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Essays on Banking in the Post-Crisis Era

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Abstract

This thesis aims to advance our understanding of banking in the post-crisis era. It makes three distinct contributions to the literature on banking.

The first chapter examines whether "too-big-to-fail" (TBTF) factors affect estimates of scale economies for large banks. Based on a standard model of bank production that does not control for any TBTF factors, we find evidence of scale economies for our sample of large banks. However, once we control for TBTF factors, we instead find evidence of constant returns to scale. These results suggest that estimates of scale economies for large banks are affected by TBTF factors.

The second chapter examines the impact of forbearance lending on firm dynamics and performance in Europe since the sovereign debt crisis. We develop a quantitative model, which features endogenous forbearance lending and endogenous firm defaults, as well as information asymmetry faced by the lender. We fit the model to key Euro Area firm statistics over the period 2011 to 2014. We show that in the absence of forbearance lending, the average firm sales growth, investment and productivity are higher than in the benchmark scenario with forbearance lending. These results suggest that forbearance lending practices have contributed to the recent economic stagnation across the Euro Area.

The third chapter introduces a novel way to identify the causal effect of bank capital on risk-taking. We use provisions for misconduct issues as an instrument for bank capital. We show that misconduct provisions are an appropriate instrument due to their strong and negative impact on bank capital, and are otherwise unrelated to asset risk-taking. Our main finding is subsequently that a negative shock to bank capital leads to an increase in risk-taking, as measured by detailed information on mortgage underwriting standards.

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Introduction

Banks carry out a variety of important roles for the economy and wider society. They monitor investors to ensure prudent use of depositor funds, thereby ameliorating information problems (Allen and Carletti, 2009). They diversify risks by lending to many individuals and businesses, such that borrowers have greater access to credit. More generally, the provision of bank credit facilitates the intertemporal smoothing of risk, consumption and investment, and contributes to economic growth (Allen and Carletti, 2009).

But the financial crisis that commenced in 2008 has led to a great deal of critical attention towards banks and the banking sector. It has become evident that the banking sector presents real costs and risks to the very economy and wider society it otherwise seeks to provide with services. In some instances, the costs arising from banking insolvencies have threatened the solvency of entire nations.

Difficult policy debates arise from the tension that exists between the benefits of a well-functioning banking system, and the costs associated with banking insolvencies and crises. In the academic literature, the financial crisis has spurred on a flood of research on banking and its regulation. In practice, the financial crisis has seen Basel II replaced soon after it was introduced, and a suite of other new measures have emerged such as "macroprudential" regulations. Both academic and regulatory responses to the crisis appear *prima facie* sensible. Yet our understanding of the post-crisis banking sector, and the broader impact of these regulations, remain thus far in an early stage of development.

This is where my dissertation steps in. While the three chapters of my dissertation each deal with distinct topics, they all aim to advance our understanding of banking in the post-crisis era. All three chapters are written and hereafter described in the first person plural.

The first chapter addresses the question: what is the impact of "too-big-to-fail" (TBTF) factors on scale economies in banking? To address this question, we first estimate scale economics for large banks from a standard model of bank production that does not control for any TBTF factors. In this analysis, we find evidence of scale economies for our sample of large banks. Next, we again estimate scale economies for large banks but this time controlling for TBTF factors using two alternative methodologies. First, we estimate scale economies from an augmented model of bank production that employs a proxy for the counterfactual price of debt that banks would face in the absence of any TBTF funding cost advantage. Second, we estimate scale economies from a model of bank production for a sample of banks considered unlikely to be TBTF. Using either method, we no longer find evidence of scale economies. These results suggest that estimates of scale economies for large banks are affected by TBTF factors. This implies that some of the cost advantages of larger banks are due to TBTF factors rather than true economies of scale. And in the absence of these TBTF factors, the private benefits to banks from increased scale may be muted.

The second chapter concerns the topic of forbearance lending. Forbearance lending occurs when a lender supports an otherwise insolvent borrower, and these lending practices are frequently associated with economic downturns, such as the Japanese "lost decade" and the economic stagnation currently affecting Europe. In this chapter, we consider the impact of forbearance lending on firm dynamics and performance in Europe since the peak of the sovereign debt crisis in 2011. For this purpose, we develop a quantitative model that features endogenous default and endogenous forbearance lending. Lenders also face information asymmetry

in the firm of not knowing firm quality with certainty. We calibrate our model using Euro Area firm-level statistics over the period 2011 to 2014, a period marked by higher than usual levels of forbearance lending. We evaluate the impact of forbearance lending by considering a scenario in which firms have the option to default but no longer have access to loan forbearance. We find that average firm sales growth, investment and productivity are all higher in our counterfactual scenario without forbearance lending as compared with the benchmark scenario with forbearance lending. A key driver of this result is that there is a larger proportion of high quality firms in our counterfactual scenario; the option of forbearance lending in the benchmark scenario prevents lower-quality firms from defaulting more quickly, which imposes a drag on average sales growth, investment and productivity. These findings suggest that forbearance lending practices may have contributed to the recent economic stagnation across the Euro Area.

The final chapter is about bank capital and its impact on risk-taking. We introduce here a novel way to identify the causal effect of bank capital on asset risk-taking, which we apply to UK data. We use provisions for misconduct issues as an instrument for bank capital. Misconduct provisions can adversely affect bank capital via their negative impact on retained earnings, and we find evidence of this for UK banks. We also find strong support for our assumption that misconduct provisions are otherwise unrelated to asset risk-taking, due to the institutional framework around, and the timing of, these penalties. We facilitate our analysis with a unique UK panel dataset of bank-level information from published accounts, merged with loan-level data on all regulated UK mortgages. Our main finding is that a negative shock to bank capital leads to an increase in risk-taking, as measured by detailed information on mortgage underwriting standards.

Reference

Allen, Franklin, and Elena Carletti. (2009) "The Role of Banks in Financial Systems," in Oxford Handbook of Banking, edited by Allen Berger, Phil Molyneux, and John Wilson, Oxford, Oxford University Press, 32 – 57.

1. Too Big to Be Efficient? The Impact of Implicit Subsidies on Estimates of Scale Economies for Banks[1]

Chapter Abstract

We examine whether "too-big-to-fail" (TBTF) factors affect estimates of scale economies for large banks. From a standard model of bank production that does not control for any TBTF factors, we find evidence of scale economies for our sample of large banks. We then control for TBTF factors by using a measure of the "implicit subsidy" that emerges from a reduction in TBTF banks' funding costs due to investor expectations of government support. We do this in two ways: first, we estimate scale economies from an augmented model of bank production that employs a proxy for the counterfactual price of debt that banks would face in the absence of any TBTF funding cost advantage; second, we estimate scale economies from a model of bank production that is estimated only for a sample of banks considered unlikely to be TBTF. After controlling for TBTF factors using either method, we no longer find evidence of scale economies for our sample of large banks. These results suggest that estimated scale economies for large banks are affected by TBTF factors.

[1]This paper is co-authored with Richard Davies, and it is copyright of the Bank of England 2014. This is the author's version of the work. It is posted here by permission of the Bank of England for personal use, not for redistribution. The definitive version was published in the Journal of Money, Credit and Banking by Wiley-Blackwell, 46(s1), pp 219-253. http://dx.doi.org/10.1111/jmcb.12088

1.1. Introduction

The financial crisis revealed that governments considered certain banks to be "too-big-to-fail" (TBTF). Authorities intervened to prevent bank failures and to avert the significant financial system disruptions and real economic costs that such failures were considered likely to cause (Financial Stability Board 2011). As well as entailing direct fiscal costs, these interventions, or more precisely the anticipation of them, may misalign incentives in a manner that makes crises more likely in the future. Policymakers have consequently initiated a program of reforms intended to tackle the TBTF problem.[2]

Many of these reforms are likely to entail, at least indirectly, a reduction in the size of individual banks. This dynamic has given the topic of scale economies for banks new relevance. Scale economies can provide an estimate of the potential economic cost of proposals that seek to limit bank size. This is an important consideration: it may be that the efficiencies gained from scale outweigh the systemic risks large banks pose, but these views cannot be confirmed without measuring these efficiencies (Mester 2010).

