & Tech (3) Creative & Multimedia (2)

Note. *Received higher education qualification | **Respondents noted that given platform is primary source of income | *** Currently working from a country defined as 'lower income economies' or 'lower-middle income economies' by the World Bank

I reached theoretical saturation at 28 interviews. In this study, I defined theoretical saturation as reaching a level of redundancy for every further interview both in terms of novelty experienced by the interviewer and new themes added in formal codes. Further, I compared my final number (n=28) and duration (28h 34min) of interviews in this second phase to methodological best practices and comparable research. Albeit in the context of research on information systems (IS), Marshall et al. (2013), recommend that 'grounded theory qualitative studies should generally include between 20 and 30 interviews' based on their analysis of the methodological choices and impact of 83 studies in highly ranked IS journals. In the platform economy literature, some studies on informal practices by remote gig workers drew on a larger number of primary interviews (Alacovska et al., 2022; Anwar & Graham, 2020; Cameron & Rahman, 2021; Wood & Lehdonvirta, 2022). Others studied worker behaviour with a smaller empirical evidence base of 20 to 26 worker interviews (Demirel et al., 2020; Jarrahi et al., 2020; Sutherland et al., 2020). Depending on their research, some of these authors supplemented their data sets with additional client or stakeholder interviews. In combination with the evidence gathered in phase 1, I concluded that my evidence base was theoretically saturated and within the methodological norms of platform economy research.

All 28 interview transcripts were transcribed and subsequently coded. While I followed the same interview guide for all interviews, I still used a grounded theory approach for coding (Corbin & Strauss, 1990). In other words, between interviews I cycled between theory and emerging empirical insights. After each interview, I thus coded each transcript line-by-line while focusing in particular for any mentions of classifications of labour by platform firms, instances of breakdown of these centralized classification systems (Bowker & Star, 2000a), and workers' own informal categorical practices

including the use of heuristics or informal codes. All these initial codes were transferred into one digital Excel file. Next, I merged these initial codes to higher-level ones (Charmaz, 2006), including the types of incompleteness of centralized classifications, as well as broader categories of workers' categorical practices. In the findings section, I have included quotations from the second phase of interviews to illustrate some of the theoretical abstractions drawn from the data.

5.4 The incompleteness of platform infrastructure

While previous research emphasizes the impact of being classified on workers' market outcomes and beyond (Fourcade & Healy, 2017), worker interviews also highlighted the limits of centrally imposed classification systems. In digital market-settings, these systems are *incomplete*, *circular*, and characterized by *evaluative frictions*.

The incompleteness of classification systems *per se* is nothing new. Every classification is always only one of many possible ways to demarcate our social world (Zerubavel, 1991). By design, classification systems that span and standardize across multiple geographies, industries, or communities need interpretation and translation by users across these specific contexts (Boltanski & Thévenot, 1983; Bowker & Star, 2000a; Desrosières et al., 1983). In online labour markets, classifications of labour are similarly abstractions by the platform firms that never intended to capture all nuances of a marketplace that spans services from video production to cyber security. One lawyer described how the established relations via the platform do not always work as intended:

'Upwork is an American outfit who has the American tendency to think that the whole of the EU is one country. That's why I get [questions like]: "Can you do a regulatory filing in Portugal?" What is it about my profile that says I can do regulatory filings in

Portugal [as my focus is clearly British law]? The reason I am getting picked-up is because they [search for] “EU”.’ (07U, Professional Services, Europe)

Every centralized classification system must weigh the benefits of generalization and standardization with ensuing indeterminacies of the system in local contexts (Bowker & Star, 2000a). For most workers and clients, the standardized classification of remote services is a mere entry point for bilateral negotiations between them:

‘[F]ew people [buy standard gigs]. They don't purchase a gig right away. They first contact you and then you send them a customer order because their needs are always individual.’ (17F, Marketing & Sales, Asia)

Other limitations are a direct consequence of how platforms categorize, classify, and codify these boundaries into the fabric of digital marketplaces. While platform firms centrally construct and intermittently revise the logic and underlying principles of the classifications of labour that organize their marketplaces (chapter 3), they rely on workers to populate such systems with information:

‘Fiverr tries to capture everyone and has sub-categories for everything. It throws stuff on the wall and sees what sticks. They’re going to create a subcategory that’s called ‘NFT’ because it’s all the rage and then they’re going to aggregate data and [evaluate] six months from now. They may drop it, merge it with something else, or leave it. It’s not costing them. It makes sense for them to cast a wide net and then it’s up to the sellers to find their spots within these categories.’ (20F, Creative & Multimedia, Europe)

In other words, platform infrastructure remains incomplete in that it requires the direct or indirect data entry by individuals who use these platforms. In online freelancing markets, workers may take deliberate actions such as setting up a new service or updating the selection of tags associated with their profile or service, or consent to the recording of their online behaviour as a more indirect data input. In digital settings, the classification systems of labour are characterized by a *circular* relationship that

involves the classifier and the classified. Workers' inputs and actions feed (back) into a system that co-constructs how they act in the first place and react thereafter.

Despite this reliance on explicit (via direct contributions) or implicit (via data collected from online behaviour) worker input, the dynamic, partially automated, and proprietary nature of platform-constructed classification systems may lead to what I call *evaluative frictions*. By *evaluative frictions*, I refer to changes to how boundaries are constructed in digital settings that add user insecurity about how to evaluate workers based on this information (Stark, 2011). The term directly relates to literature on evaluative insecurities in platform-mediated reputation systems more broadly (Kornberger et al., 2017; Rahman, 2021; Wood & Lehdonvirta, 2022). Evaluative frictions are rooted in the limited constraints placed upon and immediacy of platform firms' decision making. One successful worker explained that changes to the organization of the platform tend to happen without prior notice or much explanation to workers:

'[They have] a strict policy of not letting you know what they are going to do. It almost feels like [...] they don't give a crap about us as people. They don't consider us partners. (20F, Creative & Multimedia, Europe)

As a result, the history of changes and underlying conventions may stay hidden from users of the classification infrastructure (Bowker & Star, 2000a; Diaz-Bone, 2017). The same worker continued to describe how yesterday's changes to the categorization of remote services are often not obvious to users of these categories, for example employers who base their hiring decisions on them:

'The number of reviews doesn't tell the story, [...] it doesn't match my revenue. [...] Back in the day [...] on Fiverr, I could only sell for five bucks. Most of my reviews were for such USD 5 projects, [...] but it's not the same if it's a USD 5 project you did in an hour [compared to] a USD 15,000 project [that...] took you two months.' (20F, Creative & Multimedia, Europe)

The lack of transparency on some classifications is worsened by the fact that digital marketplaces tend to give rise to ‘heterarchies’, the articulation of ‘alternative [and parallel] conceptions of what is valuable, what is worthy, what counts’ (Kornberger et al., 2017; Stark, 2011, p. 5). Put simply, while each classification advocates for an explicit or implicit hierarchy, each hierarchy might differ depending on the classificatory tool used. One worker described how she was algorithmically demoted to a lower, algorithmically awarded quality label just to be accepted by the platform firm to participate in a more prestigious classificatory scheme shortly after:

‘Fiverr changed algorithm [...] in the fall of 2020. And I saw like a decrease in sales and traffic. [...] I got demoted from Top-Rated seller into Level 2 at [that stage] because my metrics got too low, [...] which kind of sucked. Pro verification [which happened around the same time] was a real saving grace for me. [...] Now, Fiverr is going to push my profile, I can charge way more, and that has been amazing.’ (27F, Writing & Translation, Asia)

In the case described above, for instance, there is an apparent tension between algorithmically awarded labels of quality and expert-based classification of talent (Alaimo & Kallinikos, 2021; chapter 4). Worker interviews suggest that both platform firms over time repeatedly altered and even upheaved their own classificatory logics. They were thus responsible for breaks in the established orders of worth at a given point in time. For workers, these breaks can significantly impact on economic trajectories but equally offer opportunities for improvements to their market position.

5.5 Workers categorical practices complete the loop

The limitations of centrally constructed classification systems in digital settings present workers with opportunities for worker agency. Some of my empirical findings simply support previous literature that documented workers’ reactions to digital infrastructure (e.g., Anwar & Graham, 2020; Jarrahi & Sutherland, 2019; Rahman, 2021; Wood &

Lehdonvirta, 2022), mostly in pursuit of better chances in these labour markets. Despite the opaqueness of some classification systems, especially related to job success scores (Rahman, 2021), and the fact that frequent changes to the classificatory logic of the platform infuriated informants, many argued that every change brings not only risks but also opportunities:

'This is a [new] review system now? Great, let's see how I can [...] use it to my advantage. This is a new restriction [or] feature? [Great] [...] This is what happened every time Fiverr changes: I am the first to say "Hooray", let's go for it instead of fighting change.' (20F, Creative & Multimedia, Europe)

In general, workers' experiences of being classified varied. Algorithmic categorization led some workers to vocalize uneasy emotions:

'I think it's always a bit of a nerve-wracking thing knowing that my successes in a large part are based on an algorithm.' (27F, Writing & Translation, Asia)

Others connected the 'disembeddedness' (Wood et al., 2019b, p. 946) of categories of labour used on digital platforms not to alienation but freedom from their social boundaries within their local communities:

'In my experience, most clients when I work on Upwork, they never asked me about my gender, my marriage status, my family status. They never care about it. They just focus on if I can help them to complete their projects.' (12U, Marketing & Sales, Asia)

Even though workers differed in how they experience being classified, most reported to react in some way. For example, one worker told me how knowledge about being classified based on response rates affected her behaviour on the platform:

'It does affect me. I always think that there is a benchmark I need to keep up with. For my inbox response rates, even if ... someone says "Thank you", when I don't say "You're welcome" that still [reduces] my inbox response rate ... Now, I'm always on my inbox.' (25F, Writing & Translation, Asia)

Where my findings diverge from the previous literature is in providing evidence that workers not merely react to being classified online. In fact, I find that workers' informal categorical practices *complete the loop*.

Data entry: Co-constructing the platform infrastructure

In online marketplaces, workers enter much of the data about themselves and their services as a form of unpaid labour. Once they sign up to the platform, they translate their experiences and their professional identity into what can be sold online:

'When I became a freelancer, I already worked ... for more than 10 years. ... I could make use of my past experiences.' (12U, Marketing & Sales, Asia)

'I was thinking I could do some translation [on the platform]. ... But my first jobs were ... a copywriter. ... Then, I just added new ones. I switched to Google Ads because it was more profitable and there was a big competition [for the other services].' (17F, Marketing & Sales, Asia)

However, the activity to categorize one's abilities and reduce professional experiences into a representational form involves much introspection, translation, and strategizing:

'When you go to work on this platform, you need to define what you can [and want to] do. Initially, I didn't know what I can do, [...] what I'm good at. I didn't know how to market myself, and I needed time to explore the platform. It takes some time [...maybe] two months depending on how smart and experienced you are. I'm [neither], so it took me some time to create a better profile and understand the market.' (08U, Marketing & Sales, Europe)

Such translation work is a form of digital literacy that requires experience and learning. For example, several workers pointed out that it was important to 'niche down' because clients 'actually want to hire the person that is really into the niche' and 'really understands what they want' (10U, Writing & Translation, Africa). A similar theme included how workers over time extended the boundaries of their skill set or services offered online:

'I started out as a virtual assistant... doing research for people, setting up itineraries, finding and shopping for stuff. ... As time went on, [someone] asked me: "Do you know how to update my WordPress website?" At that first moment, I did not even know what a WordPress website is. ... I started learning about WordPress. Killing myself with it. Then I decided... this is do-able ... [and went to] study computer science.' (03U, Professional Services, Africa)

A worker described how he used being classified as a 'Top-Rated' seller to make a transition to a better paying skills trajectory:

'I just woke up one day, [...] and then I changed my entire profile [...but] I still had the ratings from the previous clients who had given me jobs as an assistant. [...] Even when I changed my profile into something else, I maintained the... top-rated ... status when I changed my profile [to data science from being a digital assistant].' (03U, Professional Services, Africa)

More generally, workers noted that they strategically categorized themselves and their services. Several workers described how it was necessary to address both the client as well as the algorithmic tools of the platform:

'My gig [has been the same] for all six years. ... I've just been tweaking it little by little ever since ... to optimize the gig's performance. For instance, in the "About" section, I've spent a lot of time writing this copy. If you could watch a time lapse of this, you'd see it morphing, growing, and shrinking. ... I'm bolding some words right in the first paragraph to draw the eye and point out ... keywords that evoke certain emotions: "energetic", "engaging", "top quality", "getting it right". ... Hitting [clients] with the value propositions right off the bat there and then jumping right into describing the way that I sound in just three adjectives. And then, there are some keywords that are ... helpful for SEO purposes.' (14F, Creative & Multimedia, North America)

As is hinted at in this example, workers noted that they actively differentiate between communication aimed at automated algorithms, partially even labelling it search engine optimization, and messaging intended for prospective human employers.

Apart from such collaborative forms of co-constitution, workers also reported to antagonistically feed the system wrong information as part of their active struggle for a

better class position. For example, workers tried to avoid location tags that were rumoured to put them at a disadvantage:

'Although there are fraudsters everywhere, the ones from Nigeria have given us a very, very bad identity. ... Freelancers [from here] struggle to make it even if they're good at what they do.' (10U, Writing & Translation, Africa)

Instead, this worker opted for subverting platform classification by signing up as being from Canada due to it being English speaking, without tax obligations, and presenting a lower bureaucratic hurdle in terms of required documentation than for instance the United States. In the case of Upwork, others contested being rejected at the 'virtual borders' (Lehdonvirta, 2022, p. 89) of the platform by highlighting different data points to the classifying platform firm:

'If [a writer] isn't accepted ... because there is there are a lot of freelancers in the writing pool, what I tell them is to set up a profile for an entirely different service, ...like a profile of a ... male African voiceover artists ... [something that] a very low amount of freelancers offer... Once the profile is accepted, the person can now update the profile back to the original service they want to start offering.' (10U, Writing & Translation, Africa)

'When I first tried to register for Upwork, ... they rejected me. ... [In response,]I created myself a website. I also bought a company email from Google with the domain in order to look more professional. I even registered myself as an agency, I think. ... All so that they know that it's solid business ... that new buyers will come to Upwork because of me. I was successful [the second time].' (17F, Marketing & Sales, Asia)

In sum, all interview participants agreed in that they strategically thought about the data they supplied to the platform. Therefore, when workers enter data this way, they do not only react to but actively constitute the classification systems of labour online.

‘Last mile delivery’: Enacting boundaries in practice

The incompleteness of centralized classification systems is not limited to their construction but extends to their application. Most respondents described how they bridge cultural gaps between clients and the platform as some form of *last mile delivery*. Many described how they translate standardized categories that make automated matching and recommendations possible to concrete client situations and their context-specific problems. One IT specialist explained how he uses standardized language to describe his services as a deliberately fuzzy entry point for discussion and specification:

‘My offerings are just a broad description of [services] which a non-tech-savy persons would look for. And from there, I’m going to start the discussion, craft a custom order, and discuss their requirements and modifications.’ (02F, Software Dev & Technology, Europe)

By jumping in where the formal classification systems end, workers are presented with opportunities to maximize the economic value from each transaction:

‘When I see a business client, I’m much more likely to pitch them on our full-service offering. Because I find that a lot of people come to me for one thing, but they don’t know that I do other stuff. And I try to get my foot in the door.’ (27F, Writing & Translation, Asia)

Beyond economic benefits, workers used the structuring of each project and the individual breakdown of their services to manage risks of a platform-mediated workplace that is structured to favour clients as their fees make up most of either platform firm’s revenue. One freelancer outlined how he deliberately included an automated layer of questions that prospective clients are required to answer before finalizing a contract with him:

‘On my gig page, first, I ask for a brief description of the project, that’s free text entry. Then, multiple choice ... [where] you have to select one [answer]. It forces [clients] to

acknowledge ... a rundown of the most common disputes that crop up... So, we're just starting the interaction with, "Hey, we're both acknowledging that these are the terms and we're going to go from there." ... 99.9% of the work that I don't want to do will be filtered out either by the pricing, the description, or these terms here.' (14F, Creative & Multimedia, North America)

Several workers similarly reported using price changes to re-categorize their services for different client segments or manage demand whenever they have limited availability.

However, categorical practices not only extend to the matching and structuring of projects. Workers also enact normative categories by educating clients about the underlying principles and norms of online freelancing. For example, many workers go to great length to explain to clients the importance of public and private feedback for their continued success online:

'I include a piece of boiler plate text with every order delivery that says: ... 'If you're satisfied with the final product, please mark the order as complete, and then don't forget to leave me a review. ... I strive to make every delivery a five-star delivery. If there's anything at all that didn't meet your expectations and would cause you to leave a negative review, please let me know before reviewing, and I'll do my best to make it right. Otherwise, please take a moment to support my independent small business by writing a review.'" And I found that by including those two paragraphs on every delivery, I get ... an overall participation rate of... 55% which is a win in my book.' (14F, Creative & Multimedia, North America)

Such education of clients involves spelling out boundaries set by the platform, for instance in their terms of service, as well as by laws beyond the platform:

'You're not supposed to take people off the platform. And we are really careful because we don't want to lose our position. So, when anyone asks if we can WhatsApp... We're like, nope, nope, nope, nope, keep us on the platform. But inevitably, people research our website and email us.' (28F, Professional Services, North America)

'I get many requests, almost daily, to do illegal and unethical stuff. ... It's like the Dark Web. It just became mainstream. ... I get requests to help hack someone's Instagram, Facebook, or Gmail account... [Even though] I have a specific FAQ [excluding such services] on each one of my gigs.' (18F, Software Dev & Technology, Middle East)

Overall, only workers informal categorical practices put categories and classifications of labour to work and make them accessible to clients. They thereby enact some of the normative standards set by the platform, but also limit the ability to standardize employment relations in remote freelancing.