There is a wide literature on scale economies in banking, the findings of which have evolved over time. Earlier empirical studies found little evidence of scale economies for large banks (Mester 2008). More recent studies, however, have uncovered strong evidence of scale economies, even for the largest banks (see, e.g., Feng and Serilitis 2009, Hughes and Mester 2011, Wheelock and Wilson 2012). In fact, there is some evidence that scale economies may be even *increasing* in bank size (Wheelock and Wilson 2012).

These recent studies provide several explanations for this new-found evidence. Hughes, Mester and Moon (2001) find that scale economies exist, but are not

[2]Examples include: the policy measures to address "systemically important financial institutions" outlined by the Financial Stability Board (2011), and the Independent Commission on Banking in the United Kingdom.

uncovered in the standard analysis because of the failure to appropriately model banks' capital structure and risk-taking. Wheelock and Wilson (2012) argue that the lack of findings in earlier studies is due to inappropriate estimation techniques, changes in regulation that have made it less costly for banks to become large, and recent technological advances that have favored larger banks. This recent literature strongly suggests that reforms aimed at limiting bank size may give rise to costs in the form of foregone scale economies.

Most of these studies – the study of Hughes and Mester (2011) being a notable exception – neglect the impact of TBTF factors on the estimated scale economies for large banks. There are potential funding cost advantages for banks considered by investors to be TBTF. Bank debt investors may not demand a risk-premium that corresponds to the true risk level of a bank, owing to expectations of government support to avert its failure (Noss and Sowerbutts 2012). This theory is supported by empirical evidence: Morgan and Stiroh (2005) find that bank debt investors consider the possibility of support for TBTF banks when pricing risk.[3] As such, a bank that is considered TBTF may have access to lower funding costs and appear to be more cost efficient than is the reality. These cost savings due to TBTF factors do not represent a scale economy but rather the anticipation of favorable treatment of selected banks by the government (Boyd and Heitz 2011).

In a related paper, Hughes and Mester (2011) investigate whether TBTF factors contribute to scale economies for banks. They define banks with more than US$100 billion in assets as TBTF and conclude that scale economies exist, even for the TBTF banks. This conclusion is based on the US$100 billion threshold used as an indicator for when a bank becomes TBTF. While there is some evidence to support the use of the US$100 billion threshold for the U.S., it is not

[3]In their study, they define TBTF banks as those banks implicitly identified as TBTF by the Comptroller of the Currency, following the bail out of Continental Illinois Bank in 1984. They consider more recent spread-ratings relationships for the descendants of these TBTF banks.

necessarily the appropriate value for other countries.[4] Moreover, size is not the only determinant of TBTF; some smaller banks received government assistance during the crisis.[5]

The contribution of this paper is to use a more granular estimate of the TBTF funding cost advantage to assess the impact of TBTF factors on estimates of scale economies for large banks. In particular, we ask: to what extent are apparent scale economies for large banks due to the "implicit subsidy" they receive? We measure the implicit subsidy using an estimate of the extent to which each individual bank's funding cost is reduced due to the market's expectation that the government will intervene to prevent its failure.[6]

To estimate the implicit subsidy, we employ a method first outlined by Haldane (2010). This method uses information embedded in banks' credit ratings to determine if a bank is considered TBTF. In particular, this method examines the difference between the "support" credit rating and the "stand-alone" rating issued for each bank; this difference is sometimes referred to as the "ratings uplift". Both the support and the stand-alone ratings take into account the intrinsic financial strength of a bank. But the former explicitly takes account of the possibility that a bank will receive external (e.g. state) support to prevent a default; the latter does not. Thus, the ratings uplift encompasses the rating agency's judgment about the likelihood of support for a bank. We convert this likelihood into a monetary value for the implicit subsidy by assuming that ratings-sensitive liabilities are funded at the support rating, whilst if there was no government support

[4]The threshold is chosen to be consistent with the results from Brewer and Jatiani (2013), who find evidence of a TBTF effect for mergers that brought banks to a size greater than US$100 billion.

[5]For example, Northern Rock in the United Kingdom. Haldane (2012) refers to Northern Rock as a "medium sized bank".

[6]This paper does not consider the optimal size of banks; a full answer to such a question would need to consider both the benefits of scale with the costs of scale due to potential increases in systemic risk and crisis costs. Rather, we consider only a narrow subset of this question via an investigation of the private benefits to banks due to increased scale. And we consider how estimated scale economies are affected by TBTF factors.

banks would need to fund themselves at the stand-alone rating.[7] A relationship between bank funding costs and credit ratings has been demonstrated empirically by Resti and Sironi (2005).

Our analysis proceeds in two stages. We first estimate scale economies for large banks. To do this, we employ a standard model and estimation technique that does not control for any TBTF factors. The results from this first stage confirm the recent findings in the literature: scale economies appear to exist for our sample of large, international banks.

The second stage controls for TBTF factors, using two alternative methodologies. First, we estimate scale economies from an augmented model of bank production that adjusts the price of debt using our measure of the implicit subsidy. The adjusted price of debt represents the counterfactual cost of debt that banks would face in the absence of implicit government support by virtue of being TBTF; we refer to this as the "social price of debt". Second, we estimate scale economies from a model of bank production that is estimated based only on a sample of banks considered unlikely to be TBTF.[8] For both methods, we are attempting to uncover parameter estimates for the model of bank production that are unaffected by TBTF. From both methods, we no longer find evidence of scale economies for our sample of large banks. These results suggest that estimated scale economies for large banks are affected by TBTF factors.

Both methods we employ have limitations. The first approach does not uncover the true parameters of the cost function because it employs a counterfactual estimate for the social price of debt. As such, this approach violates the assumption that banks choose their input quantities to minimize costs with respect to the

[7] See Noss and Sowerbutts (2012) for a similar description of the implicit subsidy measure.

[8] This second approach of obtaining parameter estimates based on the non-TBTF banks only is similar to one of the approaches of Hughes and Mester (2011). The main difference being that we employ the implicit subsidy in order to identify and exclude TBTF bank observations from the estimation; Hughes and Mester (2011) employ a US$100 billion total assets threshold.

actual prices they face. However, we provide some evidence that the magnitude of this violation may not be serious.

The validity of the second approach depends on the method for identifying TBTF banks and excluding them from the estimation. Only then can we reveal the parameters of the cost function that are unaffected by TBTF factors. We find that around 75 per cent of banks that received some kind of government assistance in the recent crisis were considered *ex ante* TBTF according to our method of identifying TBTF banks. This suggests that our measure of TBTF is reasonable, but our estimates may still be affected by TBTF.

The remainder of this paper is structured as follows. Section 1.2 outlines the first part of our approach; here we specify a standard model of bank production and our empirical specification which omits any consideration of potential TBTF factors. Section 1.3 outlines the second part of our approach; here we outline the approach taken to compute the implicit subsidy and to control for TBTF factors in the standard analysis of scale economies for banks. Section 1.4 describes the data, the variable selection and provides summary statistics for the implicit subsidy. Section 1.5 summarises the results and different robustness checks. Section 1.6 concludes.

1.2. A Standard Model of Bank Costs

This section outlines a standard model of bank production and a corresponding empirical specification. We use this model to derive initial estimated scale economies said to be affected by TBTF factors. The next section will augment this model in order to control for TBTF factors.

We model bank production as one of financial intermediation: here banks borrow funds and subsequently lend those funds (Mester 2008). To make the model of bank production operational, there are several issues that need to be considered. We must select an appropriate optimization goal. We then need to specify a functional form and the variables to be included for the cost function. We discuss these issues in turn below.

1.2.1. Cost Minimization

We first choose an optimization goal for implementation of our model of bank production. We adopt a standard approach and minimize costs. Scale economies that are estimated from a cost minimization program will tell us how a change in outputs will bring about a change in costs.

In the "standard" model set out below, we employ a similar model to the minimum cash-flow function outlined by Hughes and Mester (2011) and Hughes, Mester and Moon (2001).[9] Here C is total costs; $T(\mathbf{y}, \mathbf{x}, \mathbf{z})$ is the transformation function representing bank technology; $\mathbf{y}$ is a vector of outputs; $\mathbf{x}$ is a vector of inputs; and $\mathbf{z}$ is a vector of netputs.[10] The cost of producing the output vector $\mathbf{y}$ is given by $\sum_j w_j x_j$, where w_j represents the price of input j and $\mathbf{w}$ is the vector of input

[9] The main differences concern the variable selection, particularly for the input variables. In particular, we employ less granular variables due to differences in the datasets.

[10] A netput quantity is a fixed input or output to production.

prices. The minimum cost function is described by:

$$C\left(\mathbf{y},\mathbf{w},\mathbf{z}\right)=\min_{x}\left(\sum_{j}w_{j}x_{j}\right)\text{ s.t. }T\left(\mathbf{y},\mathbf{x},\mathbf{z}\right)\leq 0 \tag{1.1}$$

Other optimization goals are suggested by the literature. For example, Hughes and Mester (2011) consider several models of bank costs. Their preferred model maximizes utility. This model is appealing because it takes into account bank managers' risk-return preferences and banks' endogenous risk taking. But it may be more affected by TBTF factors than the standard model that minimizes costs. TBTF factors are likely to affect the input price of debt which features on both the cost minimizing and utility maximizing model. However, TBTF factors may also indirectly affect the output prices which feature in the utility maximizing model. This is because the TBTF funding cost advantage may pass through to customers via output prices, depending on the competitive structure of the banking sector (Noss and Sowerbutts 2012).

1.2.2. Cost Function Specification

We next specify a functional form for the cost function as:

$$\ln\left(C_{b,t}\right)=f\left(\mathbf{h}_{b,t};\boldsymbol{\delta}\right)+\boldsymbol{\psi}'\mathbf{m}_{b,t}+u_{b}+e_{b,t}, \tag{1.2}$$

where for bank b at time t, $C_{b,t}$ measures total costs, including operating and interest expenses; f is is the translog specification of the log cost function presented in Equation (1.3) below; $\mathbf{h}=(\mathbf{y},\mathbf{w},\mathbf{z})$; $\boldsymbol{\delta}=(\alpha,\beta,\gamma,\eta,\theta,\rho)$ is the vector of parameters in Equation (1.3) to be estimated; $\mathbf{m}_{b,t}$ is the vector of environmental control variables, with a corresponding parameter vector $\boldsymbol{\psi}$ to be estimated; u_b is a fixed effect that controls for bank-specific unobservable heterogeneity; and $e_{b,t}$ is a random error term.

Dropping time and bank subscripts for ease of exposition, the translog specification[11] of $f(\mathbf{h}_{b,t};\boldsymbol{\delta})$ in Equation (1.2) takes the following form:

$$\begin{aligned} f(\mathbf{h};\boldsymbol{\delta}) = \alpha_0 \quad & + \textstyle\sum_i \alpha_i \ln(y_i) + \sum_j \beta_j \ln(w_j) + \sum_k \gamma_k \ln(z_k) \\ & + \tfrac{1}{2}\textstyle\sum_i \sum_l \alpha_{il} \ln(y_i)\ln(y_l) + \tfrac{1}{2}\sum_j \sum_m \beta_{jm} \ln(w_j)\ln(w_m) \\ & + \tfrac{1}{2}\textstyle\sum_k \sum_n \gamma_{kn} \ln(z_k)\ln(z_n) + \sum_i \sum_j \eta_{ij} \ln(y_i)\ln(w_j) \\ & + \textstyle\sum_i \sum_k \theta_{ik} \ln(y_i)\ln(z_k) + \sum_j \sum_k \rho_{jk} \ln(w_j)\ln(z_k) \end{aligned} \tag{1.3}$$

where α_0 is an intercept common to all banks and time periods.

The cost share equations, $S_j(\mathbf{w},\mathbf{y},\mathbf{z})$, which embody Shephard's lema, are derived from Equation (1.2). The cost shares are defined as $S_j(\mathbf{w},\mathbf{y},\mathbf{z}) = w_j x_j(\mathbf{w},\mathbf{y},\mathbf{z})/C(\mathbf{w},\mathbf{y},\mathbf{z})$ which are written as:

$$S_j(\mathbf{w},\mathbf{y},\mathbf{z}) = \beta_j + \sum_m \beta_{jm} \ln(w_m) + \sum_i \eta_{ij} \ln(y_i) + \sum_k \rho_{jk} \ln(z_k) \tag{1.4}$$

for $\forall j$ and $\sum_j S_j(\mathbf{w},\mathbf{y},\mathbf{z}) = 1$.

To ensure that the regularity conditions of the cost function of Equation (1.2) hold we impose a number of restrictions during estimation. The first is symmetry ($\alpha_{il} = \alpha_{li}, \beta_{jm} = \beta_{mj}; \gamma_{kn} = \gamma_{nk}$). The second is linear homogeneity in input prices $\left(\sum_j \beta_j = 1, \sum_j \beta_{jm} = 0\ \forall m, \sum_j \eta_{ij} = 0\ \forall i, \sum_j \rho_{jk} = 0\ \forall k\right)$. We divide total cost and w_j ($\forall j \neq d$) by w_d in order to impose linear homogeneity.

We estimate the cost function of Equation (1.2) jointly with two (out of the possible three) cost share Equations (1.4) in a system of seemingly unrelated regression

[11] The translog specification is employed by other recent studies such as Hughes and Mester (2011). The Fourier-Flexible specification is another candidate to the translog specification. The Fourier-Flexible functional form includes a standard translog cost function plus Fourier trigonometric terms. We consider this specification also as a robustness check in Section 5.2. More generally, Wheelock and Wilson (2012) caution that a translog specification, when based on a sample that has a wide range of bank sizes, may be inappropriate for inference about scale economies. The spread of bank sizes in our sample is wide, but we argue that the translog specification is appropriate for this study because our sample of banks is relatively homogenous. It comprises large, international and typically universal banks. Moreover, the additional bank and macroeconomic variables we include in our specification should control for remaining differences in the banks' production environments.

equations. We impose the cross-equation restrictions during estimation.

1.2.3. Computation of Scale Economies

We derive estimates of scale economies based on the parameter estimates of the cost function described by equation (2). We use a measure of scale economies similar to that of Hughes and Mester (2011) for their minimum cost function, defined as the inverse of cost elasticity of output:

$$\text{scale economies} = \frac{1}{\sum_i \frac{\partial \ln(C)}{\partial \ln(y_i)}} \tag{1.5}$$

where $\frac{\partial \ln(C)}{\partial \ln(y_i)} = \sum_i \alpha_i + \sum_i \sum_l \alpha_{il} \ln(y_l) + \sum_i \sum_j \eta_{ij} \ln(w_j) + \sum_i \sum_k \theta_{ik} \ln(z_k)$.

For each bank in each time period, we use the parameter estimates and data described by equation (2) to compute the estimates of scale economies defined by equation (5). Scale economies that are greater (less) than one imply increasing (decreasing) returns to scale.

1.3. Scale Economies and Too-Big-to-Fail Factors

In Section 1.2 above, we outlined a standard approach to derive estimates of scale economies for banks. As with most of the literature, this approach fails to allow for any TBTF factors. In this Section, we provide a framework to address these TBTF factors when analysing scale economies for banks. To do this, we employ the implicit subsidy measure of Haldane (2010). The implicit subsidy measure we employ is an estimate of the extent to which funding costs are lowered due to a market expectation that the state will 'bail out' banks deemed TBTF. As such, this measure identifies banks deemed to be TBTF and quantifies the corresponding TBTF funding cost advantages.

Other measures of the implicit subsidy have been developed. Baker and McArthur (2009) provide one of the first measures. They consider the change in funding costs for U.S. banks due to a change in bailout expectations, using the TARP intervention as a natural experiment. One limitation of their method is that the empirical strategy relies on the assumption that all banks with more than US$100 billion in assets will receive government assistance. Moreover, this measure is not suitable for our purposes because it provides an estimate of the change in the implicit subsidy since the TARP intervention, rather than an estimate of the level of the implicit subsidy.

Ueda and Weder di Mauro (2012) quantify a structural subsidy based on information contained in credit ratings. The key difference between the structural subsidy and the implicit subsidy of Haldane (2010) is the funding cost data used. The former employs long run funding costs, derived from data over the period from 1920 to 1999 while the latter employs the funding costs that banks face in each relevant period.