Application: Participating in the classification of remote gig work

Finally, workers are complicit in participating in the classification of remote gig work more broadly. They are not only classified by the platform firm, but they themselves classify.

On the one hand, workers described how they informally classified platforms and clients. Especially successful workers repeatedly highlighted their role as valuable customers to the platform. While the credibility of threatening to switch platforms decreases with time and investments in platform-specific reputation, many workers reported that their initial decision about which platform to join or prioritize was directly influenced by platform firms' categorical decisions. One writer on Fiverr described how her move to pull out of Upwork was driven by a categorization of 'online labour' that resulted in market dynamics which did not suite her:

'I hated having to bid on projects. It was just a huge waste of time. And I know Upwork has changed. But I really didn't want to spend all this time writing cover letters when that just felt the same as applying to jobs on *indeed.com*. For me, it was equally disheartening.' (27F, Writing & Translation, Asia)

Decisions by platform firms on how to classify work and workers evidently do not happen in a vacuum. Instead, they are constrained by the competitive landscape of freelancing platforms from which workers can choose.

Experienced workers further explained how they themselves classify clients before accepting or applying to a project. For example, one worker (09U, Software Dev & Technology, Asia) noted that he has 'red flags.' Based on bad experiences in the past, he only takes work off the platform if the payment is secured. Further, he analyses clients' 'tone... and whatever they are writing.' This way, 'you can figure out... what kind of expectations they have' and if they are 'much bigger than what they are thinking about telling you.' Also, good clients appreciate potential roadblocks, they would 'simply understand in one sentence.' Although less information about clients is available to workers than vice versa, respondents highlighted how they make the most of the limited information available or fall back on informal heuristics:

'There are some tools that Upwork gives us that are very useful in terms of filtering out clients. ... The tools that I would think are useful are obviously the quality of the job description ... previous jobs ... their reviews and their average rate paid.' (24U, Software Dev & Technology, Asia)

Being classified as a desirable client thus relies on past reviews, spending history, willingness to agree on hourly contracts, and verification, but also on the clarity of the project description, clients' open mindedness, their knowledge in the respective field, or style of communication. Just like geography matters for clients (Demirel et al., 2020), some workers reported to also discriminate their behaviour based on a client's location:

'In most cases, I don't like working with clients from India, Pakistan, Nepal, Bangladesh, because they feel that you're charging too much for the job. In most cases, you end up in dispute.' (10U, Writing & Translation, Africa)

While this worker generally preferred hourly contracts, he opted for fixed-rate contracts for clients from these locations.

On the other hand, workers categorized their own behaviour in normative terms. For example, workers described how they distinguished between normative acceptable and unacceptable behaviour. For example, one seller described how they adjusted prices for online marketplaces and kept most small projects on the platform. However, she equally noted that it was acceptable to move work off the platform once people researched contact details themselves and contacted them for larger projects:

'Fiverr is a bit of a 'feeder.' You're not supposed to take people off the platform. And we're really, careful because we don't want to lose our position. [...] But inevitably people research [...] and email us. And if they do, it turns into other things. We offer [services], which cost thousands of dollars [which] we typically do off [the platform...]. Otherwise, you're paying a thousand dollars just in fees to the platform. It doesn't make any sense.' (28F, Professional Services, North America)

Similarly, they rationalized negatively connotated categorizations by the platform, for example when they were demoted to a lower digital class in the form of quality labels attached to their profile (chapter 4):

'I was informed of [my demotion] via email. [At that time], I had three projects, as well as my own university essay due. One of the projects was really big, [there] was a lot of going back and forth. And we didn't really extend the delivery deadline. So, by the time I gave her back the final project, it was overdue for three days [which] in turn made me overdue for another project. So, I was just busy.' (25F, Writing & Translation, Asia)

In the end, all these findings come with an important caveat. While they point to an underappreciated dimension of worker agency, they do not suggest that workers and the platform firm meet on a level playing field. Workers are very aware that changes to the centralized platform infrastructure can have large effects on their economic

success online. Many workers, for example, were hesitant to change their informal practices too much because they feared to break a working system:

'That's the thing about the algorithm. [...] I think there are some glitches ... if you change categories, change tags, something happens and you just never get back on track. So that's a mistake I did before.' (21F, Marketing & Sales, North America)

Most recognized the power differences between them and the platform firm. While some noted that dependence decreases with experience, one successful worker summarized her situation as 'kind of nerve wracking to have a lot of your livelihood depend on an algorithm' (27F, Writing & Translation, Asia) ultimately constructed and changed by a third-party labour market intermediary.

5.6 Discussion and Conclusions

Platform firms organize digital marketplaces via 'investment in forms' (Bowker et al., 2019; Thévenot, 1984, p. 25ff), including the construction and codification of various classifications of labour (chapter 3). They categorize what constitutes online labour (Pongratz, 2018), award labels of quality that institutionalize what competencies matter in the hiring process (chapter 4), or categorize the behaviours that are recorded and feed into the digital reputation infrastructure of remote gig platforms (Kornberger et al., 2017; Wood & Lehdonvirta, 2022). In this chapter, I studied how workers interact with such classification systems by focusing on their informal categorical practices. Extant research prioritizes how individuals and workers specifically react to being classified and evaluated by platform firms or employers (e.g., Espeland & Sauder, 2007; Rahman, 2021). Based on my literature review, I was able to identify two theoretical approaches that explain workers' informal practices as either *economic optimization within* or *resistance against* the platform infrastructure imposed on them. Alas neither alternative thematized informal categorical practices explicitly so that questions remain

over how workers in practice interact with 'classification situations' online (Fourcade & Healy, 2017, p. 23). Further, and arguably most important, theorizing informal categorical practices as reactive behaviour to a workplace institutionalized from above fails to account for how workers contribute to the construction and maintenance of online markets. From previous research we know that categories and classifications are essential institutions for any type of exchange (Douglas, 1986; Fligstein, 2002).

Categorical work in online freelancing

By interviewing workers across two leading freelancing platforms, I contribute to the literature by arguing that workers also co-construct and enact the classification systems that serve as socio-technical infrastructure of online markets. This way, I complement extant literature on how workers adapt their behaviours to being classified (chapter 4), especially if understood as a basis for algorithmic control (Jarrahi & Sutherland, 2019; Rahman, 2021; Wood et al., 2019a). To make the case for a digital infrastructure that is co-constructed by workers, I first foregrounded how digitized classification systems are necessarily incomplete. All classification systems that serve as infrastructure for remote collaboration are incomplete insofar as they are abstractions that rely on informal work by users in their local communities and settings (Bowker & Star, 2000a). My work additionally highlights that digital intermediation of platform work additionally enhances the circularity of classification systems and results in evaluative frictions. Digitized categories and classifications are circular as they rely on direct and indirect (data) input by workers who themselves strategically reflect on and adapt to being classified. Evaluative frictions are driven by the frequent changes to classifications, the invisibility of these histories, the general opaqueness surrounding underlying principles of evaluation (Diaz-Bone, 2017; Rahman, 2021; Wood & Lehdonvirta, 2022), and the dynamic 'heterarchies' they result in (Kornberger et al.,

2017; Stark, 2011, p. 5). Second, and on this basis, I maintained that the limits of symbolic distinctions by platform firms lead to opportunities for an overlooked form of worker agency. This way, I directly contribute to debates on the agency of remote gig workers (Anwar & Graham, 2020; Cameron & Rahman, 2022, 2021; Wood & Lehdonvirta, 2021).

Put differently, it requires workers' informal categorical practices to complete the *classificatory loop*. My contribution to this debate lies in demonstrating that workers not only react to but co-construct platform infrastructure via data entry, enact the resultant boundaries in their encounters with clients, and are complicit in the categorization of remote gig work. Scholars tend to discuss data collection by platform firms in extractive terms, 'wherein data is taken without meaningful consent and fair compensation' (Sadowski, 2019, p. 7). While some respondents indeed struggled with categorizing and making themselves calculable (Callon, 1998a), many recognized their direct and indirect supply of data as an avenue for individual action in the 'struggle played out at the level of the interface' with employers and the platform (van Dijck, 2013, p. 199). In fact, deliberate data entry as observed in online freelancing might be an individual-level case of 'classification struggles' for better market outcomes in digital settings (Bourdieu, 1984/2010, p. 486). Mundane and often invisible practices such as tweaking self-descriptions, choosing from a limited number of skill tags, or categorizing services to be attractive to clients and algorithms alike matter because they indeed are a 'forgotten [or new] dimension of class struggle' (Bourdieu, 1984/2010, p. 486). Beyond co-construction, workers are instrumental to the *last mile delivery* of boundaries drawn by platform firms. I find that their workarounds to failures of standardization and the enforcement of normative principles of classification bridge the gap between platform and clients of various contexts. This finding relates to studies of Chinese ride-hailers

(J. Y. Chen, 2018a, p. 2692) and modern knowledge workers in general (Erickson & Sawyer, 2019) who have been credited with unpaid 'infrastructural labour' in the interest of platforms or their clients. Last, I find that workers are themselves complicit in the categorization of remote gig work. They, for example, rely on heuristics to informally categorize platforms and their clients (Anwar & Graham, 2020), or adapt their messages depending on whether their intended audience is an algorithm or a human client.

Interpreting my empirical observations, I propose to theorize the above practices as *categorical work*, a so far underappreciated dimension of worker agency. The concept was originally coined by Bowker and Star (2000) when researching classification infrastructures such as the International Classification of Diseases. They introduced the term to capture human work which manages 'mismatches between memberships and naturalization' and involves the 'juggling of meanings' (Bowker & Star, 2000a, pp. 310–311). The original meaning of categorical work therefore covers what I summarized as making categories and classifications of labour work in concrete client interactions. However, categorical work as proposed in this chapter goes beyond platform workers' role as intermediaries that enact centralized classifications. It includes worker input along the entire 'statistical chain' (Desrosières et al., 1983; Diaz-Bone, 2017). In platform work, the statistical chain includes everything from the construction of classifications, encoding them into the platform interface, collecting and providing data, assigning classes, and putting them to use. Theorized this way, categorical work is another important form of 'marketization' (Çalışkan & Callon, 2010) or 'market work' in general (Cochoy & Dubuisson-Quellier, 2013; Garcia-Parpet, 2008) needed to construct, maintain, and shape the 'social infrastructure' of digital marketplaces (Aspers & Darr, 2022). Other forms of market work in online freelancing

include relational work such as fostering positive and ideally repeat relationships with clients (Alacovska et al., 2022) or reputation work like reminding clients to leave a positive review (Fine, 2019; Wood & Lehdonvirta, 2022). Categorical work thus shapes the socially 'emergent' order (Aspers & Darr, 2022) that complements and at times challenges the (therefore partial) organization of digital marketplaces by private companies (Ahrne et al., 2015; Kirchner & Schüßler, 2019). As a concept, it recognizes workers' activities as unpaid externalities which generate value for platform firms and clients (Fuchs, 2010) just as much as part of their struggles to shape and undermine the digital infrastructure for better market outcomes. Overall, the finding underlines that digital marketplaces rely on 'the work of a number of individuals with an interest in the market, together with acceptance by others who have also found it to their advantage to obey to the rules of the game' just like marketplaces with a physical presence (Garcia-Parpet, 2008, p. 45-46). Theorizing informal categorical work in this way marks a difference to debates in the platform economy literature where agency is explained within the context of platform-mediated employment relations (e.g., Wood & Lehdonvirta, 2021).

Applications beyond online labour

Although I studied categorical work in a remote setting, the concept may have purchase in the local gig economy. Online freelancing platforms on average afford more room for worker autonomy than is usual in other platform contexts (Howcroft & Bergvall-Kåreborn, 2019). In the locational gig economy, for example, delivery workers or providers of ride-hailing services tend to have less flexibility than online freelancers as they do not set prices or chose their clients. Still, the concept of categorical work offers another means to foreground this heterogeneity of platforms, specifically how their infrastructure is constructed and upheld, comparatively but also over time

(Cansoy et al., 2020; Schor, 2020). For instance, it could be a fruitful exercise to compare categorical work in remote and locational gig work. Just like online freelancers are confronted to make normative decisions about when to enforce platform-constructed, normative categories of sanctioned behaviour, ride-hailing drivers deal with consumers that attempt to bend platform rules in their favour in everyday interactions (Ramizo, 2022). Similarly, ride-hailing workers have been shown to enact the infrastructure of platforms in ways similar to the *last mile delivery* of classification systems in online freelancing. For example, drivers have been shown to act as the interface between passengers and the platform to overcome mismatches in this economic relationship and allow ride-hailing platforms to thrive in the Chinese context (J. Y. Chen, 2018a). More generally, categorical work emerges as an overlooked and underrecognized aspect of unpaid human labour that not only sustains but co-constructs 'information infrastructures' like online labour platforms (Bowker et al., 2019; Bowker & Star, 2000a; Erickson & Sawyer, 2019). Thereby, it also intersects with recent studies on the (classificatory) human work embedded in artificial intelligence applications (Bechmann & Bowker, 2019; Kotliar, 2020; Newlands, 2021; Tubaro et al., 2020) but also other contexts of knowledge production such as knowledge standardization and archiving (Plantin, 2021).

Finally, this chapter contributes to the broader question of how users of digital economies interact with the perpetual 'classification situations' that algorithmically determine economic worth based on individual and platform-specific past activities (Fourcade & Healy, 2013, 2017). Just like Orlikowski and Scott (2014, p. 888) who argue that moving evaluation online and democratizing it has led to a 'reconfiguring of the phenomenon of valuation itself', the use of classification for platform organization has transformed it. While it remains a social and contested process (Douglas, 1986;

Zerubavel, 1991), my empirical findings suggest that digitization has enhanced the role of feedback loops (Fourcade & Johns, 2020) and evaluative frictions due to decreased temporal reliability, multiple (and potential contrasting) orders of worth (Stark, 2011), and their opaqueness (Diaz-Bone, 2017). However, rather than leading to resignation these properties may provide users with unique opportunities to not only struggle against but also co-construct their (digital) classes. The concept of categorical work thus offers a means to study informal, largely hidden practices of users in digital settings, without *a priori* assuming these actions to be antagonistic or collaborative. As social institutions, classifications always imply association between things or people as well as division from others (Zerubavel, 1991). Just as every society is ‘powered by [these] two fundamental, sometimes contradictory forces[;] stratification and association, vertical and horizontal difference’ (Fourcade & Johns, 2020, p. 826), so are digital marketplaces. The concept of categorical work identifies users’ self-descriptions, reflective actions, and informal heuristics and codes to evaluate one another as scarce but ever more important areas of human agency. By foregrounding ‘who does [otherwise invisible] work’ (D’Ignazio & Klein, 2020, p. 47) along the manual steps that feed into the ‘statistical chain’ (Desrosières et al., 1983; Diaz-Bone, 2017), it offers a methodological challenge to the power of the classifier, the platform firms who dominate much of modern life.

6. Putting the social back into classification: An integrated discussion

6.1 Introduction

In the prologue, our journey began by following Hardy's (1874) account of a hiring fair in 19th century England. The simplifications of literary narrative helped me emphasize how categories and classifications are a necessary social institution for any type of exchange, including that of labour power. It illustrated how a worker like Gabriel Oak drew on work categories and signals accepted in his community to appeal to employers, how he adapted his behaviour in face of adversity, and suffered the consequences of being judged as unfit for employment based on communal standards. The experiences of platform workers who I surveyed and interviewed for this thesis were not all that different. Although only 24% of the Europe-based workers relied on online freelancing as a primary source of income, outcomes still mattered greatly for another 42% of respondents who used remote gig work as a secondary means to earn a living (chapter 4, n=723). Just like Gabriel Oak, the workers I interviewed tried to increase their economic success by changing gig or skill categories, experimenting with self-descriptions, seeking to be awarded quality labels, or safeguarding their reputation by using heuristics to judge a client's fit prior to contracting. While the organization of hiring fairs was deeply embedded in rural communities, contracts for example being timed in accordance with 'seasonal rhythms of the farming year' and enforced by 'intervention of the courts and [...] local officials' (Roberts, 1988, p. 124), my empirical work revealed how digital marketplaces are instead organized by platform firms (Ahrne et al., 2015; Kirchner & Schüßler, 2019). Digital marketplaces may no longer be a 'meeting ground [...] between the sphere of work and the wider society' (Roberts, 1988, p. 120). I shall still conclude that categories and classifications remain

social institutions at the heart of these markets. Digitized or not, they remain embedded in workers' social practice and context on and off the platform.