Noss and Sowerbutts (2012) outline a contingent claims based approach as a measure of an implicit subsidy. They estimate a subsidy as an expected payment

from the government to the banking system to prevent its assets falling below a threshold value. The contingent claims approach does not identify banks deemed TBTF however; these must be selected by the researcher in order to obtain an estimate of the subsidy. Further, this approach also does not directly address funding cost advantages in the way that the implicit subsidy does. As such, the implicit subsidy measure of Haldane (2010) provides an appealing method to identify banks considered TBTF and to quantify any associated TBTF funding cost advantage.

We next describe the methodology we use to compute the implicit subsidy of Haldane (2010). We then outline two alternative methodologies to address TBTF factors when analyzing scale economies for banks. The objective of both methods is to uncover the underlying production technology which is unaffected by TBTF factors. The corresponding parameter estimates can then be used to isolate those scale economies that are unaffected by TBTF factors.

1.3.1. Measurement of the Implicit Subsidy

Using the methodology of Haldane (2010), we compute the implicit subsidy as: the reduced funding cost due to TBTF, multiplied by the amount of liabilities which are sensitive to a bank's credit rating. To do this, there are four main steps:

Step 1. We first need a measure to identify TBTF banks. This information is embedded in credit ratings. Ratings agencies typically issue banks with several types of ratings, including a "support" rating and a "stand-alone" rating. Both the support and the stand-alone ratings take into account the intrinsic financial strength of a bank. But the former explicitly takes account of the probability that a bank will receive external (e.g. state)

support to avoid a default; the latter does not. Thus, a ratings agency's judgment about the expected external support to a bank is encompassed by the difference between the "support" and the "stand-alone" ratings that the bank is issued. We refer to this difference as the "ratings uplift". We consider a bank to be TBTF if its ratings uplift is greater than zero.[12]

Step 2. We compute the "rating sensitive liabilities" for each bank in each time period as total liabilities less the sum of total deposits and derivative liabilities. We do not assume that customer deposits are sensitive to credit ratings because in many jurisdictions these are insured.[13]

Step 3. Before we can finally obtain our estimate of the implicit subsidy, we must make an assumption about the rate at which banks fund their rating-sensitive liabilities. We assume that ratings-sensitive liabilities are funded at the support credit rating. But, in the absence of any implicit government support due to a TBTF perception, banks would need to fund themselves at the stand-alone credit rating. Thus, the implicit subsidy represents the difference between the costs of funding at the support credit rating and at the stand-alone credit rating.

Step 4. Finally, we compute the implicit subsidy, using the estimates of the ratings uplift and the ratings-sensitive liabilities with the assumption about funding costs. We do this for each bank by taking the yearly average for the relevant geographic region for each bank of: the index spread corresponding to its stand-alone rating, and also to its support rating. The difference between the two spreads is then multiplied by rating sensitive liabilities.

[12] As noted by Noss and Sowerbutts (2012) banks' subsidiaries support ratings will take account of the possibility that their failure would be prevented by a bail out from their parent company. We consider ratings for bank holding companies or otherwise a subsidiary that represents a significant proportion of the bank holding company. Thus, it seems reasonable to assume that any support rating considered in our analysis captures only the potential for extended help by the government.

[13] Our measure of deposits also includes deposits by banks. Deposits by banks may be sensitive to credit ratings. We do not have a more granular breakdown for deposits however. The impact of subtracting these additional deposits will be to make the estimate of the implicit subsidy smaller which would ultimately make our results more conservative.

The implicit subsidy for bank b at time t can therefore be described as:

$$\text{Implicit subsidy}_{b,t} = \left(I_{b,t}^{Support} - I_{b,t}^{Stand-alone}\right) \times \text{Ratings sensitive liabilities}_{b,t} \quad (1.6)$$

where $I_{b,t}^{Support}$ is the average index spread over period t (for the relevant geographic region) that corresponds to the support credit rating for bank b at time t; $I_{b,t}^{Stand-alone}$ is the average index spread over period t (for the relevant geographic region) that corresponds to the stand-alone rating for bank b at time t.

We typically use Moody's senior unsecured (domestic) ratings and bank financial strength ratings to represent the "support credit rating" and "stand-alone rating", respectively. To estimate the rate at which banks fund themselves we use Merrill Lynch, Pierce, Fenner & Smith Incorporated bond indices data. Appendix 1.A provides greater details regarding the calculation of the implicit subsidy calculations and relevant data sources.

1.3.2. An Augmented Cost Function Specification that Adjusts for TBTF Funding Cost Advantages

We now outline the first of two tests that we employ to determine the impact of TBTF factors on the estimates of scale economies. We employ the implicit subsidy to develop a proxy for the "social price of debt", w_d^*. We compute w_d^* by adjusting the numerator of original price of debt, w_d, as follows:

$$w_d^* = \frac{\text{Total interest expense} + \text{Implicit subsidy}}{\text{Total deposits} + \text{Short-term debt} + \text{Long-term debt}} \quad (1.7)$$

The social price of debt provides us with a counterfactual estimate for the price

of debt banks would face in the absence of any TBTF funding cost advantage. We wish to uncover the underlying production technology that is unaffected by TBTF factors. To do this, we use this proxy for the social price of debt to re-estimate our model of bank production in order to determine if TBTF funding cost advantages are driving scale economies at large banks.[14] We refer to this parameterization as the "augmented cost function" or the "augmented model".

A serious weakness of this approach is that it violates the assumption that banks minimize costs with respect to the *actual* prices they face. And if banks were faced with the social price of debt they may choose different input demands than those observed for their actual costs. This approach will, therefore, not uncover the true parameters of the cost function.

To determine approximately how serious this violation is, we compute the own- and cross-price elasticities of input demand, using the parameterisation from the standard model, as:

$$\begin{aligned} \zeta_{dd} &= \tfrac{\beta_{dd}}{S_d} + S_d - 1, \\ \zeta_{jd} &= \tfrac{\beta_{jd}}{S_j} + S_d \text{ for } j \neq d \end{aligned} \tag{1.8}$$

The elasticities described by Equations (1.8) show how the demand for input j changes, *ceteris paribus*, with respect to changes in the price of debt. These elasticities, when combined with the average change in the price of debt due to the implicit subsidy, provide a rough estimate of the extent to which the input vector might change if banks were faced with the counterfactual estimate of the social price of debt.[15] We refer to the resulting estimate of the input vector as the "adjusted input vector". We can attempt to gauge the magnitude of the aforementioned violation by considering the difference between the original input

[14] All other variables in the cost function, including total costs and the cost shares, remain the same.

[15] We calculate these estimates at the mean values for: the cost shares and the change in the price of debt due to the implicit subsidy.

vector and the adjusted input vector.

Additionally, we examine whether the change in the input vector would result in large changes to cost. We first estimate total costs based on the adjusted input vector combined with the price vector that includes the adjusted social price of debt. Next, we estimate total costs based on the original input vector combined with the price vector that includes the adjusted social price of debt. All vectors are evaluated at the mean values. Once more, we can roughly approximate the potential magnitude of the violation by considering the difference between these two estimates of total costs. If these differences are minimal, this suggests that the violation may not be serious in terms of magnitude.

1.3.3. A Cost Function Parameterized for Non-TBTF Banks

Here we outline the second of two tests that we employ to determine the impact of TBTF factors on the estimates of scale economies. We now estimate scale economies from a model of bank production that is estimated based only on a sample of non-TBTF banks, in accordance with our implicit subsidy measure. This approach is similar to one of the approaches of Hughes and Mester (2011). The main difference being that we employ the implicit subsidy measure in order to identify and exclude TBTF bank observations from the estimation; Hughes and Mester (2011) employ a US$100 billion total assets threshold.

Once more, we are attempting to uncover parameter estimates for the model of bank production that are unaffected by TBTF. We employ these parameter estimates based only from the sample of non-TBTF banks to estimate scale economies for the entire sample including the TBTF banks. From this approach, we should be able to determine whether TBTF factors contribute to observed scale economies.