To build up my thesis, I first recall what motivated my research, how it is situated in the socio-economic literature, and the context of my research question: *How and to what effect are work and workers classified in online labour markets?* I proceed by reviewing the self-contained arguments of each empirical chapter. From this basis, I distil how the chapters add to my overall argument. By means of integration, I conclude that my doctoral project *puts the social back into classification*. While my findings support the view that classificatory tools are predominantly constructed by platform firms, I argue that social context and practices, especially *categorical work* by online freelancers, still matter a great deal for constructing and sustaining digital markets. Upon elaboration on this key point, I demonstrate how my thesis is situated in discussions on the construction and organization of (digital) marketplaces, as well as the classification of workers in digital workplaces and its effects. I conclude by reflecting on the relevance of my work for practitioners and how my thesis is an effort to make visible the power of platform firms as classifiers.

6.2 Putting the social back into classification

Recalling my motivation and the gap in the literature

In chapter 1, I provided motivation for why the study of categories and classifications as social institutions (Bowker & Star, 2000a; Douglas, 1986) is a productive lens to theorize the platform economy. In recent years, several scholars revisited categorization and classification as essential social processes for understanding digital economies. On the one hand, these processes lie at the core of the construction and maintenance of the information systems that facilitates collaboration across

communities (Bowker & Star, 2000a), including digital platforms (Bowker et al., 2019; Jarrahi et al., 2020). For example, categorization and classification are foundational for the datafication of user behaviour, that is whenever platform firms 'encode' social practices and relations into data to extract value (Alaimo & Kallinikos, 2017, p. 176; Diaz-Bone et al., 2020; Kitchin, 2014). As such, human classificatory work is an integral part of any statistical analysis of this data (Desrosières, 1998), for example of artificial intelligence applications like machine learning (Bechmann & Bowker, 2019; Faraj et al., 2018) or cluster analysis (Kotliar, 2020). Since algorithms order digital markets (Ahrne et al., 2015; Kirchner & Schüßler, 2019), for example by assessing risk or recommending services, it is paramount to study categorization and classification as underlying social processes for such market organization (Aspers & Darr, 2022; Beckert & Musselin, 2013).

At the same time and partially as a consequence, 'classification situations' (Fourcade & Healy, 2013) are central outputs of the classificatory tools employed by platform firms. The use of technologies that 'sort and slot people into categories of taste, riskiness or worth' (Fourcade & Healy, 2017, p. 9) to extract additional value from users is a core feature of platforms that collect individual-level data on a large scale (Alaimo & Kallinikos, 2017; Fourcade & Healy, 2017). It is this 'evaluative infrastructure' (Kornberger et al., 2017, p. 79), the assemblage of 'accounting practices' that relate and evaluate user behaviours against one another, that enables the governance of digital marketplaces for goods or services. For individuals, being classified matters because the resulting boundaries come with stratifying potential. Symbolic boundaries impact how material and symbolic resources are distributed across society (Bourdieu, 1984/2010; Lamont & Molnár, 2002) and shape the normative understanding of what actions are available to us (Bowker & Star, 2000a; Douglas, 1986). My project draws

the connection between these discussions on classification in digital market-settings to older debates on the classification of work and workers in conventional labour markets. As a nexus of these debates, I suggested that online labour platforms for knowledge work offer a fertile ground for inquiry.

I further made the case that online labour platforms like *upwork.com* and *fiverr.com* are socially relevant in and off themselves. There are millions of workers who earn some or all their livelihood remotely through such platforms (Kässi et al., 2021). The Covid-19 global pandemic, its stay-at-home mandates, and the pressure to enable remote collaboration across traditional workspaces further increased the need to study how work is organized remotely, including online freelancing as a frontrunner of such setups. In the Web of Science Core Collection, publications that mention 'remote work' in their title, abstract, or keywords⁴⁴ rose by almost 55% between 2019 (pre-pandemic) and its high in 2021. The number of new projects posted across several online labour platforms that make up more than 70% of the market as measured by traffic equally rose by more than 15% between 2018 and 2022 (Stephany et al., 2021).⁴⁵ Online freelancing and work from home in general, made possible via various digital platform solutions for remote collaboration, play an ever-growing role in people's lives. They are likely to remain a core feature of what commentators refer to as the *future of work*.

In chapter 2, I started my inquiry by connecting recent debates on classificatory tools in digital markets to economic sociology literature on boundaries in labour markets and society at large. I discussed three exemplars of categorization in conventional (as

⁴⁴ Including so-called 'KeyWords Plus' which are 'words ... that frequently appear in the titles of an article's references, but do not appear in the title of the article itself' (Clarivate, 2022: https://support.clarivate.com/ScientificandAcademicResearch/s/article/KeyWords-Plus-generation-creation-and-changes?language=en_US; accessed on Nov 14, 2022).

⁴⁵ The cited index daily reports a 30-day moving average normalized for May 2016. For this analysis, I compare the average of the index of 2018 to the average Nov 14 (2021) to Nov 13 (2022).

opposed to online) labour markets. My discussion included an official classification of employment status in France, how executive search firms use informal categorical practices for labour market intermediation, and an occupation-led classification of nursing interventions. From this basis, I concluded that categories and classifications are essential social institutions that enable the exchange of labour power and matter for their consequences for the individual worker. I summarized that in labour markets they *inform* by making horizontal distinctions possible, *divide* by allowing for hierarchical ordering, and *control* by making normative claims about what actions are possible and desirable. From the review of the literature, I arrived at a simplified proposition to start my empirical investigation: With the ascent of digitized marketplaces, the *who* (does the classifying), *how* (is the classifying done), and *what* (is being classified) of classification have changed in comparison to more conventional labour markets. I concluded that more research was needed to appreciate the processes and effects of categorization and classification in digital marketplaces.

Summarizing the study-specific contributions

My empirical chapters fulfil a dual function. Taken together, they serve as building blocks for my broader theoretical argument about classification in digital market-settings. Considered individually, however, each study makes a self-contained argument situated in concrete theoretical debates within the platform economy literature. In the following, I recap these study-specific contributions.

In chapter 3, I examined how labour platforms categorize work and workers to produce heterogeneity in workers' market outcomes. Scholars tend to explain such diversity of outcomes by pointing to either (categorical) variations in workers' *inputs* or the impact of the (continuous) measurement, presentation, and accumulation of their *outputs*. By

inputs, I referred to categorical differences in workers' circumstances and characteristics such as their economic dependence on a particular platform (Schor et al., 2020). By *outputs*, I referred to how platform firms construct, record, aggregate, and selectively publish metrics on workers' actions and the client feedback they receive in response. In such theorizations, success is mediated by individual ability but conceptualized as a continuous variable which largely depends on the accumulation of platform reputation, as measured and codified by platform firms (Lehdonvirta et al., 2019; Wood et al., 2019a). Neither approach is well placed to explain acts of categorization by platform firms like restricting market access or attaching quality labels to workers' profiles. My findings suggest that platform firms rely on many explicit and implicit classifications of labour to construct, organize, and govern their digital marketplaces (Ahrne et al., 2015; Kirchner & Schüßler, 2019). Classification systems constructed by platform firms are thus an essential part of the 'social infrastructure' of digital marketplaces (Aspers & Darr, 2022). The resultant boundaries impact workers' success online. In fact, platform firms' use of classificatory tools and practices effectively places workers in at least four market categories: those (*effectively excluded, global competitors, industry professionals, and platform superstars*). Workers in these categories tend to differ in the clients they serve, how they are evaluated, and their distributional outcomes. In other words, platform firms shape and institutionalize categorical variations in workers' experiences and outcomes on their platforms.

In my second empirical study (chapter 4), I investigated why platform firms award quality labels such as being 'pro-verified' to online freelancers. The answer to this question matters because such classifications of labour are linked with who succeeds and fails in platform work (chapter 3). One leading theory is that such quality labels function as signals which reduce employer uncertainty during hiring (Kässi &

Lehdonvirta, 2022; Lehdonvirta et al., 2019; Pallais, 2014). Another popular theory proposes that platform-constructed quality labels are a form of 'algorithmic management' insofar as they are only awarded to workers who comply with the platform firms' strategic interests as codified in their rules of engagement (Rahman, 2021; Stark & Pais, 2020; Wood et al., 2019a). I challenge both approaches by conceptualizing worker quality as the outcome of qualification, a negotiation between workers, employers, and intermediaries at a specific point in time (Callon et al., 2002). In this view, quality is a mix of a worker's intrinsic traits and a function of factors that are external to the worker such as hiring practices or client needs (Beckert & Musselin, 2013; Eymard-Duvernay & Marchal, 1997). Interpreting quality labels as 'market devices' (Callon et al., 2007) which help employers qualify potential hires (Aspers & Beckert, 2011), I argue that the award of quality labels by platform firms is an act of market categorization to institutionalize worker categories that align with companies' growth and profit objectives (van Doorn & Chen, 2021). My contribution lies in uncovering that these labels actively constitute the competencies valued by employers at the hiring stage. In other words, platform firms co-construct 'what qualifies as [workers'] qualities' (Aspers & Beckert, 2011, p. 14). Signalling theory fails to acknowledge the constitutive character of awarding quality labels. Work on algorithmic management only pertains to the management but not the hiring of remote gig workers. Theorizing platform-constructed quality labels as market categorization explains why workers noted positive effects from labelling on the scale and quality of employment.

In my final empirical chapter (chapter 5), I studied how centralized classification systems constructed by platform firms intervene with workers' informal work practices. Although platform-constructed classifications of labour impact workers' labour market outcomes, little is known about whether workers are at odds with the resultant

boundaries. In the platform economy literature, scholars largely theorize workers' informal categorical practices as reactions to being classified (e.g., Rahman, 2021). In these views, workers use categorical practices to either optimize within (e.g., Sutherland et al., 2020) or resist against (e.g., Wood & Lehdonvirta, 2021) the imposed platform infrastructure. By theorizing informal categorical practices as reactive behaviour in response to platform-mediated workplace, these approaches ignore how categories and classifications are also essential to constructing and ordering platform-mediated marketplaces (Beckert & Musselin, 2013; Fligstein, 2002). In fact, my findings highlight that centrally constructed classification systems, as one aspect of platform infrastructure, are always incomplete. Only workers' informal categorical practices complete the *classificatory loop* by entering data and implementing classification systems in specific client contexts. My original contribution therefore lies in showing that workers are in some ways complicit in co-constructing and enacting the classification systems that organize digital marketplaces. I propose that informal categorical practices are best conceptualized as a form of 'categorical work' (Bowker & Star, 2000a, pp. 310–311), an underappreciated dimension of worker agency in platform work. In its original meaning, categorical work was more narrowly defined as the human work needed for translating classification systems across contexts. I extend the concept to include all categorical work needed from the conception of a classification to data collection, class assignment, and evaluation. Theorized this way, categorical work is another form of 'market work' sustaining, enacting, and shaping the social infrastructure of digital markets (Aspers & Darr, 2022; Cochoy & Dubuisson-Quellier, 2013; Garcia-Parpet, 2008). The concept of categorical work is helpful because it offers a means to study informal categorical practices without *a priori* assuming them to be antagonistic or collaborative.

Integrating these findings to an overarching thesis

By integrating findings from each chapter, I now move beyond these specific contributions and problematize the view that ‘classification situations’ (Fourcade & Healy, 2013) in digital markets are somewhat removed from social practice.

By removed from social practice, I do not imply that any of the cited authors (who after all paved the way for this thesis) prescribe to the view that categorization or classification in digital settings are removed from social practice *per se*. For example, several scholars examined how classificatory tools are embedded in the social practices of their designers (e.g., Bechmann & Bowker, 2019). However, in chapter 2, I attempted to show that in much of research, classification in digital settings is portrayed as largely divorced from practices of the classified users and their social contexts. In my literature review, I more formally proposed that the primary classifier, the process of classification, and its informational basis have changed in online freelancing markets compared to conventional labour markets. By stating that classifications are removed from social practice, I thus summarize three observable shifts. First (*who classifies labour*), private or publicly-traded platform firms invest in ‘classifying instruments’ that not only ‘value’ individuals but maximizes ‘value extraction’ from them (Fourcade & Healy, 2017, p. 10; Thévenot, 1984). It has been proposed that this marks a break from classifications of labour which are constructed by state governments (Scott, 1998) or emerge from within a specific community, as was the case in Hardy’s account of a hiring fair in Victorian England. Second (*how is labour classified*), the classification occurs dynamically and automatically, ‘backed by algorithmic techniques’ (Fourcade & Healy, 2017, p. 10), and thus tends to make invisible the conventions of how digital class boundaries are drawn (Cheney-Lippold, 2017; Diaz-Bone, 2017; Fourcade & Healy, 2017). Hence, how knowledge is

constructed differs markedly from community-based or expert-based classifications (Alaimo & Kallinikos, 2021; Cheney-Lippold, 2017; Wood & Lehdonvirta, 2022). Third (on *what* basis is labour classified), workers are classified based on data collected on their individual and platform-specific actions rather than their employment relations or their economic, social, or cultural forms of capital (Fourcade & Healy, 2013, 2017).

In contrast, findings from the preceding chapters suggest that there are limits to how removed from social practice classifications of labour in digital marketplaces really are. Worker input revealed that classification systems of labour constructed by platform firms remain incomplete. Instead, workers are complicit in co-constructing and enacting digital boundaries. They enter data points, implement classifications in 'last mile' client interactions, and make use of the systems themselves. In other words, only workers' informal practices complete the *classificatory loop* of an otherwise lacking platform infrastructure. In addition to the firms that build and apply them (Alaimo & Kallinikos, 2021; Bechmann & Bowker, 2019; Kelkar, 2018; Kotliar, 2020) and those who use them (Boltanski & Thévenot, 1983; Lomborg & Kapsch, 2020), my work thus adds those who are being classified as an important group whose social practices shape the classificatory tools that construct and sustain digital markets (the *who*). Additionally, I found evidence that many consequential boundaries resulted from platform firm employees' manual choices rather than from automated algorithms (the *how*). Examples for such manual work include interviews to identify expert freelancers, categorizing what constitutes remote gig work, or deciding on who qualifies as a platform worker. Thus, platform firms only partially rely on data-driven, platform-specific, and automated classificatory tools at scale, that is they only partially 'see as markets' (Fourcade & Healy, 2017). Instead, platform firms fall back on manual categorical practices if they deem it strategically necessary. In fact, I find that in these

instances platform firms break with algorithmic regimes of evaluation and behave more like the traditional intermediaries they set out to supplant. Last, my findings highlighted that platforms also evaluate and categorize workers based on information on their behaviour before joining the platform (the *what*). When platform firms manually label worker quality, for example, their evaluation moves beyond platform-specific information such as client reviews or productivity metrics. Instead, platform firms manually vet applications for such labels and even interview workers whenever necessary (chapter 4). This way, they base their judgment also on known signals of quality such as professional networks, educational qualifications, or work experience.

In conclusion, I therefore arrive at my thesis that classifications of labour continue to be deeply embedded in social structures beyond those of their designers. They are co-constructed and enacted by the workers they set out to classify in completion of what I termed the classificatory loop. My overarching contribution therefore lies in *putting the social back into classification*. Rather than essentializing technologies such as recommender algorithms powered by artificial intelligence and thus enacting narratives marketed by platform firms, we should acknowledge that much of the platform infrastructure that enables remote work builds on human categorical work and social structures beyond the platform. As part of the 'social infrastructure' of digital marketplaces, classifications of labour are social institutions that rely on central organization and codification as well as individual and collective practices of users (Aspers & Darr, 2022). In other words, classification systems which organize digital platforms are socio-technical constructs which rely on social practices and human choices just as much as the technical feasibility of data collection and statistical analysis (Bowker & Star, 2000a; MacKenzie & Wajcman, 1999).

Answering my research question

This overarching thesis leaves us with two sets of answers for my overall research question: *How and to what effect are work and workers classified in online labour markets?* Both have implications for how we think about categorization and classification in digital market-settings. In fact, my work follows many scholars who have made us more attuned to the powerful role of classifications in constructing information systems and other technologies (e.g., Bechmann & Bowker, 2019; Bowker & Star, 2000a; Desrosières, 1998), providing structure to organizations (e.g., Alaimo & Kallinikos, 2021; Foucault, 1977; Thévenot, 2016), making markets intelligible (Beckert & Musselin, 2013; Boltanski & Thévenot, 2006; Callon, 1998b; Fligstein, 2002), and ultimately ordering society (Bourdieu, 1984/2010; Douglas, 1966/2002; Durkheim, 1963/2010; Foucault, 1966/2002).