A limitation of this method concerns our method for identifying TBTF banks. We

will only reveal the parameter estimates of the cost function that are unaffected by TBTF factors if we exclude all TBTF banks from the estimation. In the next Section, we show that around 75 per cent of banks that received some kind of government assistance in the recent crisis were considered *ex ante* TBTF. This suggests that our method of identifying TBTF banks is reasonable, but the estimates from this method may still be affected by TBTF.

One appealing feature of our sample is that it is relatively evenly divided between TBTF and non-TBTF bank observations. Moreover, there are both TBTF and non-TBTF bank observations in all size groups (Table 1.1). This means that we are not required to estimate an out-of-sample forecast of scale economies for the TBTF banks based on the parameter estimates based on the non-TBTF banks.

Both methods we employ to determine the impact of TBTF factors on the estimated scale economies have limitations. Nonetheless, we believe that these methodologies provide some insights regarding the impact of these TBTF factors. We consider the results from the standard model and the two alternative specifications in Section 1.5.

1.4. Data

Here we outline our data sources, bank sample and descriptions of the variables selected for the cost functions. We provide summary statistics for all variables included in the cost functions. We also provide summary statistics for our measure of the implicit subsidy.

1.4.1. Data Sources

For estimation of the cost function, we require bank-specific and macroeconomic data. We obtain bank-level income statement and balance sheet data from the S&P Capital IQ database over the period 2001 to 2010.[16] All bank-level data are converted to U.S. dollars by the S&P Capital IQ database. Further, we convert all nominal data to constant 2010 prices using respective country-level inflation data.

We obtain macroeconomic data from several sources, including the International Financial Statistics database of the IMF and the World Bank.[17] We also employ data from the Banking Regulation and Supervision Surveys of Barth, Caprio and Levine (2004, 2008).[18]

1.4.2. Bank Sample

Our sample comprises the ultimate parent companies (UPCs[19]) of all interna-

[16] We supplement some missing data with data from Bloomberg and banks' published accounts. Where possible, we still use the same U.S. dollar conversion rates for data from banks' published accounts as S&P Capital IQ.

[17] We supplement several missing macroeconomic data points with data from the IMF World Economic Outlook Database (April 2011) and other sources.

[18] We supplement some missing data, primarily with various central banks' statistics.

[19] We obtain the ultimate parent bank by applying the S&P Capital IQ filter to obtain banks with 'operating' status. Companies with 'operating' status are not controlled (that is, no majority stake held) by any single company. It may be non-strategically controlled (i.e. majority stake held) by a financial buyer. Following the arguments of Hughes, Mester and

tional commercial banks with more than US$50 billion in consolidated assets as at 2010.[20] We filter the sample to exclude the central bank, government and multilateral institutions.[21] We add to the sample any global systemically important financial institutions (G-SIFIs), as defined by the Financial Stability Board (2011), that are not already included.[22] Our sample includes 26 of the 28 G-SIFIs; the two G-SIFIs not included are investment banks.[23] All of the 26 G-SIFIs included in our sample were considered TBTF in 2010, according to our measure of the implicit subsidy. The final sample includes 152 UPCs in 37 countries.

We place a lower bound on bank asset size of US$50 billion in assets as at 2010, which coincides with the implicit definition of systemic bank holding companies outlined by the Dodd-Frank Wall Street Reform and Consumer Protection Act.[24] The lower bound ensures our sample is not dominated by small U.S. banks with models of bank production that differ to that of the larger and typically international, universal banks we are most interested in. This is important because we employ parametric techniques in this study. Our sample selection attempts to minimize the problems that may incur from imposing the same parametric estimates on a sample of banks with different models of bank production.[25]

Moon (2001), we employ UPCs and not individual banks because the investment strategies of individual banks reflect the composite strategy of the top holding company and so are not necessarily independent. We delete around three banks captured using our selection criteria that are marked as 'UPCs' by S&P Capital IQ but are in fact a subsidiary of a UPC already captured in the sample.

[20] We use the S&P Capital IQ definition for 'Commercial Banks'.

[21] We also exclude some observations that have no, or very limited, bank-level data in a given year.

[22] We need to make these additions due to S&P Capital IQ's definition of banks which does not classify certain G-SIBS as 'Commercial Banks'. It is not because these G-SIBs have assets of less than $50 billion as at December 2010.

[23] These investment banks are excluded because they do not engage in commercial banking, and so are likely to have a different model of bank production.

[24] The Act created an Orderly Liquidation Fund (OLA) to fund the liquidation of a non-bank or non-security financial company's liquidation. The OLA is capitalized from risk-based assessment fees on any "eligible financial company", defined as "any bank holding company with total consolidated assets equal to or greater than $50 billion and any nonbank financial company supervised by the Board of Governors."

[25] Feng and Serilitis (2010) and Wheelock and Wilson (2012) both highlight that a translog specification is suitable only for a sample comprised of relatively homogeneous firms.

Despite the lower bound on bank size, the range of bank sizes included our sample is sufficiently large to facilitate a scale economies analysis. Around 20 per cent of the banks in the sample have less than US$50 billion in the period prior to 2010. The sample includes a wide range of bank sizes, with total assets ranging from about US$5 billion to almost US$4 trillion.

1.4.3. Variable Selection

Given our data, we now specify an appropriate choice of variables for our model of bank production. The simplest way to impose the financial intermediation approach to modeling bank production is to define assets as outputs and liabilities as inputs.[26] We follow this approach. In our model, we include three inputs, five outputs and one netput. We also include some environmental variables.

Table 1.8 in Appendix 1.B provides a summary of all variables included in the cost function, how these are calculated, and their corresponding data sources. Table 1.9 and Table 1.10 in Appendix 1.B provide summary statistics for all variables in the cost function, organized by region of bank origin and by bank size, respectively.

For the dependent variable, C, the financial intermediation approach calls for a measure of total costs (Mester 2008). We compute total costs as the sum of total interest expenses and all other operating expenses which coincides with the sum of all variable input expenditures.[27] We define an output vector y similarly to that of Hughes and Mester (2011), consisting of five variable outputs to bank production: y_1, liquid assets; y_2, securities; y_3, loans; y_4, other non-loan financial assets; and y_5, off-balance sheet activities. We measure off-balance sheet activities using the non-interest income method outlined by Clark and Siems (2002). The

[26] See Berger and Humphry (1992) for a more detailed discussion of the approaches to defining bank outputs.

[27] All other operating expenses are measured by 'non-interest expenses'.

non-interest income measure is simply non-interest income less service charges on deposits.[28]

Consistent with other studies, such as Altunbas et al. (2001), that include non-U.S. banks in the sample, our three variable inputs to bank production, $\mathbf{x}$, are: x_d, demandable debt and other types of debt; x_l, labor; and x_p, physical capital. The corresponding three variable input prices are: price of debt, w_d, calculated as the total interest expense divided by the sum of total deposits, short term debt and long term debt[29]; price of labor, w_l, calculated as personnel expenses divided by total assets[30]; and the price of physical capital, w_p, calculated as non-interest expenses less personnel expenses divided by total assets.[31]

The vector $\mathbf{z}$ consists of fixed netput quantities that may influence bank produc-

[28] Wheelock and Wilson (2010) adopt this measure of off-balance sheet activities and claim it to be the most consistent measure across banks and time. Although Hughes and Mester (2011) use the credit-equivalent measure outlined by Clark and Siems (2002), citing the fact that the non-interest income measure is subject to distortion from realized losses. Ultimately, in the absence of cross-country regulatory return data we are unable to compute the credit-equivalent measure.

[29] Bank efficiency studies based on U.S banks typically employ more than one input category for debt. This is not possible here due to limited data availability. Granular interest expense data are available for about 50 per cent of our sample only in the S&P Capital IQ database. In some jurisdictions, banks may only be required to report their total interest expense, and not specific expenses for different types of liabilities. Rime and Stiroh (2003) note this is the case for Swiss banks. Our approach is consistent with other studies of bank efficiency that consider a sample not restricted to U.S. banks (see, e.g., Humphrey and Vale 2004, Koetter 2006, Lozano-Vivas and Pasiouras 2010).

[30] We employ total assets rather than the number of employees due to limited data availability, consistent with other studies of bank efficiency that employ an international sample of banks (see, e.g., Lozano-Vivas and Pasiouras 2010).