On the process of categorization, my project has foregrounded the social character of constructing and sustaining classification systems that organize digital markets. I identified how workers and platform firms co-construct digital markets via formal and informal, as well as manual and automated categorizations of labour. Automated categorical practices based on behavioural data encoded and collected online is what sets platform firms apart. As input for machine learning applications such as search- or recommender algorithms, automated labelling of worker quality, or the automated detection of behaviours that violate a platform-defined code of conduct, it allows platform firms to build and govern digital marketplaces at scale. In fact, platform firms combine two approaches to categorization that previously were mutually exclusive. On the one hand, platform firms have the power to construct and enforce classifications of labour *top-down*, comparable to states and their bureaucracy (Scott, 1998) or companies and their internal 'investments in forms' (Thévenot, 1984). On the other,

they collect large amounts of individual-level data to classify workers from the bottom-up, in automated as well as manual fashion. By putting individual data in relation to other users, platform firms can hierarchically order workers based on observed proxies for traits conventionally embedded within the social ties of local communities such as social trust (Wood & Lehdonvirta, 2022) or failures to oblige with normative role expectations (Zuckerman, 1999). Thus, user classifications in digital markets result from expert labour by employees of the platform just as much as approximations of community-based knowledge through the categorization, encoding, collection, and automated analysis of user behaviour (Alaimo & Kallinikos, 2017).

On the effects of classifications of labour in digital markets, my work foregrounds that digitized boundaries *inform* by distinguishing between work and workers horizontally, *divide* resources by ordering offerings hierarchically, and *control* by making individual behaviour visible and setting normative standards. As platform firms touch ever more areas of our lives (Kenney et al., 2021), I used the case of online freelancing to show how user classifications in digital markets shape the distribution of resources in markets and beyond (Fourcade & Healy, 2013; Lamont & Molnár, 2002). However, classifications of labour in digital markets differ in their speed (of change) and scope to conventional labour markets. Since platform firms classify to extract more value from workers in the short term (Fourcade & Healy, 2017), the rate of change of classification systems has increased rapidly in digital markets compared to, for example, state classifications. To measure and track changes over time, the 'horizon [of state classifications] is measured in decades rather than years', while any structural changes always 'necessitate the revision of categories' (Amossé, 2022, section 1). The same author reminds us that the French occupational classification introduced in chapter 2 was updated by bureaucratic experts only three times (1982, 2003, 2020) since their

construction in 1954. Online freelancers instead described how changes to classification systems occurred much more frequently and without consultation or warning, so that it was difficult to reliably depend on any of such structures in the long run. In fact, the insecurity around classification systems explains some of the uncertainty experienced by workers around online reputation systems (Rahman, 2021; Wood & Lehdonvirta, 2022).

This thesis adds value by pointing out the dynamic and circular nature of classification systems. As these systems rely on constant user input, automated processes of categorization, and illicit quasi-instant user feedback, they take the shape of a *classificatory loop*. The study of online freelancing offers a concrete, in-depth illustration of the recursive or ‘loop-y’ nature of artificial intelligence applications (Beer, 2022; Fourcade & Johns, 2020). My findings concretize the limitations of such systems and show how human interventions are necessary to make them work.

6.3 Situating my theoretical contributions

Platform firms only do half the work of organizing digital marketplaces

My thesis contributes to debates on the organization of marketplaces twofold (Ahrne et al., 2015; Aspers & Darr, 2022; Kirchner & Schüßler, 2019). First, my project illustrates how theories of categorization and classification allow for studying the organization of digital marketplaces from first principles, that is *one category at a time*. Grounding my project in observations on online freelancing, I manage to reframe the debate on platforms as market organizers. I present the case that platform firms only do half the work and rely on workers’ informal categorical practices to complete the platform infrastructure.

My research is situated within a small but growing collection of studies on platform work that foreground the social organization of digital marketplaces (e.g., Aspers & Darr, 2022; Kirchner & Schüßler, 2019; Kornberger et al., 2017). Much research on remote gig work otherwise centres on platforms as digital workplaces. My project builds on work by Aspers and Darr (2022, p. 824) who study how the centrally ‘decided social infrastructure’ of digital marketplaces is constructed and changed over time. In a way, I put their theoretical framework to work by narrowing my focus on symbolic boundaries constructed by platform firms. In chapter 3, for example, I demonstrate how the idea of ‘investment in forms’ by traditional corporations (Thévenot, 1984, p. 25ff) translates to the context of digital platforms as a workplace and shapes the labour process of remote gig work (Gandini, 2019). By categorizing and classifying workers and their services, platform firms construct digital marketplaces that ‘consist of infrastructure, rules, and customs through which information is exchanged and transactions are made’ (Roth, 2018, p. 1610) and give rise to online labour markets. The resultant boundaries are institutionalized as code and serve the platform firms’ objective to make matching more efficient by reducing transaction costs (Pissarides, 1984; Stiglitz, 1975) and employer uncertainty (Akerlof, 1970). Remote contracting only is and remains feasible if a platform firm addresses problems of remote collaboration such as low levels of trust, lack of direct managerial oversight, and high search costs on platforms with millions of users (Lehdonvirta et al., 2019; Parker, 2016). To protect their corporate interests in growth and profitability, platform firms therefore take boundary decisions on user access and the interface intermediating the exchange (Gawer, 2020).

My first contribution lies in providing empirical evidence that the institutionalization of (market) categories and the codification of a cognitive framework of how workers and employers interact is another dimension of said platform organization (Ahrne et al.,

2015; Kirchner & Schüßler, 2019; Pujadas & Curto-Millet, 2019). In fact, categorical practices by platform firms span across all five dimensions of organizing digital marketplaces: 'membership, rules, monitoring, sanctions, and hierarchy' (Ahrne et al., 2015, p. 11; Kirchner & Schüßler, 2019). My data suggests that categorical practices may lead to the (effective) exclusion of workers ('membership'), form the basis for any form of statistics ('algorithmic rules') or metric comparisons ('monitoring'), are institutionalized via quality labels ('sanctions'), and define the structural 'hierarchy' of remote gig work. I therefore propose that studying the construction of boundaries allows for theorizing the social construction of digital markets and changes to their social order from first principles (Beckert, 2009). While my findings are in alignment with claims that digital marketplaces are constituted through 'various forms of sorting, categorizing and valuating of economic subjects and objects' (Krenn, 2017, p. 7), it also emerged that some of the boundaries most impactful for workers relied on manual work by employees of platform firms rather than on automated forms of assigning classes (e.g., categorization of online labour, classifying membership criteria). In fact, I find that some practices even marked a reversal back to tried and tested methods such as interviewing for the award of quality labels.

More broadly, my work is thus situated in the (economic) sociology of markets. There are few economic sociologists or even economists who would question that aspects of any marketplace or exchange are socially constructed. The point has been made forcefully for many empirical examples ranging from regional fruit markets (Garcia-Parpet, 2008) to financial exchanges (MacKenzie, 2006). In labour markets, workers, employers, and intermediaries rely on categories and classifications as 'cognitive infrastructure' to qualify one another, and thus bring order to competition and exchange (Beckert & Musselin, 2013; Callon et al., 2002; Diaz-Bone, 2017, p. 240; Karpik, 2010).

Categorization and classification solve coordination problems given uncertainty (Beckert, 2009). They impact the constitution of preferences, competition, and risk inherent to conducting exchange. For example, executive search firms typecast ideal executive candidates to alter hiring preferences of their clients (Faulconbridge et al., 2009), socially constructed market categories define industry expectations and curtail individuals' career choices (Zuckerman et al., 2003), and professions spend considerable resources on defending professional boundaries to establish trust in their expertise towards solving a particular human problem (Abbott, 1988). Employers can evaluate and hire workers only once market categories are institutionalized, workers are horizontally differentiated by being associated to these categories, and then vertically ranked according to their worth (Beckert & Musselin, 2013). On labour platforms, reputation scores or labels of quality can serve as 'judgment devices' to further aid employers to make hiring decisions with respect to otherwise singular service providers (Karpik, 2010). The empirical focus on actual practices of market participants, including their use of such market devices, also puts emphasis on conventions of equivalence and evaluation at the core of employers' hiring choices (Boltanski & Thévenot, 2006; Diaz-Bone, 2018; François & Emmanuelle, 1997; Thévenot, 1984).

Second, and arguably more important, I propose that workers' informal *categorical work* is needed to close the *classificatory loop* (chapter 5) of an otherwise incomplete platform infrastructure. On the one hand, my work expands on what Aspers and Darr (2022, p. 824) conceptualized as the dynamics between the 'decided and emergent order of online marketplace[s].' On the other hand, it reframes the discourse on worker agency in platform work that are largely theorized as 'reactivity' (Espeland & Sauder, 2007) to the imposed structures of a platform-mediated workplace (Rahman, 2021). In

its place, I identified categorical work as another form of ‘marketization’ (Çalışkan & Callon, 2010) needed for the construction of markets, and ‘market work’ needed for the maintenance of such markets more broadly (Cochoy & Dubuisson-Quellier, 2013). By filling out their profiles, updating their skills or services on offer, and generally bridging the gap between platforms and clients, workers co-construct, perform, and enact underlying conventions of remote gig work (Callon, 1998b; MacKenzie, 2006). For example, the employment relationship between worker and clients on platforms is structured along market logics. It thus tends to be commodified and be perceived as socially disembodied (Wood et al., 2019b). Other forms of market work include workers’ ‘relational work’ to reign in this market logic, for example when building longer term relationships with platform clients (Alacovska et al., 2022), incentivized ‘community work’ (Aspers & Darr, 2022), or managing ‘reputational insecurity’ (Wood & Lehdonvirta, 2022). Ultimately, these forms of market work also point to areas where platforms and their communities of workers move past their inherent tensions (e.g., commodification versus community) to support ‘a shared temporality and space of practices’ that makes platform work possible in the first place (de Vaujany et al., 2020).

My empirical focus on online freelancing complements extant studies that highlight the role of human classificatory and categorical practices for the design of digital platforms. However, like my project, most studies rely on ‘outside-in’ case studies, for example of how categorization lies at the core of turning observed user behaviour into data (Alaimo & Kallinikos, 2017; Cheney-Lippold, 2017; Flyverbom & Murray, 2018) or shapes platform firms as an organizational form (Alaimo & Kallinikos, 2021; Gawer, 2020). Other authors studied the role of human classificatory work in automated statistical analysis by gaining access to teams that worked on such technologies in non-platform contexts (Bechmann & Bowker, 2019; Kotliar, 2020). Future research should aim for

collaborations with platform firms to study how managers, engineers, and designers categorize and classify users and their behaviours (e.g., Kelkar, 2018; Shestakofsky & Kelkar, 2020). Studying categorical practices and their consequences in these settings will be an opportunity to question 'data universalism', that is the conception of data as something universal outside its specific social, cultural and historic context (Milan & Treré, 2019, p. 324), and uncover potential inequalities built into the foundation of digital economies. Another avenue for future inquiry are comparative studies of centralized categorical work by platform firms to study and account for heterogeneity of digital platforms (Schor, 2020). Such heterogeneity includes intra-platform changes over time as well as inter-platform differences based on the type of platform work (e.g., microwork, locational gig work), their geography, and industry specialisation.

Workers engage in 'classification struggles' in platform-mediated workplaces

By relying on their input across all empirical chapters, I purposefully put workers at the centre of my investigation. By focusing on those being classified, my work complements research on the role of categorization and classification in collecting, structuring, and analysing data to build knowledge and extract value (Bechmann & Bowker, 2019; Cheney-Lippold, 2017; Flyverbom & Murray, 2018; Kotliar, 2020). In fact, my thesis explores how digitization mediates a core concern in the sociology of work: Do symbolic boundaries such as occupational distinctions matter, and if so, what are the implications for those classified (Abbott, 1989)? In this section, I proceed to discuss how my thesis is situated in debates on workers' experiences online, their skill development, what qualities matter in labour markets, and collective action.

On the platform, categorical choices by platform firms impact the success of workers online. My unique contribution lies in uncovering how platform firms effectively place

workers into distinct market categories. Theorizing worker heterogeneity as a result from categorization by the platform firm is helpful because the identified classes of workers offer a litmus test of theory on platform work. For example, *global competitors* embody much of the imagery evoked by scholars who theorize remote gig work in terms of algorithmic control or precarity (Kalleberg & Vallas, 2017; Wood et al., 2019a; Wood & Lehdonvirta, 2022). On the contrary, the arguably largest category of workers, those who remain (*effectively*) *excluded* from platform work, receives little to no voice in most scholarship. Notable exceptions include research on structural barriers to platform work (Newlands & Lutz, 2020; Shaw et al., 2022) or the (in-)visibility of certain groups within the platform economy. (Gregg & Andrijasevic, 2019; Gruszka & Böhm, 2020). My work underlines that boundaries do not only shape the experience of those on the platform but are felt painfully also by those who they exclude from labour market integration in the first place. At the same time, the class of *industry professionals* supports the view that ‘classification situations’ in digital marketplaces may also perpetuate advantages and inequalities from society at large (Fourcade & Healy, 2017). In digital marketplaces, Bourdieu’s concept of ‘classification struggles’ (Bourdieu, 1984/2010) shines in a new, more individual light. The fact that workers co-construct the classification systems and enact them with clients implies that the struggle for more recognition and resources within the digital infrastructure plays out more frequently and at a faster rate than before. It is neither only antagonistic nor collaborative. While one Chinese professional described how her journey into the digital classification systems of platform work allowed her to flee stereotypes in local labour markets, another freelancer described her futile struggles to escape her current digital class for a more profitable one to be able to make a living from gig work.

To succeed in platform-mediated workplaces, workers rely on categorical work. By theorizing informal categorical practices this way, my project is situated in the debate on skills developed by online freelancers. My findings link to what others have described as 'gig literacies' needed to address the challenges inherent to online labour markets (Sutherland et al., 2020). These include learning the robes of 'obtaining work on the platform' (Cedefop, 2020, p. 18) including 'self-branding strategies' (Blyth et al., 2022), efforts to manage 'reputation insecurity' (Wood & Lehdonvirta, 2022), 'relational work' to assuage the commodification of employment relations (Alacovska et al., 2022; Wood et al., 2019b), but also 'maintaining productivity' in remote and non-organizational settings (Sutherland et al., 2020, p. 466f), for example by 'cultivating holding environments' (Petriglieri et al., 2019). Categorical work is theoretically helpful because it recognizes another form of market work which serves as a positive externality to platform firms. Just like unpaid work in general (Fuchs, 2010), it appears to have purchase beyond online freelancing. In the locational gig economy, for instance, authors have identified practices that resemble categorical work. Locational gig workers also consciously feed data to an algorithmically-mediated environment (Vasudevan & Chan, 2022), bridge gaps between platform infrastructure and users (J. Y. Chen, 2018a), or enact normative behavioural categories (Ramizo, 2022). In fact, categorical work might be considered a more advanced form of digital literacy acquired in an algorithmically-mediated workplace (Jarrahi et al., 2021). For example, interviewed workers implied a complex awareness of the platform infrastructure and its limits. As a result, some reported to differentiate communication styles aimed at the technologies that generate automated matches and clients who ultimately decide on the hire. In a future where algorithmically mediated work becomes more common, we

might expect categorical work to become a more solution-oriented awareness of algorithms (Gran et al., 2021) that constitutes part of broader digital literacy.⁴⁶

Next to the development of such platform-specific skills, the way platform firms categorize work and classify workers on the platform also calls into question which human attributes matter online. The classification, measurement, and aggregation of client feedback or workers' past behaviour on the platform (e.g., number of projects completed, value per project generated, response rate and speed) is used by platform firms to flatten 'organic social regulation of exchange' into a more reduced form of symbolic capital captured 'with platform code' (Wood & Lehdonvirta, 2022, p. 2). For digital economies more broadly, Fourcade and Healy (2017, p. 14) even argue that individuals accumulate a new form of digital capital they call 'übercapital'. By 'übercapital', they suggest that workers' actions and traces left behind in digital contexts accrue to a new form of digital capital. In other words, platform firms and other 'market institutions' categorize, collect, and aggregate data on workers' digital footprint to increase matching efficiency, exercise normative control, and maximize the value extracted from them. Their proposal builds on Bourdieu's work on various forms of capital embodied by individuals. He noted that

[t]he social world is accumulated history [...] Capital is accumulated labour (in its materialized form or its [...] embodied form) which, when appropriated on a[n...] exclusive basis by agents or groups of agents, enables them to appropriate social energy in the form of reified or living labour' (Bourdieu, 1986, p. 14).

My findings concretize why Fourcade and Healy (2017) caution that such 'übercapital' largely remains 'in potentia' as it mostly pertains only to a specific digital market rather than being a coherent, empirical number attributed to each individual across the web.

⁴⁶ I will later in this chapter propose that platform workers and their experience with categorical work might be helpful for platform regulation, for example when auditing algorithmic systems.

Specifically, my findings highlight how in online freelancing, 'übercapital' might be more accurately described as the flattening of previously social forms of capital, for example a freelancer's reputation (Wood & Lehdonvirta, 2022), into symbolic capital codified within (and restricted to) the platform infrastructure. Further, I found evidence that platform firms were able and did upheave such forms of accumulated history (Bourdieu, 1986) at their will and in comparably short intervals, for example by undermining the value of algorithmically calculated platform reputation scores by introducing manual quality labels. Instead, my findings align with other research that points to how non platform-specific forms of capital, that is economic (e.g., J. B. Schor et al., 2020), cultural (e.g., Demirel et al., 2020) and social (Wood et al., 2019b) capital, remain key to workers' success online.