[31] We employ total assets as the denominator because non-interest expense less personnel expenses includes many items that are unrelated to physical capital. Some examples of such items unrelated to physical capital expenses include: amortization of goodwill and intangible assets, loss/gain on the sale of loans and other assets, selling and marketing expenses, preferred stock dividend of subsidiary, and payroll taxes. Some studies appear to employ a similar numerator but fixed assets as a denominator in order to compute the price of physical capital. We do not feel this is appropriate due to the large inconsistencies between the items pertaining to the numerator and the denominator, but we include this alternative price proxy as a robustness check. Other studies compute the price of physical capital as: depreciation and other capital expenses divided by fixed assets. This appears to be the most sensible measure. We consider a similar measure as a robustness check, but we do not employ this price measure for our 'baseline model' due to limited data availability for the more granular expense data. As a final robustness check, we also model physical capital as a fixed netput, rather than a variable input, to bank production. Our results are almost always robust.

tion. This includes equity capital, k. Equity capital is an important and now frequently included variable in models of bank production, following the work of Hughes and Mester (1993). Equity capital is often treated as a netput because no reliable price data exist. Treating equity capital as a netput implies that the level of debt, labor and physical capital minimize cost with respect to a given level of equity capital.[32] We calculate equity capital as the sum of total equity and allowances for loan losses.[33]

In addition to equity capital, Hughes, Mester and Moon (2001) and Hughes and Mester (2011) incorporate some other aspects of risk-taking into their standard minimum cost function. They include the amount of non-performing loans, n, said to be an ex post measure of asset quality. We include n as a netput in our specification as a robustness check outlined in Section 1.5.

We also include several variables to control for the heterogeneity of production environments across time and different countries. These include: real GDP growth, per capita GDP, nominal interest rates, credit as a per cent of GDP, and banking system concentration. Real GDP growth is as a proxy for economic growth. Economic growth is likely to affect both the supply and demand for various banking services (Lozano-Vivas and Pasiouras 2010). Increased supply or demand for various banking services is expected to result in a general increase in banking activities, and as such the scale of banking activities. To the extent that scale economies exist, economic growth may therefore be an important factor.

[32] This assumption is reasonable because banks are subject to minimum capital requirements; banks do not face complete flexibility to choose a cost minimizing level of equity capital. Further, there is evidence that capital requirements for U.K. banks affect bank behaviour over and above the influence of banks' own internally generated capital targets (Ediz, Michael and Perraudin 1998, Francis and Osborne 2010).

[33] This is a proxy for regulatory capital. In reality, total regulatory capital comprises of Tier 1 (common equity as well as hybrids and innovative Tier 1 instruments) and Tier 2 capital as well as deductions and prudential filters under Basel II. For these purposes we have included total equity and allowances for loan losses. Although typically only a proportion of allowances for loan losses are included in Tier 2 capital. Eligible subordinated debt is also included in Tier 2 capital, but we do not include this because these data are unavailability in S&P Capital IQ.

We include nominal interest rates because high nominal interest rates may increase the interest costs of banks and reduce efficiency in activities, such as risk management via greater uncertainty and risk (Fries and Taci 2005). We include per capita GDP as a proxy for development, as in Fries and Taci (2005) who argue this could be important as a proxy for skill levels. As the level of skills increases, so too should general bank efficiency, and so this may influence bank costs.

The credit as a per cent of GDP variable is included as a measure of financial intermediation.[34] Lozano-Vivas and Pasiouras (2010) employ a similar measure; they argue that higher financial intermediation implies greater banking activity via an increase in loans. This increase in the scale of banking operations may have an impact on bank costs, should it improve or damage efficiency.

Finally, we include banking system concentration as a control variable in our cost function, consistent with several other studies of bank efficiency (see, e.g., Lozano-Vivas and Pasiouras 2010). Banking sector concentration may influence bank costs for two reasons. On the one hand, a high level of concentration may reflect successful survival and consolidation of highly efficient banks; we would expect these banks to have lower costs. On the other hand, banks in a highly concentrated sector may have market power; we might expect these banks to have higher costs due to potential inefficiency (Fries and Taci 2005).

Given that our sample contains large international banks that often have global operations, we considered creating macroeconomic index variables, tailored for each bank. For example, a GDP growth index could be calculated for each bank as the average GDP growth for all countries, weighted by the country exposure for each bank. But after an examination of the geographic exposures for the largest 25 banks in our sample, we decided against this approach. These banks

[34] More specifically, we employ domestic credit provided by the banking sector as a per cent of GDP.

exhibit strong home country exposure bias; almost half of these banks (11 banks) have home country exposure greater than 80 per cent.

1.4.4. The Price of Debt and TBTF Funding Cost Advantages

We now provide more detailed summary statistics for the variable in the minimum cost function that we argue is affected by TBTF funding cost advantages: that is, the price of debt. Table 1.1 reports the proportion of banks that are considered to be TBTF, as determined by the ratings uplift, broken down by region, size and year. Table 1.1 also reports the mean price of debt for three different scenarios: the unadjusted price of debt for the group banks of banks that receive no implicit subsidy; the unadjusted price of debt for the group of banks that do receive an implicit subsidy; and the social price of debt which is adjusted by the implicit subsidy, for the group of banks that receive an implicit subsidy.

Table 1.1 provides *prima facie* evidence that there is a funding cost advantage for banks deemed TBTF; with one exception, the mean (unadjusted) price of debt is consistently greater for those banks with no implicit subsidy than for those banks with an implicit subsidy. Moreover, the mean social price of debt for the banks with an implicit subsidy approaches the mean price of debt for those banks with no implicit subsidy, providing some support for the implicit subsidy as a measure of the TBTF funding cost advantage.

Table 1.1.: The impact of the implicit subsidy on the price of debt

	(1) Number of bank observations	(2) Proportion of banks with an implicit subsidy (per cent)	(3) Mean price of debt for banks with no implicit subsidy, $w_d \times 10^2$	(4) Mean price of debt for banks with an implicit subsidy, $w_d \times 10^2$	(5) Mean social price of debt for banks with an implicit subsidy, $w_d^* \times 10^2$
Panel A. By region, for the period 2001 to 2010					
Full sample	1,381	53.8	3.7	2.9	3.7
Americas	288	22.9	3.7	3.3	3.7
Asia and Oceania	431	74.2	2.8	1.9	2.4
Europe	591	56.0	3.6	3.8	4.9
Middle East and Africa	71	36.6	6.8	2.6	2.8
Panel B. By total assets (US$), for the period 2001 to 2010					
<100bn	579	49.7	3.7	2.5	2.9
100bn–500bn	501	50.9	3.7	3.4	4.5
500bn–1tn	150	64.0	4.1	3.0	3.9
1tn–2tn	112	61.6	3.3	2.5	3.6
>2tn	39	89.7	3.2	2.7	3.5
Panel C. By year					
2001	118	26.3	5.1	4.1	4.7
2002	127	36.2	3.9	3.4	4.2
2003	137	40.1	3.1	2.6	3.6
2004	140	37.9	2.9	2.5	2.9
2005	146	39.0	3.2	2.8	3.2
2006	146	40.4	3.9	3.0	3.3
2007	144	77.1	4.6	3.6	3.8
2008	136	75.7	4.2	3.5	4.2
2009	144	83.3	3.5	2.4	4.4
2010	143	75.5	2.6	1.9	2.6

However, any interpretation of Table 1.1 requires caution. Other important factors are likely to contribute to the observed differences in funding costs, such as: time variation, regional variation, and differences in banks' business models. Note also that some banks have different funding mixes. Deposits may be sticky and a cheaper source of funding than debt. As such, smaller banks that tend to have higher deposit funding ratios may have lower overall funding costs despite these smaller banks being less likely to receive TBTF funding cost advantages.

1.4.5. Characteristics of the Implicit Subsidy

Here we provide summary statistics for the key features of the implicit subsidy in Table 1.2. We present the implicit subsidy as a ratio over total assets. This ratio can also be interpreted as the increased return on asset attributable to the implicit subsidy. Table 1.2 also includes estimates of the mean funding cost reduction due to the implicit subsidy. We compute the funding cost reduction due to the implicit subsidy as:

$$\text{Funcing cost reduction} = \frac{\text{Implicit subsidy}}{\text{Total interest expense} + \text{Implicit subsidy}} \tag{1.9}$$

The numerator of Equation (1.9) corresponds to an estimate of the TBTF funding cost advantage and the denominator corresponds an estimate of the counterfactual funding costs that a bank would face in the absence of any TBTF funding cost advantage.