Beyond the platform, platform firms' efforts to commodify workers and their services limits workers' ability to organize collectively. In the remote gig economy, workers' protests are thus not only aimed at employers or the state but also platform firms (Wood et al., 2021). In online labour markets, platform firms reduce workers to bundles of skills rather than recognizing them as being part of a larger social group (Bergvall-Kåreborn & Howcroft, 2014; Stephany, 2021; Wood et al., 2019b). In many ways, worker fragmentation in the gig economy is just another case of a broader strategy by capitalist firms to break labour power, for example by dividing up complex work into a collection of menial tasks in the modern workplace (Wood et al., 2019a), and to extract more value from them, for example by moving previously unpaid work 'inside the knot' of paid labour that is directly productive for capitalist firms (Huws, 2014). While my research thus explains how platform firms, knowingly or not, construct roadblocks to effective organization, it also offers potential paths forward. Bourdieu's concept of 'classification struggles' points out the need for online freelancers to establish a

symbolic, common identity (e.g., being an 'online freelancer') to rally behind and engage in collective action (Bourdieu, 1984/2010). A parallel from history is the struggle by a collection of loose social groups to establish an occupational class called 'cadres' that is unique to the French context (Boltanski, 1987). For now, evidence that online freelancers engage in collective action beyond the platform is mixed. It is unclear whether software developers, for example, will side with other freelancers on the platform or solidarize with their broader occupation including their peers formally employed by platform firms (Huws, 2014). That said, recent occurrences of offline protests by online workers, for example against a Serbian tax reform on foreign income organized by a loose association called Association Of Internet Workers, surely point to the potential for collective action of remote gig workers as a social group on the national or even international level.⁴⁷ If remote gig workers (or a subset of them) manage to denaturalize and thus challenge efforts of commodification by platform firms, they might indeed choose to organize as a new (middle) class that exercises power collectively and simultaneously restricts the dominance of platforms (Dorschel, 2021; Huws, 2014; Lehdonvirta, 2022).

From these four themes, various avenues for future research emerge. First, scholars have discussed the impact of online freelancing for policy issues such as economic development (Graham et al., 2017) or labour market integration of immigrants (van Doorn et al., 2022). That said, less attention has been placed on how policy makers could support those at the margins of the digital platform, the group I called the *effectively excluded*. For example, colleagues and I suggested to fund 'micro-internships' to reduce the risk of employers to hire workers without any digital

⁴⁷ <https://lefteast.org/gig-work-protests-of-serbian-freelancers/> (Accessed on 29.05.2021). Credit goes to Alex Wood who highlighted this article on Twitter.

reputation (Cedefop, 2020). It is less clear, however, how policies could support workers who failed to get access to the platform in the first place. Second, the transferability of categorical work as a new type of skill set in platform-mediated workplaces, including organizations and their internal human resource or knowledge management systems, calls for a more systematic analysis across different forms of locational gig work as well as more conventional organizational contexts. Last, the link between research on the self-categorization of workers and their willingness to organize as a social group should be further explored. For example, workers' self-identification has already been identified as one explanatory factor in differences of attitude towards collective action (Newlands et al., 2018).

6.4 Reflections on practical relevance

I now continue by reflecting on the practical relevance of this project for workers, platform firms, and policy makers.

Workers: How to succeed in online freelancing

From the outset, one goal was to make relevant insights accessible to the wider community of online freelancers, or individuals interested in earning income this way in the future. Several respondents participate in research only because they consider academia one engine to make platform work better for them and others. After all, in the status quo, online freelancers experience vastly heterogenous outcomes (chapter 3), and there are valid concerns around the risk of precarious employment due to job insecurity, low pay, and other stressors related to remote gig work (Blaising et al., 2021). I therefore wondered what practitioners can learn from the analysis of rather mundane symbolic boundaries to mitigate such risks, especially since most of my participants highlighted the economic opportunities, they associate with labour

platforms. 98% of surveyed freelancers from chapter 4 (n=723) stated that they intend to continue working on their platform of choice in the future. More than 80% said the statement ‘I enjoy working on [platform name]’ was true most of the time or always true. Less than 2% opted for ‘Not at all true.’ For some workers, online freelancing has the potential to offer labour market integration (van Doorn et al., 2022).⁴⁸ For example, one in three of my survey respondents had an immigration background in that they freelanced from a different country than the one they had been born in (compared to 13% in the general EU population in 2021).⁴⁹

As a concrete output, I compiled a short manual on *‘How to succeed in online freelancing: A researcher’s perspective.’* Since my project was about foregrounding mundane processes that construct and sustain online labour markets (Bowker & Star, 2000a), I discussed and analysed work practices ranging from the broad (e.g., motivation to join a freelancing platform) to the specific (e.g., evolution of worker profiles, break-down of own professional abilities as standardized services or skill tags). In simple language, the document raises questions to consider before starting a career as a freelancer, when signing up to a platform, while working in remote service provision, and when planning one’s career around it in long term. A draft version is attached in appendix A.4. I intend to publish it as a blog post on the departmental website as well as on relevant discussion boards. Many interview partners mirrored that our discussions were a valuable opportunity to reflect on their own practices. The document is similarly designed as a collection of resources that aims to start a

⁴⁸ The authors of the cited study also argue that gig work simultaneously makes working conditions worse.

⁴⁹ Eurostat (2022, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Main_characteristics_of_foreign-born_people_on_the_labour_market#Profile_of_foreign-born_people; last accessed on Nov 15, 2022)

discussion or trigger reflections on one's work process rather than a prescriptive path towards success. First, workers' circumstances are too individual to achieve such a feat (Schor et al., 2020). Second, I personally have never worked as an online freelancer—an active choice in my research design (chapter 1)—and solely rely on the data and insights collected from others. Where I can add value is in aggregating individual experiences to broader themes of challenges and opportunities, connect them to insights from academia, and provide workers a means to contextualize their own successes and failures through a summary of their peers' experiences.

Platform firms: How to use workers' market work productively

The knowledge that digital marketplaces are embedded in social practices and the context of their users may also help technology companies to build better marketplaces. Concretely, I found that many classificatory tools that had the largest impact on the order of digital marketplaces originated from manual practices by employees of platform firms (chapter 3, chapter 4). At the same time, the year 2022 has been characterized by a wave of reductions to the workforces employed by technology companies from Meta⁵⁰ to Amazon⁵¹. In 2022, Fiverr equally reduced its workforce by about 8%.⁵² Such developments obviously raise questions about how platform functionality will be impacted. In many cases, the argument goes that tasks

⁵⁰ Meta announced to cut more than 10,000 employees in November 2022 (<https://www.ft.com/content/348068b1-24d9-434b-9ae7-6599027bf84f>; last accessed on Dec 6, 2022)

⁵¹ Amazon started to reduce around 10,000 corporate and technology roles (<https://www.reuters.com/business/retail-consumer/amazon-plans-lay-off-10000-people-starting-this-week-nyt-2022-11-14/>; last accessed on Dec 6, 2022)

⁵² With their 'Second Quarter 2022 Results', Fiverr announced a reduction in their workforce by around 60 employees (<https://investors.fiverr.com/press-releases/press-releases-details/2022/Fiverr-Announces-Second-Quarter-2022-Results/default.aspx>; last accessed on Dec 14, 2022). The 8% are calculated based on the 787 employees reported as of December 31, 2021 (https://s23.q4cdn.com/749308338/files/doc_presentations/2022/11/FVRR-Company-Presentation-November-2022.pdf; last accessed on Dec 14, 2022).

previously carried out by affected employees will instead be completed by automated systems. However, my research has pointed out some limitations of automated systems in the case of categorization and classification (chapter 3). Further, I showed how manual practices, for example the manual labelling of worker quality often come with a different set of affordances than automated alternatives (chapter 4). Beyond such concerns about functionality, research has shown that personal interactions between platform firms and workers 'allow... to establish a more motivating and encouraging work environment' and reduce worker turnover (Gegenhuber et al., 2020, p. 23). My discussions with workers equally provided evidence that account and community management by platform firms, so called 'relationship labour' (Shestakofsky & Kelkar, 2020), might be an underappreciated lever for improved platform efficiency. That said, my research obviously does not allow for any conclusive analysis of the costs and benefits of account and community management in general. Instead, my project shifts the narrative of building and running platforms towards potential levers for pareto improvements which make all involved stakeholders better off by enabling and channelling users' informal work practices. For example, *fiverr.com* usually requires workers and employers to communicate via in-platform chat. However, manually labelled, pro-verified sellers are allowed to take communication off the platform after contracting as long as it is sufficiently documented. Judging by the input of my participants, this switch had become necessary for the platform to be a feasible solution for larger corporation as well as professionals who deliver on complex projects. In both cases, chat-based communication often does not suffice. There also lies untapped value in collaborations between researchers and platform firms to voice freelancers' experiences at an aggregated level to platform organizers in an anonymous manner. For example, I was twice able to present results of the worker

survey (chapter 4) on skill development to research and policy teams employed by a major freelancing platform. In these interactions, the representatives of the platform were especially interested in how workers responded to changes in the interface, their informal practices that set successful freelancers apart from others, suggestions for pareto improvements, and broader policy discussions around worker classification.⁵³

Policymakers: How to regulate platforms and support workers

Last, renewed attention to human categorical practices in digital infrastructure may provide a helpful frame for regulating digital platforms. National governments traditionally face difficulties regulating global platforms (Lehdonvirta, 2022). Recently, however, the European Union reached agreements on two pieces of legislation to address this obvious pain point: the Digital Markets Act (DMA) and the Digital Services Act (DSA). The DMA sets out to regulate gatekeeper platforms with more than 45 million monthly users to ‘to ensure contestable and fair digital markets’ (Radley-Gardner et al., 2016a, p. 265/3). While the DMA will thus not (yet) apply to online freelancing platforms, the DSA will. It aims to ‘ensure an adequate level of transparency and accountability’ of providers of intermediary services (Radley-Gardner et al., 2016b, p. 277/13). The DSA includes an obligation for platform firms to inform users about how recommender systems order information, including the ‘most significant [criteria] in determining the information suggested’ and ‘reasons for the relative importance of those parameters’ (Radley-Gardner et al., 2016b, p. 277/19). Based on this information, the key categories of data which feed into recommender systems should become more transparent to users.

⁵³ After submission, I therefore plan to reach out to both platform firms who were the sites of my research to discuss the potential to present select findings and recommendations that follow.

My research suggest that foregrounding the human categorical work along the entire 'statistical chain' (Desrosières et al., 1983) underlying recommender or search algorithms could be a meaningful methodological tool for discussing these systems with civil society. Once input categories to algorithms are discussed with those affected, individuals who are classified can be a valuable source of information for regulators to point out how certain categories of data might or might not be a source of structural disadvantages for their community. For example, my interview participants were able to distinctly point out instances where they experienced algorithmic classifications as alienating because they clashed with the realities of their professional lives (Seberger & Bowker, 2021). Those being classified by algorithms will be able to highlight problematic categorical work along the chain from algorithmic design, data collection, data cleaning, analysis, and ultimately application (Bechmann & Bowker, 2019) as a complement to more quantitative approaches to algorithmic fairness.⁵⁴ At the same time, the literature on classification systems (e.g., Bowker & Star, 2000a) serves as a reminder that such systems will always be social and contested, and work better for some people than others. As such, there will be no such thing as an unconditionally unbiased system but rather one that is intermittently made visible, probed for who is (effectively) excluded, and whether the implicit normative claims are in alignment with the values of our democratic societies.

Beyond regulation, my research has already been used to inform policy makers. The survey data set used for chapter 4 was created as part of my work as a research assistant for a project on skill development and matching funded by the European

⁵⁴ Quantitative approaches to algorithmic fairness like 'anti-classification', that is the exclusion of demographic variables and close substitutes of the likes of gender or race, or 'classification parity', that is the achievement of parity in how predictions work for various groups in terms of error rates (Corbett-Davies & Goel, 2018) come with their own limitations (Davis et al., 2021). Both approaches refer to classification as an important concept.

Centre for the Development of Vocational Training (CEDEFOP). Its insights were thus also used to make recommendations for policies to support workers in their skills matching and development online (Cedefop, 2020). In addition to parts of this doctoral thesis, the survey data set has further been used for scholarship on protest in the gig economy (Wood et al., 2021), social mobility on labour platforms (Martindale & Lehdonvirta, 2021), and a methodological contribution that I co-published on how to measure online freelancers' learning practices (Margaryan et al., 2022). I also presented my work on the award of quality labels (chapter 4) in the context of a CEDEFOP-organized webinar on '2030 on the horizon: skills in the online platform economy' to a broader audience of policy makers to inform European skills and vocational policy, including a strategy on the future of micro-credentials.⁵⁵

6.5 Conclusion

As I write these concluding paragraphs, the realities of remote work have changed. Remote work has arrived at the centre of society. Last year, Hayden Brown, the CEO of Upwork observed that 'we're in the midst of a [...] tectonic shift in how work gets done.'⁵⁶ Her words were spoken in the context of a global Covid-19 pandemic that had already been going on for more than a year. When I embarked on my doctoral journey in October 2018, pre-pandemic, platforms for remote collaboration were still in their infancy. Only amidst the pandemic, video conferencing software provider Zoom reported a rise in daily meeting participants, both free and paid, from 10 million in

⁵⁵ For more information on the event including a video of the presentations please refer to the CEDEFOP website (<https://www.cedefop.europa.eu/en/events/2030-horizon-skills-online-platform-economy>; last accessed on December 11, 2022).

⁵⁶ Press release 'Upwork Introduces Work Marketplace' (Upwork, 2021: [https://www.upwork.com/press/releases/upwork-introduces-work-marketplace-category#:~:text=\(Nasdaq%3A%20UPWK\)%20today%20announced,help%20them%20achieve%20more%20together](https://www.upwork.com/press/releases/upwork-introduces-work-marketplace-category#:~:text=(Nasdaq%3A%20UPWK)%20today%20announced,help%20them%20achieve%20more%20together); last accessed on Dec 19, 2022).

December 2019 to 300 million in April 2020.⁵⁷ Today, more employees work from home. Although such opportunities are not equally distributed across society, the share of workers in the UK who ‘did any work from home’ increased from 27% in 2019 to 37% in 2020.⁵⁸ At the same time, the phenomenon of online freelancing keeps growing. Upwork’s gross service volume, that is the amount spent by users of the platform, almost doubled from \$1.8 billion in 2018 to \$3.5 billion in 2021.⁵⁹ Over the past four years, the world of work has become more digitally connected, more remote, and is more often mediated by platforms. Consequently, my project on online freelancing as a pioneering form of remote, for-profit collaboration has only increased in relevance.

In this project, I asked *how and to what effect work and workers are classified in online labour markets*. With this question, I created a link between the empirical phenomenon of platform work and the sociological tradition of paying systematic attention to the categories and classifications that invisibly divide and structure our lives (Zerubavel, 1991). I started from two premises. First, I acknowledged that ‘conventions of equivalence, encoding, and classification’ are a necessary condition for having any ‘cognitive and social tools’ (Desrosières, 1998, p. 236) from statistics to machine learning applications that underpin much of the cognitive and digital infrastructure of online marketplaces (e.g., Bowker et al., 2019). Second, I worked from the assumption that classifications of labour impact individuals’ outcomes in the labour market and

⁵⁷ Zoom (2020, Annual Report, <https://investors.zoom.us/static-files/a6b3b254-94ff-415f-bb3b-8c3146b061d4>, last accessed on Dec 6, 2022)

⁵⁸ Office for National Statistics (2021, <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/businessandindividualattitudestowardsthefutureofhomeworkinguk/apriltomay2021>; last accessed on December 15, 2022).

⁵⁹ Upwork Annual Reports 2018 (<https://investors.upwork.com/static-files/8d67d7b3-1e42-48c0-92db-e839a6d323f2>; last accessed on Dec 15, 2022) and 2021 (<https://investors.upwork.com/static-files/f9770045-d71e-48c5-a793-20ccde8be73f>; last accessed on Dec 15, 2022).

beyond (e.g., Fourcade & Healy, 2013). Based on my findings, I concluded that platform firms categorize work and classify workers not only via automated classificatory tools but also via manual practices whose outcomes are codified in digital interfaces or the formalized rules of conduct. That said, my work emphasized that resultant classifications remain incomplete. While classification systems always require contextualization in local settings (Bowker & Star, 2000a), their construction in digital markets additionally resembles a dynamic loop and users are often required to manage multiple, competing hierarchies of worth. It is workers' informal categorical practices that complete the circular process, enact the system 'on the last mile' with clients, and thus ultimately co-construct the infrastructure of digital markets. Digital boundaries serve platform firms in organizing digital marketplaces in pursuit of economic efficiency, profitable worker behaviour, and maximum value extraction. By using classificatory tools for market organization, platform firms effectively put workers into discrete boxes that impact distributional outcomes online. From global competitors to platform superstars, digital boundaries impact workers' everyday practices needed to obtain work, the clients they interact with, how they are evaluated by these employers, and ultimately their level of market success.