A general observation from Table 1.2 is that there are differences in the ratio of the implicit subsidy to total assets across regions, bank sizes and time. These differences appear to be driven largely by the differences in two variables: the ratings uplift and the ratio of non-deposit funding to total funding. This is to be expected, given that these two variables are direct inputs in the computation of the implicit subsidy.

We consider the relationship between bank size and the implicit subsidy, implied by Table 1.1 and Table 1.2. Table 1.1 suggests that a larger bank is more likely to be considered TBTF (Panel B, Column 2). But conditioning on a bank being considered TBTF by the implicit subsidy measure, Table 1.2 illustrates that the average ratings uplift does not monotonically increase with bank size (Panel B, Column 3). This may be because many banks in our sample are not necessarily global SIFIs, but rather domestic SIFIs. Domestic SIFIs may be only a fraction

of the size of their global counterparts, but they are often one of the largest banks in a given country and so may enjoy the benefits of implicit government support. However, the mean funding cost reduction does increase with bank size (Table 1.2, Panel B, Column 5). This appears to be because larger banks employ a greater proportion of "ratings-sensitive" debt to fund their balance sheet (Table 1.2, Panel B, Column 4). As such, they attract a funding subsidy across a greater proportion of their balance sheet. Overall, larger banks appear more likely to be deemed TBTF. But there does not appear to be an "optimal size" that maximizes the implicit subsidy.

Finally, we consider the predictive power of the implicit subsidy to accurately identify banks that are considered TBTF. To do this, we compare the implicit subsidy measure in 2007 with the observed government assistance for banks observed during the financial crisis. Government assistance here typically includes: government assisted mergers, capital injections, emergency funding, TARP, or new access to lender of last resort facilities.[35] For the banks that received some kind of government assistance, around 75 per cent of these were considered TBTF in 2007 according to our measure of the implicit subsidy. These statistics provide some support for the implicit subsidy as a measure to identify banks that are considered TBTF.

[35]For information regarding government assistance during the crisis, we employ the dataset of Laeven and Valencia (2010). In order to match our bank dataset, we supplement their dataset with information primarily obtained via internet searches of the bank name and several key words such as "government assistance", "bail out", "capital injection" and "emergency funding".

Table 1.2.: Characteristics of the implicit subsidy

	(1) Number of bank observations with implicit subsidy	(2) Mean ratio of the implicit subsidy to total assets (per cent)[a]	(3) Mean ratings uplift[a]	(4) Mean ratio of non-deposit funding to total funding (per cent)[a]	(5) Mean funding cost reduction due to the implicit subsidy (per cent)[a]
Panel A. By region, for the period 2001 to 2010					
Full sample	743	0.6	3.1	27.0	19.8
Americas	66	0.3	1.8	23.5	13.7
Asia and Oceania	320	0.4	3.7	14.6	22.3
Europe	331	0.9	2.9	41.2	19.6
Middle East and Africa	26	0.1	2.2	6.9	6.4
Panel B. By total assets (US$), for the period 2001 to 2010					
<100bn	288	0.4	2.8	17.2	16.1
100bn–500bn	255	0.8	2.9	32.3	18.9
500bn–1tn	96	0.7	4.3	32.8	22.0
1tn–2tn	69	0.8	4.1	31.4	31.0
>2tn	35	0.6	2.6	43.4	28.5
Panel C. By year					
2001	31	0.5	2.6	22.9	14.0
2002	46	0.6	2.7	20.7	16.5
2003	55	0.7	3.4	21.9	20.8
2004	53	0.3	3.7	22.4	18.1
2005	57	0.3	3.4	24.3	16.9
2006	59	0.2	3.3	23.4	13.4
2007	111	0.1	2.7	30.2	6.1
2008	103	0.5	2.8	30.5	16.0
2009	120	1.5	3.5	29.4	36.5
2010	108	0.6	3.2	29.5	27.3

(a) Presented results for the mean statistic are calculated as the conditional mean, where we condition on banks being deemed TBTF, as indicated by the implicit subsidy measure. In other words, the mean statistic is computed only for banks deemed TBTF.

1.5. Results

1.5.1. Evidence of Scale Economies

We first consider the estimated scale economies from our standard model of bank costs. We compare these with the estimates from the augmented model which adjusts the price of debt using the implicit subsidy in an order to address TBTF factors. Table 1.3 presents the estimated scale economies from these models; Figure 1.1 provides a corresponding graphical representation.

Prior to a discussion of these results in Table 1.3, we provide some intuition for these results. Consider the banks with more than US$2 trillion in assets as an example. Here the mean estimated scale economies are 1.146 from the standard model. This can be interpreted in the following way: a 1 per cent increase in all outputs is expected to give rise to a 0.87 per cent increase in total costs. That is, scale economies exist because an increase in all outputs results in a less than proportional increase in costs.

The results from the standard model suggest that, on average, scale economies exist for our sample of large banks. Moreover, these appear to increase across the bank size groups. Although there is a statistically significant difference in the mean estimated scale economies between consecutive assets classes for only one of the four possible pairs.[36] These results appear to confirm the recent findings of Feng and Serilities (2010), Hughes and Mester (2011) and Wheelock and Wilson (2012).[37]

The standard model fails to control for any potential TBTF factors however. As such, we consider the results for the augmented model. These results suggest that,

[36] This is the 100bn–500bn compared with the 500bn–1tn asset classes.

[37] Our results are, however, derived from a different model of bank costs and estimation technique to those employed in these recent studies.

Table 1.3.: Estimated mean scale economies[(a),(b),(c)]

		Standard model[(d)]		Augmented model, w_d^* adjusted for TBTF funding cost advantages[(e)]		Standard model, parameterised for non-TBTF banks[(f)]	
Total assets (US$)	N	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Full sample	1,381	1.066***	0.014	0.999	0.020	1.005	0.020
<100bn	579	1.042***	0.015	1.020	0.026	1.001	0.021
100bn–500bn	501	1.065***	0.014	0.986	0.021	1.007	0.022
500bn–1tn	150	1.099***	0.021	0.994	0.030	0.997	0.037
1tn–2tn	112	1.120***	0.028	0.966	0.035	1.017	0.043
>2tn	39	1.146***	0.035	0.975	0.043	1.019	0.050

(a) The results are for the estimated scale economies over the period 2001 to 2010. A value equal to one, less than one, or greater than one implies constant returns to scale, scale diseconomies, and scale economies, respectively.
(b)Total assets have been adjusted to constant year-2010 prices using country level inflation rate data.
(c) Presented results are for the mean statistic are calculated as the mean of the estimated scale economies for each point in the sample, rather than scale economies evaluated for the mean of the sample. The standard error of this mean statistic is computed via the delta method.
(d) From a standard model of bank production.
(e) From an augmented model of bank production, adjusted for TBTF funding cost advantages via the implicit subsidy measure.
(f) From a standard model of bank production, estimated for banks deemed not to be TBTF. The parameter estimates obtained for the non-TBTF banks only are applied to the full sample. TBTF status of banks is determined by the implicit subsidy measure.
***, **, and * refers to the value being significantly different from 1 at the 1 per cent, 5 per cent, and 10 per cent level, respectively.

on average, constant returns to scale exist for our sample of large banks when we adjust the price of debt by the implicit subsidy. Estimated scale economies for large banks, therefore, appear to be affected by TBTF funding cost advantages.

In Section (1.3) we mentioned that this approach violates the assumption that banks minimize costs with respect to the actual prices they face. To roughly gauge how serious this violation might be, we provide estimates of the own- and cross-price elasticities of input demand, based on the estimates of the standard model, combined with the price of debt due to the implicit subsidy.[38] We find that the average change in the price of debt due to the implicit subsidy leads to an increase in the demand for labor and physical capital of 2.0 and 1.3 per cent, respectively, and a decrease in the demand for debt of 1.5 per cent. We use

[38]We calculate these estimates at the mean values for: the cost shares and the change in the price of debt due to the implicit subsidy.

this estimated input demand vector, combined with the price vector that includes the social price of debt, to obtain a corresponding estimate of total costs. We alternatively estimate total costs, based the original input vector combined with the new price vector that includes the social price of debt, where all vectors are evaluated at the mean values. We estimate that there is about a 0.08 per cent difference between these two estimates of total costs. These results suggest, roughly, that the magnitude of the violation may not be serious.