In the end, I suggested that even in digital settings, classifications of labour remain embedded in the social practices and contexts of the workers who are classified. However, *putting the social back into classification* is only the beginning. By making visible the automated and manual classifications of labour engrained in the infrastructure of digital marketplaces, my work is only a small part in the context of wider societal efforts to understand platform power and hold platform firms accountable. These firms combine symbolic power to categorize and classify with the capacity to codify and apply boundaries at scale across their digital infrastructures. In

contrast to nation states (Scott, 1998), however, platform firms lack democratic processes as direct mechanisms of feedback and control on their governance (Lehdonvirta, 2022). Thus, my research marks a first step to foreground their power as classifiers and the implicit value judgments of whose work counts. Categories and classifications are social institutions that *hold things together* (Desrosières, 1998, p. 9ff), for example when encoding, collecting, and structuring data (Alaimo & Kallinikos, 2017; Flyverbom & Murray, 2018) that feed into search- or recommender algorithms of digital marketplaces. By foregrounding classifications of labour on online labour platforms, we can start asking questions about who holds classificatory power (D'Ignazio & Klein, 2020) and whose voices are (not) heard or represented adequately (Bowker & Star, 2000a).

Thereby, my unique contribution lies in uncovering categorical work as an unrecognized form of worker agency across the platform economy. It transfers Bourdieu's idea of 'classification struggles' (Bourdieu, 1984/2010, p. 481ff) to online (labour) markets. Institutionalized symbolic boundaries have long moved individuals and social groups to engage in struggles to improve their access to resources, challenge forms of control, and shape the resultant social hierarchies of worth (Boltanski, 1987). On platforms, categorical work neither presupposes antagonistic nor collaborative worker behaviour. Where 'classification situations' (Fourcade & Healy, 2013) are commonplace but circular, such informal practices instead become an essential part of a new digital literacy that allows for communication with machines and humans alike, bridging the gap between them. In this context, the classificatory loop offers workers unlikely opportunities to not only react to but also co-construct and shape digital economies.

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Appendix

A.1 Appendix for chapter 1

In appendix A.1, I have included project information shared with interview participants, an interview questionnaire used for guidance, and impressions from data collection.

Information shared with interview participants

Figure 12. General project information shared with interview participants

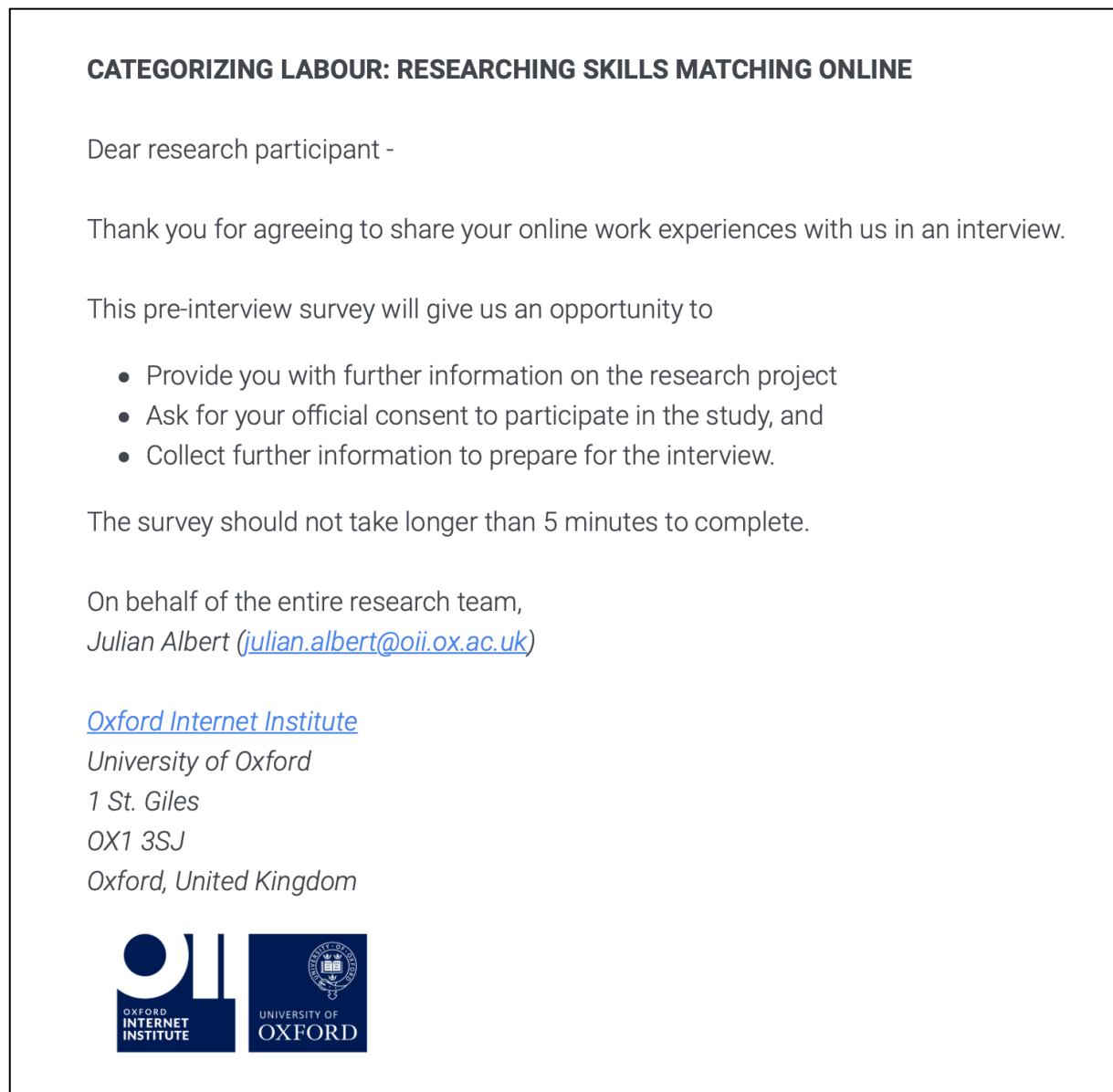


Figure 13. Project description shared with interview participants

Section 1/5: **ABOUT THE PROJECT**

Please read this carefully before filling out the pre-interview questionnaire and participating in the research interview!

With online work experiencing continuous growth, **this study seeks to understand how online workers successfully match with clients on online freelancing platforms.** You have been asked to participate in this study because you work in an area of online freelancing and on a specific platform we are interested in.

The interview will take **no longer than 60 minutes** and will be **conducted via Zoom**, an independent video-conferencing software. Hence, none of your individual information will be shared with Fiverr.

In our interview, we will talk about:

- Why you decided to start working online and what services you usually offer,
- How you position yourself, your abilities and services as a freelance worker online,
- How you evaluate and select clients as well as projects, as well as
- Your interactions with clients and the platform technology in the process leading up to a successful match.

Throughout the interview, it will be useful to **think about concrete situations, interactions or projects on Fiverr** during which you had to strategically position yourself (e.g. when creating/changing your worker profile, when writing a proposal to a potential client), evaluate or select a client, or engage with Fiverr's platform technology.

There are no right or wrong responses to these questions. Please tell us how you typically behave, rather than how you feel you should behave.

If you have any further questions, please email Julian Albert (julian.albert@oii.ox.ac.uk).

Figure 14. Consent form shared with interview participants

Section 2/5: **INFORMED CONSENT**

By selecting 'Yes' below, you confirm that you have read the previous information sheet for this study, had the opportunity to consider the information, ask any remaining questions and consent to participating in this study.

Your **participation is voluntary** and you are **free to withdraw your consent at any time** without giving any reason.

The interview will be recorded for the sake of transcription. This is to ensure that we have an accurate response record of your responses.

All information you provide will be treated confidential. Your individual responses will be shared only with researchers at the University of Oxford. **Any personally identifiable data, such as the video- or audio recordings or personally identifiable profile data, will be securely deleted once the study is completed.** Only pseudonymised, non-identifiable data will be stored for future research.

Overall findings from the interview, the pre-interview questionnaire and any further materials provided by you will be published in a doctoral thesis, journal publications, research reports, or other (social) media, but **you and your responses will not be identifiable individually.**

This project has been approved by the University of Oxford Central University Research Ethics Committee. The researcher is funded by the Foundation of Germany Business.

If you have any other questions about this research, please contact Julian Albert (julian.albert@oii.ox.ac.uk).

I give my consent and agree to participate in the research project:

Yes

No

Interview questionnaire

Interviews with all workers covered the following broad dimensions:

- **Introductions**
- **Online work in the context of participants' professional careers**
 - Motivations for engaging in remote gig work
 - Platform work in the context of a workers' professional career
 - Nature of remote gig work
- **Setting-up as a freelancer: Categorization of labour**
 - Signing-up to the platform
 - Setting-up a worker profile
- **Finding your niche as a freelancer: Attribution of labour**
 - Process of finding work as a remote freelancer
 - Pricing your services
 - Self-promotion on the platform (e.g., labelling, tags, ...)
 - The role of the platform (e.g., access, use of technologies, ...)
 - The client's perspective (e.g., evaluation)
- **Judging and being judged: Evaluation and matching**
 - Selecting projects to apply for and accept
 - Conversing with clients prior to and during a project
- **Success and failures: Matching and other outcomes of online work**
 - Skills matching on the platform
 - Matching failures
- **Future (professional) steps**
- **Closing remarks**

Table 7. Questionnaire for in-depth interviews

Domain	Interview question	Probes	Motivation
<i>Introduction</i>	<p>This interview is about how you match with clients on online freelancing platforms. I would like to understand the entire matching process, including</p> <ul style="list-style-type: none"> • The way you determine which services to offer, • How you position and price your services, • How you negotiate with clients, and • Select and secure a project proposal. 		
Online work in the context of participants' professional careers (max. 10 minutes incl. introduction)			
<i>Motivations</i>	<ul style="list-style-type: none"> • How did you get started with online freelancing? • What motivates you to work online? 	What were your alternatives at the time?	<i>Context and motivation</i>
<i>Professional career</i>	<ul style="list-style-type: none"> • Could you place online work in the wider context of your career (e.g., education, previous professional experience)? 	Reference to specific information collected in the pre-interview survey	<i>Professional career</i>
<i>Nature of work</i>	<ul style="list-style-type: none"> • What type of projects do you normally do on [Platform]? • Could you describe a typical project to me? 	What are you typically asked to do?	<i>Nature of work</i>
Notes. This section serves to add context on a worker's professional background, and the motivation for online freelancing.			
Setting-up as a freelancer: Categorization of labour			
<i>Sign-up</i>	<ul style="list-style-type: none"> • How did you pick the platforms you eventually signed-up for? • How did the sign-up process work? • How did you pick the skills or services to offer online? • <i>[Insert platform-specific questions that apply]</i> 	Why did you decide against other platforms?	<i>Categorization of services</i>
<i>Setting-up a profile</i>	<ul style="list-style-type: none"> • How did you describe yourself in your online profile? 	What skills did you purposefully not include in your profile?	<i>Self-promotion strategies</i>

	<p><i>Suggest 'walk-through' of online profile via screen sharing:</i></p> <ul style="list-style-type: none"> • Do you regularly change your worker profile? If so, how and why? • What other principles are you following in terms of your self-description on [Platform]? • Are there any parts of you that are not well captured in your profile? • <i>[Insert platform-specific questions that apply]</i> 	<p>What is your tagline and why?</p> <p>Could we go through your self-description?</p> <p>What do you consider your most important features of your profile?</p>	
<p>Notes: This section serves to explore the type of work freelancers do, how they categorize themselves and their services, their strategies in terms of self-promotion, and where the standardized set-up of platforms might fail them.</p>			
<p><i>Finding your niche as a freelancer: Attribution of labour</i></p>			
<i>The process of getting hired</i>	<ul style="list-style-type: none"> • Could you walk me through the entire process from advertising your services to getting a project on [Platform]? • What categories do you place your gigs in/apply for? • How do you make sure that people find you/you find the right projects? 	<p>Could you talk me through a typical day as an online freelancer?</p>	<i>Work process</i>
<i>Pricing your services</i>	<ul style="list-style-type: none"> • In which category do you normally position your services? • Have the services your offered changed since you signed up to the platform? If so, why? • How do you price your services (e.g., an individual gig, hourly wage)? 	<p>What advice would you give new workers defining/pricing a gig?</p> <p>Are you influenced by what other workers do?</p>	<i>Pricing; Market categories; Category change</i>
<i>Using the platform for self-promotion</i>	<ul style="list-style-type: none"> • What strategies do you use to make yourself visible on [Platform]? • What are the most important tricks or features to receive work offers? • Who are you competitors? How do you respond to their competition? 	<p>Thinking about concrete job offers you have received, what did you do to make them happen?</p>	<i>Self-promotion; Technology Use; Strategies for matching</i>

<i>Platform technology</i>	<ul style="list-style-type: none"> • How is the platform helping or intervening in matching you with clients? • What platform technologies (e.g., search engine, worker profile, ...) are most important in attracting attention of clients? • How has the platform changed the way you receive work as a freelancer in comparison to offline work? 	<p>Have platform affordances changed over time?</p> <p>What functionalities are missing from the platform?</p> <p>What concrete actions do you take to take advantage of the platform technology (e.g., appear at the top of the search engine)?</p>	<i>Role of the platform</i>
<i>Client's perspective</i>	<ul style="list-style-type: none"> • From your experience, what are clients looking for in an online freelancer? • Do you ever work as a client yourself? • Does your relationship with clients differ to offline freelancing/ traditional employment? 	<p>Is there any specific negative/positive feedback you have received upon your proposals/messages?</p> <p>What differentiates you from other freelancers in your field?</p>	<i>Hiring as a client; Heuristics</i>
<p>Notes: This section serves to highlight the workers' pricing and marketing strategies to attract client interest. For this purpose, the client perspective is discussed, as well. In addition, it explores how workers engage with platform technologies and how they perceive the role of the platform intermediary.</p>			
<p>Judging and being judged: Evaluation and matching</p>			
<i>Quality labels</i>	<ul style="list-style-type: none"> • How do you think about quality labels? • Are they useful to you? • What was the process of getting them? 	Have you ever been demoted?	<i>Market devices</i>
<i>Selecting projects</i>	<ul style="list-style-type: none"> • How do you decide on which project to take/write a proposal for? • How do you decide whether to work with a client or not? 	Do you have any rules by which you evaluate projects and a client?	<i>Evaluation; Judgment devices</i>
<i>Conversing with clients</i>	<ul style="list-style-type: none"> • How do the conversations with clients leading up to a project look like? • Do you remember any examples when the discussion of the project did not match the description? • How do you ensure whether you have the skills the client 	Could you describe a discussion with a client discussing one of your services?	<i>Informal classification; Negotiation; Evaluation</i>

	<p>is looking for/necessary to complete the gig?</p> <ul style="list-style-type: none"> • What elements of you or your services do you try to convey in these conversations? 		
<p>Notes: This section discusses the evaluation part of any exchange, i.e., the negotiation, evaluation, and selection of projects to apply and clients to work for.</p>			
<p>Success and failures: Matching and other outcomes of online work</p>			
<i>Skills matching</i>	<ul style="list-style-type: none"> • Could you describe an instance in which matching worked well and one in which matching did not work well? • How did the two situations differ? 	What are the biggest factors influencing matching on [Platform]?	<i>Skills matching; Factors for success/failure; Learning</i>
<i>Problems with clients</i>	<ul style="list-style-type: none"> • What problems did you ever have with clients? Were they preventable? 	Looking back, what were the biggest mistakes you made when selecting a project/client?	<i>Discrimination; Skill mismatch</i>
<p>Notes: This section is about the actual matching and the factors that make a match happen and then (un-)successful. Similarly, the discussion includes when matches went wrong and problems with a client occurred.</p>			
<p>Future (professional) steps</p>			
	<ul style="list-style-type: none"> • Looking ahead, what is your plan with online freelancing and your career more generally going forward? 	Are you planning to spend more/less time online freelancing?	<i>Career development; Boundary work;</i>
<p>Notes: This section is designed to understand workers' intentions and plans when it comes to online freelancing and their career.</p>			
<p>Closing remarks</p>			
	<ul style="list-style-type: none"> • Is there anything you would like to add about the things we've talked about? 	Would you recommend online freelancing to a friend/your child?	<i>Reflection; Summary/Opinion</i>
<p>Notes: The closing remarks cover reflective and purposefully open questions that might elicit responses or thoughts that have been missed in the previous discussion. They are an opportunity for the participant to offer a concluding opinion.</p>			

Impressions from data collection

Figure 15. Project proposal shared with freelancers on upwork.com

Job details

Support Oxford University Research with Online interview (~60 min) on Platform Work

Online Research Invite-Only
Posted 14 days ago

[Worldwide](#)

Needs to hire 5 Freelancers

Overview:
We are looking for someone to help us contribute to our University of Oxford research on skills matching on online platforms like Upwork.

Deliverable:
* Online interview via Zoom - video or audio only, the choice is yours - to talk about your experiences as an online worker on Upwork (~45 - 60 minutes)
- Short pre-interview survey (~5 minutes)

Rewards:
Apart from a small financial token of appreciation for your time and effort spent on this project, we would like to invite you to view this project as a way to contribute to the policy discourse on the future of work.

Process:
After accepting our offer, we will share a personalized pre-interview survey link with you to take in your own time. Upon completion, we will schedule and conduct the interview with you.

Background:
We are researchers from the University of Oxford studying how online workers match with clients online. This project anticipates a future in which online freelancing continues to grow in importance and explores how platform owners, workers and clients categorize and evaluate workers, their skills and available projects online in pursuit of successful matching, how the platform infrastructure shapes this process, and to what effect.

We would be extremely grateful, if you took the time to have a conversation with us!

Thanks and all the best,
Julian

\$20
Fixed-price

Intermediate
I am looking for a mix of experience and value

Project Type: One-time project

Activity on this job

Proposals: 📌 Less than 5
Last viewed by client: 🕒 9 days ago
Hires: 6
Interviewing: 0
Invites sent: 5
Unanswered invites: 3

[Edit posting](#)
[Reuse posting](#)
[Remove posting](#)
[Make public](#)
[View hires](#)

About the client

🔒 Payment method verified
★★★★★ 4.98 of 299 reviews

United Kingdom
Oxford 09:38 pm

437 jobs posted
100% hire rate, 1 open job

\$4k+ total spent
447 hires, 0 active

Member since Mar 19, 2019

Job link

<https://www.upwork.com/job/>

[Copy link](#)

Note. Screenshot taken on May 10, 2021

Figure 16. Screenshot during worker interview on Zoom

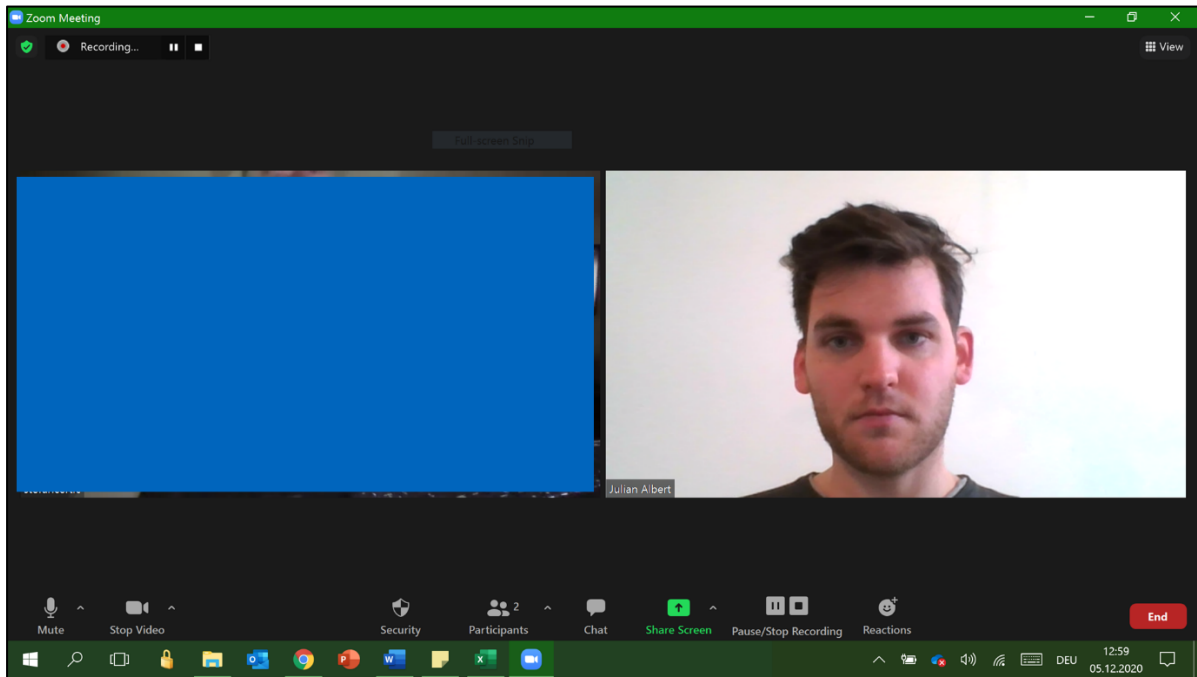


Figure 17. Landing page of odesk.com on Feb 3, 2005 (via archive.org)

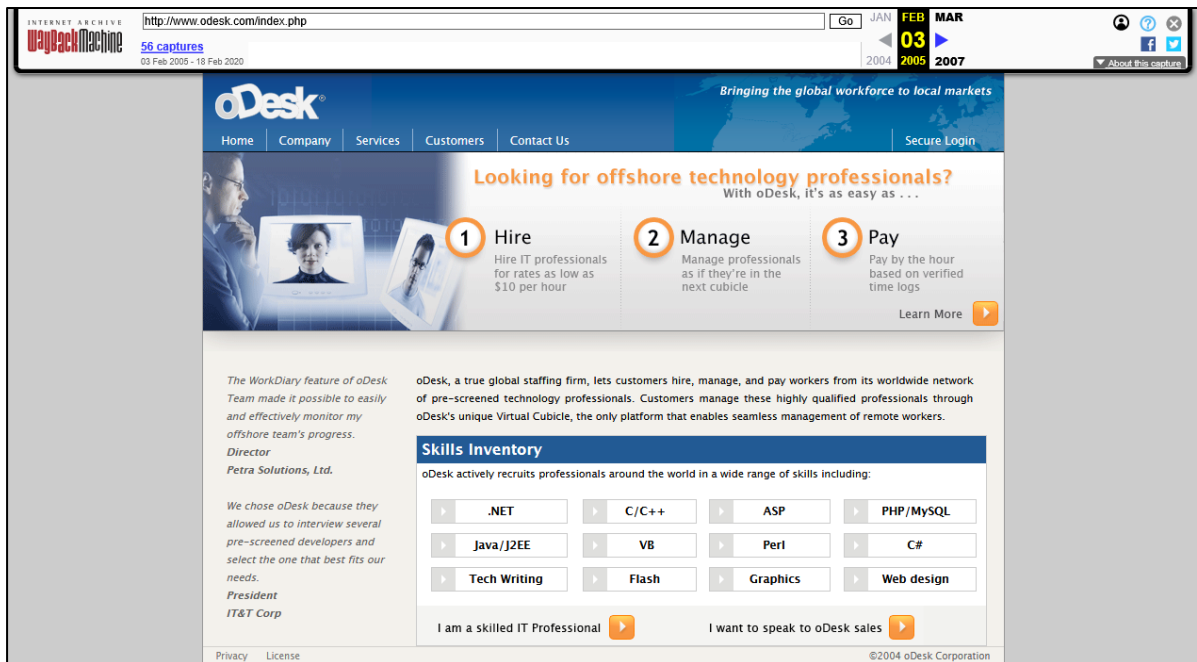


Figure 18. Landing page of elance.com on May 20, 2000 (via archive.org)



Figure 19. Landing page of fiverr.com on Jan 22, 2010 (via archive.org)



A.2 Appendix for chapter 3

This is a short summary of the insights from my walk-through of the interfaces on *upwork.com* and *fiverr.com*, as well as the analysis of contextual documents. In contrast to the rest of this thesis, citations are included as footnotes. I followed the labour process of the average worker from sign-up to project completion. All identified classifications of labour are listed in Table 8.

Signing-up to the platform. To participate in an online labour market, workers must sign-up to one or multiple marketplaces of their choice. While Fiverr positions itself as an ‘off-the-shelf’ e-commerce service, Upwork presents online labour as a core component of a broader hybrid workforce which centres around human relationships. Both platform firms engage in *externally facing* categorical practices. Once workers decide to join a platform, for instance, they must agree to the terms of services set out by the platform firm. In this contract, platform firms define their legal relationship with the worker:

‘Nothing in this Agreement is intended to or should be construed to create a [...] employer-employee relationship between Upwork and a User.’ (Upwork, User Agreement, Section 4.1, Effective April 5, 2021)

The contract is of significance to platform firms because it locates them within the wider institutional landscape, legally classifies online freelancers as independent contractors, and thus minimizes obligations to workers and regulation by the state.⁶⁰

Beyond these widely discussed legal issues, platforms also engage in *internally facing* categorical practices. As a first example, platform firms specify what categories of

⁶⁰ Erlich, Mark. “Misclassification in Construction: The Original Gig Economy.” *ILR Review* 74, no. 5 (October 2021): 1202–30. <https://doi.org/10.1177/0019793920972321>.

services may be offered, defining the normative boundaries of what type of remote work is permissible. Ghost-writing academic output and offering any kind of pornographic content, for instance, are not permitted on either platform. Offering such services can lead to the suspension of a worker's account. Second, platform firms define rules of engagement which complement the categorization of online labour. As a result, workers often prefer one platform over the other:

'I like Upwork more than Fiverr because on Fiverr you can't apply, you just prepare your gigs and wait for customers to approach you. At Upwork, we have 'Connects' and I can submit offers [to clients] with them.' (06U, Sales & Marketing Support, Middle East)

This is an example of how the heterogeneity of platforms leads to heterogeneous experiences in platform work. That said, I find evidence that a more general market category of *remote knowledge work* is emerging, and local practices on both platforms start converging. One driver of this convergence are the limits of the commodification of remote work, especially for higher value, complex projects. In addition to their categorization of what counts as online labour and how it is offered, Upwork specifically reserves the right to regulate access to their platform. The firm draws the boundary of who gets to participate in their marketplace. Although Fiverr does not actively exclude people from joining its platform, some workers expect this to change in the future:

'[In] a couple of years, I see Fiverr trying to raise the bar, because [...] [...] currently] there's no bar [...] no price to pay, no test to go through [before sign-up].' (20F, Creative & Multimedia, Europe)

Creating a profile. After sign-up, workers are asked to complete standardized profiles. Both platforms modularize online labour to varying degrees. In Figure 20, I provide an overview of the history of top-level classifications of services offered on both platforms. Over time, both firms have increased complexity by adding vertical categorical layers. While Upwork has reduced the average number of first-level categories, it features an

entire taxonomy of online labour which relates top-level categories to specializations, skills, and more in-depth dimension such as deliverables. At the time of writing, a worker in 'Web, Mobile & Software Development' could be active in 24 specialities (e.g., 'Mobile App Development'), knowledgeable across 7 devices, in 24 app features, 16 mobile programming languages, 52 mobile application development skills, and use 73 databases. Still, even this level of depth is unable to capture nuances in the respective fields of expertise:

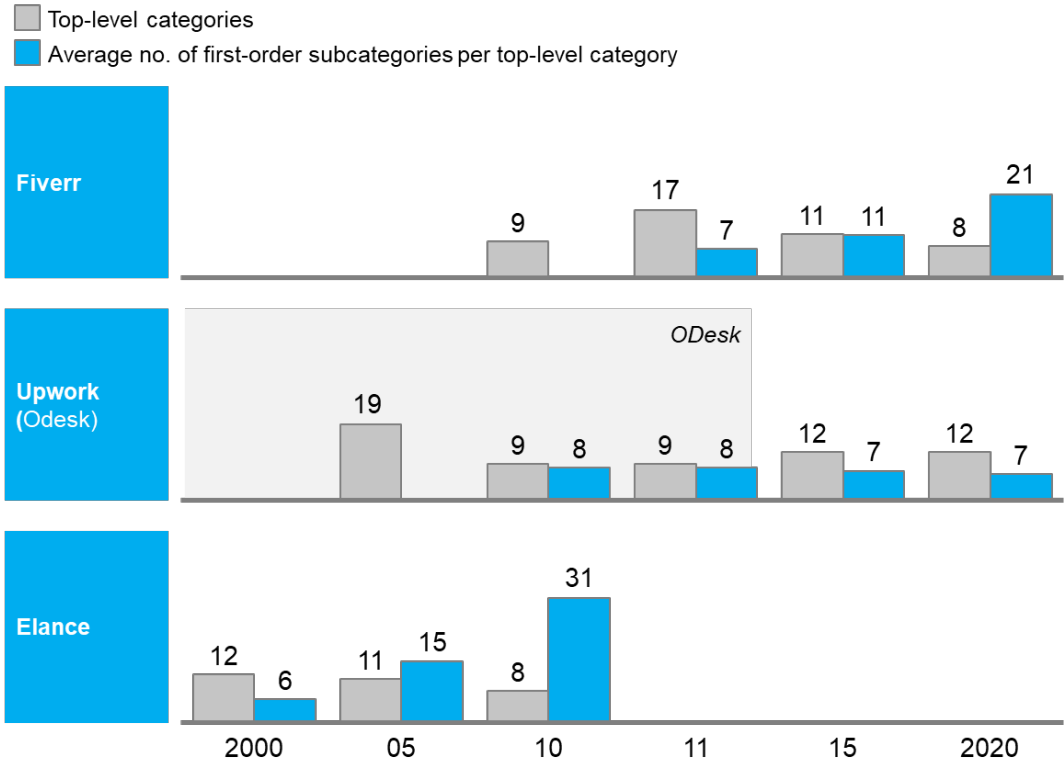
'Upwork is an American outfit who has the American tendency to think that the whole of the EU is one country. That's why I get [questions like]: "Can you do a regulatory filing in Portugal?" What is it about my profile that says I can do regulatory filings in Portugal [as my focus is clearly British law]? The reason I am getting picked-up is because they [search for] "EU".' (7U, Professional Services, Europe)

As is typical for classification systems, platform firms' categorical work and categorization histories remain largely hidden from users. However, workers still take notice of how platform firms categorize them and their services:

Fiverr tries to capture everyone and has sub-categories for everything. It's throwing stuff on the wall and seeing what sticks. They're going to create a subcategory that's called 'NFT' because it's all the rage and then they're going to aggregate data and see [what came off it] six months from now. They may drop it, merge it with something else, or leave it be. It's not costing them. It makes sense for them to cast a wide net and then it's up to the sellers to find their spots within these categories. (20F, Creative & Multimedia, Europe)

Most input required from workers is standardized, presumably to ease data collection and analysis. At the level of the worker profile, platform firms take multiple categorical decisions, for example what information to request from the worker, what metrics to make visible on the platform, or what skills to certify via platform-mediated tests such as the 'Upwork Readiness Test' or via 'Learn from Fiverr'.

Figure 20. Number of categories for gigs (Fiverr) and freelancers (Upwork)



Note. Data presented from the 1st of January of each year, or the nearest available point of data, using the Wayback Machine Internet Archive (*archive.org*).

Searching for/advertising work. Platform firms not only establish the market categories for their platforms but also assign workers to said categories and highlight differences of worth within them. On the one hand, workers are left with much of the manual labour inherent to job search (*upwork.com*) or advertising services (*fiverr.com*). Autonomy in advertising and pricing their services, finding work, and deciding on proposals is why many online freelancers consider themselves self-employed.⁶¹ Platform firms exercise power by deciding on the incentive structure, for example defining a platform-specific currency to make applications by workers deliberate and

⁶¹ Wood, Alex J., and Vili Lehdonvirta. “Antagonism beyond Employment: How the ‘Subordinated Agency’ of Labour Platforms Generates Conflict in the Remote Gig Economy.” *Socio-Economic Review*, March 19, 2021, 1–44.

scarce (*upwork.com*) or offering paid-promotions to a subset of workers (*fiverr.com*). On the other hand, platform firms actively manage visibility by classifying workers according to a mix of transparent and opaque principles. Such categorization occurs via automated or manual labelling (chapter 4):

[Being] Top-Rated is an automated badge. Then, there is a curated [badge] one step above the Top-Rated. There is Top-Rated. There is being Top-Rated Plus and there is [being expert-vetted]. That's a very good feature that they have introduced. I'm still waiting for my invitation. (09U, Software Dev & Technology, Asia)

Automated labelling is typically linked to achieving pre-specified, platform-specific, and quantifiable performance goals around being responsive, accepting most client requests, satisfying their demands, and keeping worker profiles updated. As a result, both platform firms established a hierarchy of workers ranging from the general workforce to those with more experience on the platform. In addition, and (partially) in competition with this algorithmically constructed hierarchy, platform firms manually label worker quality. Examples include the manual vetting and certification of top talent via interviews or portfolio checks (chapter 4), the presentation of workers as 'rising talents', or the promotion of services on the homepage.

Matching with clients. Matches with clients are impacted by platform-constructed filters. Platform firms rely on several classificatory devices such as algorithms that support with searching and recommending workers at scale. Platform firms selectively intervene in this automated classificatory logic and engage in forms of 'hand-vetted' curation. On *fiverr.com*, for example, a subgroup of workers is invited to an exclusive marketplace open only to business clients. In other words, platform firms cater to specific market needs, such as the need to classify labour supply into those who are and who are not deemed able to provide services at the highest professional level. Other corporate clients book hands-on matching support:

'Most of the time I don't apply [for gigs]. Now, a talent scout looks at you [...] and maybe sees a job that would be a perfect match. So, the scout will now reach out based on your experience, your availability and skill set [...] Normally when that happens and you apply for that job, most certainly get it.' (03U, Professional Services, Africa)

'The client can assign a talent specialist who helps them in recruiting someone. Those talent specialists reach out to and prepare a chat room where they join me and the client. [...]. For me, that happens only 1-2% of the time.' (09U, Software Dev & Technology, Asia)

These human-led interventions appear to be motivated by profit opportunities. If strategically helpful, platform firms complement, intervene, or change the automated classification infrastructure which otherwise organizes their marketplaces at scale.

Providing services. Platform providers do not actively control the work relationship between workers and clients. Instead, they rely on their classificatory infrastructure to provide both sides with resources to collaborate successfully while setting behavioural boundaries. On the one hand, breaches of rules of engagement that directly result in lost profits, such as taking work off the platform, are monitored algorithmically. One example are automated warnings following certain 'black-listed' words such as discussing 'payment' options. At the same time and key for algorithmic control, platforms decide on which work activities to monitor, for example intervals of screen captures and the choice of productivity metrics such as the recording of keystrokes during hourly projects (*upwork.com*). Platform firms similarly decide on productivity metrics used to nudge workers towards behavioural change.

Completing projects. Upon completion of a project, workers and clients can evaluate one another. Platform firms construct these feedback forms and decide on the aggregation method into a single score. However, platform firms strategically make invisible most of the categorical choices that feed into a worker's feedback score which

contributes to feelings of being in an ‘invisible cage.’⁶² As a side effect, clients make hiring decisions without any context or knowledge of the history or underlying assumptions of reputation scores:

‘The number of reviews doesn’t tell the story, [...it] doesn’t match my revenue. [...] Back in the day [...] on Fiverr, I could only sell for five bucks. Most of my reviews were for such USD 5 projects, [...] but it’s not the same if it’s a USD 5 project you did in an hour [compared to] a USD 15,000 project [that...] took you two months.’ (20F, Creative & Multimedia, Europe)

‘My score is at 84%, that’s the problem. [...] I [had] an accident and I was not even able to get online for more than a month, and in freelancing clients do not wait that long. They cancelled the projects [...] It directly affects your job success score.’ (09U, Software Dev & Technology, Asia)

Deviant behaviour as defined by the platform firm is implicitly encoded and thus punished via the algorithmically produced hierarchies which materialize as search results, recommendations, or reputation scores. Platform firms take further normative decisions around how disputes are settled and the protection of payments.⁶³

⁶² Rahman, Hatim A. “The Invisible Cage: Workers’ Reactivity to Opaque Algorithmic Evaluations.” *Administrative Science Quarterly*, April 21, 2021, 000183922110101. <https://doi.org/10.1177/00018392211010118>.

⁶³ Shevchuk, Andrey, and Denis Strebkov. “Safeguards against Opportunism in Freelance Contracting on the Internet: Safeguards against Opportunism in Freelance Contracting on the Internet.” *British Journal of Industrial Relations* 56, no. 2 (June 2018): 342–69. <https://doi.org/10.1111/bjir.12283>.

Table 8. Categorical practices by platforms along the labour process

Labour process	Classifications of Labour	Examples
Signing-up to platform	Industry classification of online labour <i>(what is online labour)</i>	Repositioning as ‘work marketplace’ (U), Superbowl commercial (F)
	Legal classification of online freelancers <i>(what is the employment relationship)</i>	Terms of Service
	Access decisions <i>(who has access)</i>	Vetting process of new profiles (U), documentation necessary for sign-up
	Definition of value unit <i>(what can be offered)</i>	Buy pre-defined gigs from sellers (F)
	Rules of engagement <i>(how is labour offered)</i>	Reasons for account deactivation, Minimum gig costs (F)
Creating a profile	Classification of online labour <i>(how is labour modularized)</i>	Project classification and underlying taxonomies of online labour (e.g., skills)
	Profile standardization <i>(what information is requested)</i>	Limited number of skills per person (U), Number of gigs per experience level (F)
	Worker certification <i>(what skills/capabilities are tested)</i>	‘Upwork Readiness Test’ (U), ‘Learn From Fiverr’ (F)
	Visibility of worker and platform data <i>(what information is visible & to whom)</i>	Selection of statistics on display, ‘Expert- vetted’ only visible to business clients (U)
Searching for/ advertising work	‘Hand-vetted’ curation <i>(who is ‘manually’ emphasized)</i>	‘Fiverr Pro’ (F), ‘Expert-vetted’ (U)
	Automated curation <i>(who is curated based on platform stats)</i>	Platform-specific experience badges
	Set-up of incentive structures <i>(what behaviours are valued)</i>	Platform-specific currency (U), Visibility via paid gig promotion (F)
Matching with clients	Recommender logic and algorithm <i>(what is the hierarchical order)</i>	Personal recommendations (F)
	Search logic, filters, and algorithm <i>(what attributes matter)</i>	Filters to narrow down search results (U)
	Personal matching support <i>(who is recommended)</i>	‘Talent Scouts’ (U)
Providing services	Monitoring for breaches of rules <i>(what behaviour is flagged)</i>	Automated warnings in chat (F)
	Logging of work activities <i>(what work is counted)</i>	Intervals of screen capture and choice of productivity metrics (U)
	Personal productivity statistics <i>(what metrics are recorded)</i>	Response time and response rate (F)
Completing projects	Construct feedback form <i>(what makes a good worker)</i>	Dimensions and scale to be rated on
	Aggregation of reputation score <i>(what actions count)</i>	Calculation methods of reputation scores (e.g., time frame, weighting, ...)
	Dispute resolution/payment protection <i>(what qualifies for protection)</i>	Fee protection for hourly contracts (U)

Note. (U) or (F) notes that the example is specific to Upwork or Fiverr respectively. Grey shading highlights what we coin ‘externally facing categorical work.’

A.3 Appendix for chapter 4

Table 9. Correlation matrix of independent variables

<i>Independent variables</i>	X ₁	X ₂	X ₃	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₆
Platform-mediated signals										
X ₁ : Badge/certificate	1	-	-	-	-	-	-	-	-	-
X ₂ : Reviews (ln)	0.36	1	-	-	-	-	-	-	-	-
X ₃ : Success score	0.23	0.21	1	-	-	-	-	-	-	-
Platform controls										
C ₁ : Platform A dummy	0.02	-0.46	-0.25	1	-	-	-	-	-	-
C ₂ : Platform experience	0.13	0.38	0.10	0.17	1	-	-	-	-	-
C ₃ : Platform dependence	0.19	0.11	0.10	-0.06	-0.05	1	-	-	-	-
C ₄ : Hourly wage (ln)	0.16	0.13	-0.10	0.17	0.09	0.02	1	-	-	-
Socio-demographic controls										
C ₅ : Male	-0.01	0.04	-0.03	-0.15	-0.03	-0.04	0.07	1	-	-
C ₆ : University graduate	-0.03	-0.08	-0.09	0.12	-0.02	-0.13	0.04	-0.20	1	-
C ₇ : Age	0.10	0.11	-0.01	0.29	0.37	-0.11	0.21	-0.08	0.20	1

Note. Correlations were calculated using the R function `cor()` and Spearman's rank correlation coefficient (ρ).

A.4 How to succeed in online freelancing: A researcher's perspective

— UNPUBLISHED DRAFT —

Today, millions of people earn money in the remote gig economy. They offer services such as software development, transcription, or logo design on platforms like Upwork and Fiverr. In this blog post, I explore if there are known tricks to be successful online.

I am a researcher at the University of Oxford who has studied labour platforms for the past four years. In this post, I reconcile learnings from my analysis of Upwork and Fiverr, interviews with many workers who are active on these platforms, and the review of academic research on online freelancing.

My goal is to start a discussion and self-reflection on what is needed to be successful as a freelancer online, rather than prescribing a definite path to success.

Should I join an online freelancing platform?

From a survey with more than 700 workers, we know that more than 80% of Europe-based respondents generally enjoy working on Upwork and Fiverr. However, research also tells us that individuals enter a freelancing career under diverse circumstances and with varying motivations. If you are financially dependent on income from gig work, for example, you tend to experience it as less satisfactory and more precarious. Prior to taking up remote gig work, you should therefore think through some of the tensions inherent to this line of work:

- *Global opportunity versus intense competition:* On the bright side, platforms afford client connections all around the world. You are no longer restricted to your local labour market and the wages paid there. However, you also compete with more workers including those who might be willing to work at a lower price point (e.g., due to differences in regional living costs).
- *Flexibility versus platform control:* On Upwork and Fiverr, you are technically free to decide on when and from where to work, the projects and clients you take on, and the prices you demand. That said, platforms control your behaviour in more tacit ways: You want a quality label? All you have to do is respond as quick as possible and never hand projects in late! You don't feel like working on a bank holiday? Be prepared to risk a bad review from a client who is!
- *Lower quality versus higher quantity:* Especially if you are based in the Global North, chances are you will be paid less for your work online. In contrast, a presence on Upwork or Fiverr has the potential to increase the quantity of projects you complete. Many successful workers thus describe the platform as a pipeline to generate new client connections.
- *Skill-based meritocracy versus statistical discrimination:* In online freelancing, you are judged primarily on the skills you offer. While this provides many opportunities, it also requires some soul-searching: Which of your skills lend themselves for such an environment and are in-demand? At the same time, be prepared to experience some statistical discrimination. For example, some clients avoid workers from certain geographies.
- *Just-in-time learning versus a highly educated workforce:* The online freelancing workforce is higher educated and comes from a more privileged class

background than the average population. While some commentators claim that formal education no longer matters, it certainly seems to play a role for breaking into online labour markets. In one project, we found that successful freelancers brought many skills to the platform (e.g., technical skills, professional skills, language skills), while also showing a high motivation to learn *'just-in-time'* for each individual project.

What do I need to know when signing up?

In general, you should recognize that starting on Upwork or Fiverr is not the same as a few years ago. Unless you have a specialized and in-demand skill set, competition is likely to be fierce. At the same time, more employers start using these platforms to source talent. When signing-up and completing your worker profile, you should keep a few things in mind:

- *Different platforms, different ways of working:* Make sure to familiarize yourself with the differences between platforms. On Fiverr, you offer services as standardized 'gigs' and clients need to find and contact you. On Upwork, you can directly apply for projects that are publicly listed by clients. Similarly, the average price point per project differs on both platforms (Fiverr's being lower). There are many more of these differences. Which setup works best for you?
- *Beware of potential barriers to entry:* Inform yourself about legal barriers to entry (e.g., what documents do I need for verification, do you need an international credit card to accept payments, ...). Further, browse community forums on additional barriers of entry to a platform. Upwork, for example, rejects applications of workers who offer services that are oversupplied already. Hence, think carefully about how to appeal to platform administrators at sign-up.

- Be prepared to break down your professional identity: Even with a successful career outside platform work, it might not come naturally to turn your professional identity into marketable services. Where else do you go from ‘Hello, I am a consultant’ to ‘Hello, I build your market model in Excel’?
- Online freelancing requires specific skills: Being a freelancer is different from working within an organization. Amongst other things, you need to connect to clients, manage your own time, promote yourself, manage an insecure working environment, handle disputes, price your services, and know about the legal requirements in the country you live in. Think about which of these skills come easy to you and which you might still need to develop.
- Identify your market niche: To break into the market and gain experience, many workers suggest identifying a niche to minimize competition. As an added benefit, clients who look for your exact service (e.g., ‘blockchain whitepaper writer’) are more likely to notice your profile given smaller competition than in broad categories (e.g., ‘writer’). You likely won’t get your profile or service exactly right from the start. Most people we talked to keep iterating and improving their skill categories, self-description, or service offerings over time.

How do I attract business once I am online?

In online freelancing, the hardest part is to attract your first client, and receive your first positive review. One common theme in interviews with online freelancers is that many subscribe their first project to sheer luck. That said, others suggest several potential routes to increase your chances of success:

- *Bring offline clients onto the platform:* If possible, rely on your relationships from outside the platform to break into the market, and secure your first 5-star review and detailed (positive) public feedback.
- *Offer a lower price point to attract your first client:* Many workers report to have accepted lower price points at the start to build up their online reputation, that is trading poorly paid hours for reviews.
- *Optimize the parameters that are under your control:* Get to know your platform of choice intimately and put that knowledge to use. You write a proposal for a job on Upwork? It should be flawless and on-the-point. You upload a gig on Fiverr? Make sure it addresses a market need and demonstrates that you are a professional and trustworthy business partner. You wonder how the recommender algorithm works? The terms of service and official documentation provided by Upwork and Fiverr provide considerable insights about which variables feed into their reputation scores and recommender algorithms. Optimize all variables that you can control (e.g., availability, response times).
- *Know all platform-specific options to signal your quality:* What options do you have to signal your specific competencies? Is there a badge for newcomers? If yes, try to fulfil all the criteria from the start (e.g., 100% complete profile).
- *Use tried-and-tested signals to attract clients:* You have previously worked for a known brand or graduated from a renowned university? Great, some employers still care about such signals. Others prefer to work with someone in their country, local language or time zone. To get your first job, all these seemingly trivial factors can make the difference between being hired or not.

How do I keep my clients and the platform happy?

The secret to happy clients is similar to more conventional forms of freelancing. Be professional! Apart from your clients, in online freelancing you also need to consider the effect of your actions on your algorithmically awarded reputation, and your relationship to the platform:

- *Be aware of red flags in clients:* Experienced workers turn down clients. Some red flags include unspecific project descriptions, a visible lack of understanding of the subject matter, sending a project invitation without prior contact, immediate desire to take work off the platform, no previous experience on the platform, a history of low hourly wages, bad feedback from workers.
- *Scope your projects:* Be crystal clear on the scope of your project (e.g., what are the deliverables, what should these deliverables look like in detail, how many revisions are included) and the timeline. Ideally communicate this on the platform (e.g., via the chat) so that you have a paper trail to refer to if necessary.
- *Deliver according to the highest professional standards:* Successful workers have one thing in common. They deliver their services to the highest professional standards from start to finish. Examples include the delivery of services as advertised, being on time, scoping the project at the start, friendly and frequent communication throughout, and actively educating clients on the norms of online freelancing (e.g., “Your review is incredibly important for my further professional trajectory on the platform.”).
- *Try to make the interaction personal:* Successful workers establish meaningful connections with their clients to turn them into repeat customers and avoid negative feedback. It is thus worth reflecting on your current level of customer

service to identify any areas of improvement. Similarly, think about ways to socially connect with your platform, for example via paying a monthly fee to have access to a human point of contact. Once you have this kind of access, use it!

- Embrace changes to the platform with curiosity: Platforms tend to make changes on the platform without clear communication to freelancers. Once such a change takes effect, do not lament it but think about the reasons behind the change, and how you need to change your behaviour in response.

Is online freelancing a good option in the long run?

There are several considerations when you are thinking about a long-term career in online freelancing. Most importantly, make sure that you are not entirely dependent on just one platform!

- Think about your career holistically: Compare your long-term goals with your development potential on the platform. Consider about how you want your career to progress over the next years and compare that plan to what online freelancing will offer you.
- Reduce your dependence on a single platform: Diversify your income stream so that you are not entirely dependent on one platform. What happens if your account gets deactivated for reasons beyond your control? What if the platform goes broke or you simply experience a dip in traffic to your profile? Most successful workers report to take a fraction of their clients outside the platform in the medium to long run, especially once trust has been established.
- Find a peer group: Many people need a sense of community at their workplace. Online freelancing can therefore feel socially isolated. Think about how to build

up or join a peer-group online (e.g., community forums, Facebook groups) or make local connections to other workers (e.g., co-working spaces, meet-ups).

- Consider joining a freelancer union: Once you spend more time freelancing, consider joining a union. Unions are powerful organizations, and it makes sense for workers to make their voices heard collectively. Unions also often provide information on topics such as health insurance or taxation.
- Be creative: There are many possible ways of how to engage with platform work. To give you some ideas, let me list a few approaches that other workers shared with me. You could start a platform-specific agency or use gig work to improve your skills. If you have your own company, test your business ideas on Fiverr. If you no longer have time for freelancing, you can share your account with one or multiple people, outsource jobs to other freelancers or local collaborators, or reduce your engagement to the minimum to keep your online reputation intact (e.g., how much do you need to earn to keep a quality label).

Finally, I would like to repeat that this post is not intended to suggest a guaranteed path to succeeding online. Instead, I would like to invite you to reflect about your own approach to online freelancing. It might help you make a more informed decision on whether you want to give platform work a try or change your current strategy.

If you disagree with any of these points, think I have missed important bits, or have suggestions on what could be covered in more depth, please feel free to reach out (julian.albert@oii.ox.ac.uk).

A.5 Chronological list of other publications

Margaryan, A., Albert, J., & Charlton-Czaplicki, T. (2022). Workplace learning in Crowdwork Questionnaire (WLCQ): Measuring self-regulated learning and skill development in online platform work. *International Journal of Training and Development*, 26(3), 495–515. <https://doi.org/10.1111/ijtd.12268>

Lehdonvirta, V. & Albert, J. (2020). *How workers learn skills in the online platform economy, and how platforms, policies, and learning providers can support them*. Oxford Internet Institute. <https://www.oii.ox.ac.uk/blog/how-workers-learn-skills-in-the-online-platform-economy-and-how-platforms-policies-and-learning-providers-can-support-them/>

Cedefop. (2020). *Developing and matching skills in the online platform economy*. European Centre for the Development of Vocational Training (CEDEFOP). <https://www.cedefop.europa.eu/en/publications-and-resources/publications/3085>

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2017). *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*. McKinsey Global Institute. <https://www.mckinsey.com/~media/BAB489A30B724BECB5DEDC41E9BB9FAC.ashx>⁶⁴

⁶⁴ I was a consultant on the research team but not listed as official author of the report. For confirmation, please refer to the acknowledgements section.