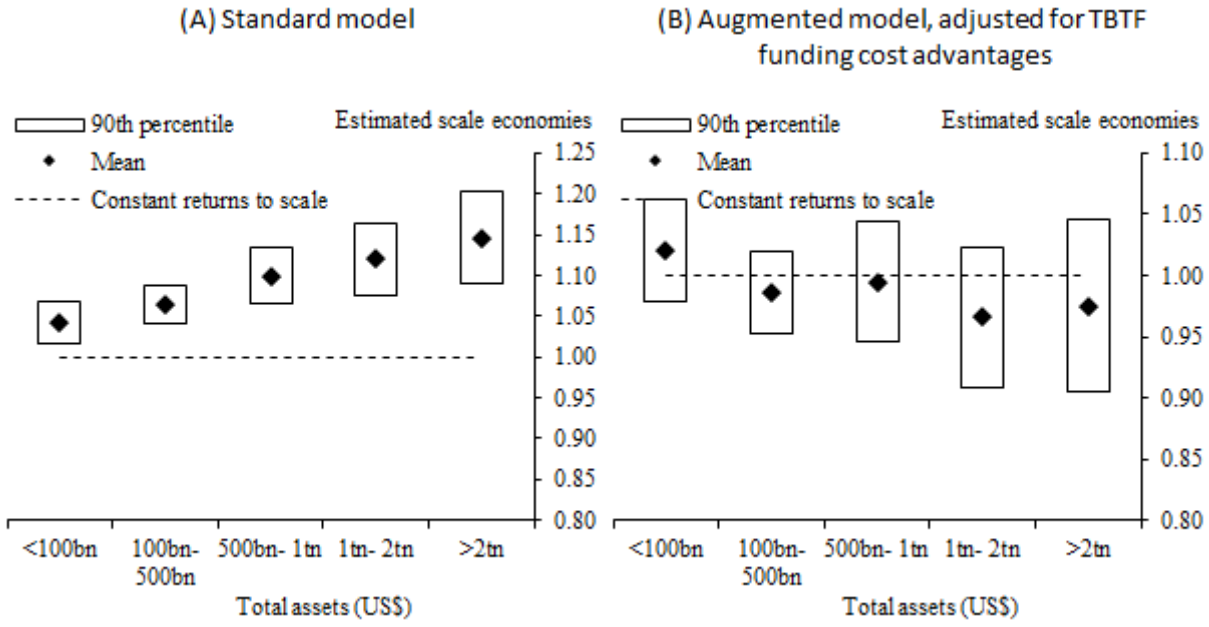


Figure 1.1.: Estimated scale economies

Notes: The results are for estimated scale economies over the period 2001 to 2010. A value equal to one, less than one, or greater than one implies constant returns to scale, scale diseconomies, and scale economies, respectively. Presented results are estimated at the mean and standard error of the estimated scale economies for each bank in each time period. Total assets have been adjusted to constant year-2010 prices using country level inflation rate data.

We now consider the estimated scale economies from our standard model of bank costs that is estimated based only on a sample of non-TBTF banks, in accordance with our implicit subsidy measure. We apply these parameter estimates to compute scale economies for the entire sample including the TBTF banks. As with the augmented model, the purpose of this approach is to uncover the true parameter estimates for the cost function that unaffected by TBTF. Table 1.3 presents the corresponding estimates. Based on this alternative approach, we find no evidence of scale economies for the banks in our sample. These results provide further evidence that estimated scale economies for large are affected by TBTF factors.

1.5.2. Robustness

Table 1.4 presents 10 different robustness checks of our results; each panel of the table represents a separate check.

We begin by considering the robustness of our results to a number of alternative model specifications. First, we incorporate some aspects of risk-taking into the minimum cost function (Panel A). We do so by including the amount of non-performing loans – an *ex post* measure of asset quality – as a netput to bank production, as done for the minimum cost function of Hughes and Mester (2011). The significance of the estimated scale economies remains the same; there are small differences in the magnitude of these estimates.

Second, we consider equity capital as an input to bank production rather than a netput (Panel B). We can derive estimates of scale economies for this alternative model specification from the original minimum cost function if we make the assumption that the observed level of equity capital is cost-minimizing.[39] The

[39]More details of how to derive this estimate of scale economies can be found in Hughes, Mester

results of this check remain broadly similar, although there are no longer significant scale economies from the standard model for bank observations with more than US$1 trillion in assets.

Next, we consider physical capital as a netput to bank production rather than an input (Panel C). This treatment of physical capital is in line with other studies, such as Wheelock and Wilson (2012) and Berger and Mester (2003). The motivation for this alternative specification is due to the potential unreliability of price data for physical capital. We also consider two alternative measures of the price of physical capital. We measure the price as occupancy expenses over fixed assets (Panel D). The results remain robust both of these checks. We also measure the price as other non-interest expenses less personnel expenses over fixed assets (Panel E). From both alternative methods that attempt to uncover the true bank production technology that is unaffected by TBTF factors, we now find evidence of scale economies for this robustness check. This last price measure, however, is considered problematic due to the large inconsistencies between the items contained in the numerator and the denominator, causing this price measure to typically be greater than 1 (that is, an overestimate) with very high variation amongst banks.

Next we cut our sample in a number of ways. First, we consider the robustness of our results across different time periods. We include time fixed effects and find our results to be robust to this specification.[40] We exclude 2009 data from our analysis to test whether the large spike in the implicit subsidy for this period is driving our results (Panel F). Similarly, we exclude the 'crisis period', from 2008 to 2010 (Panel G). The motivation for the latter two robustness checks is to ensure our results are

and Moon (2001).

[40]These results are not reported here but are available upon request.

Table 1.4.: Robustness checks for estimated mean scale economies[a],[b],[c]

		Standard model[d]		Augmented model, w_d^* adjusted for TBTF funding cost advantages[e]		Standard model, parameterised for non-TBTF banks[f]	
Total assets (US$)	N	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Panel A: Includes non-performing loans, n, as a measure of ex post asset quality, as an additional netput							
Full sample	1,290	1.060***	0.014	1.001	0.022	1.014	0.020
<100bn	520	1.053***	0.017	1.029	0.028	1.032	0.023
100bn–500bn	475	1.059***	0.015	0.987	0.022	1.008	0.022
500bn–1tn	144	1.075***	0.020	0.987	0.029	0.989	0.035
1tn–2tn	112	1.073***	0.025	0.960	0.035	0.993	0.041
>2tn	39	1.089***	0.031	0.966	0.042	0.999	0.047
Panel B: Includes financial equity capital, k, as an input rather than a netput							
Full sample	1,381	1.019**	0.007	1.018	0.012	1.007	0.011
<100bn	579	1.017**	0.008	1.019	0.013	1.015	0.012
100bn–500bn	501	1.019**	0.008	1.020	0.013	1.005	0.012
500bn–1tn	150	1.023**	0.011	1.022	0.017	0.997	0.017
1tn–2tn	112	1.020	0.013	1.009	0.019	0.996	0.020
>2tn	39	1.016	0.015	1.009	0.021	0.998	0.022
Panel C: Includes physical capital, x_p, as a netput rather than an input							
Full sample	1,382	1.062***	0.016	0.980	0.026	0.996	0.023
<100bn	580	1.047**	0.018	1.008	0.033	1.008	0.026
100bn–500bn	502	1.047***	0.016	0.953*	0.025	0.992	0.025
500bn–1tn	150	1.086***	0.024	0.968	0.037	0.983	0.044
1tn–2tn	111	1.137***	0.033	0.968	0.046	0.983	0.049
>2tn	39	1.185***	0.043	0.998	0.059	0.966	0.055
Panel D: Measures the price of physical capital alternatively as w_p = occupancy expenses/fixed assets							
Full sample	786	1.083***	0.026	0.978	0.038	1.041	0.046
<100bn	341	1.084**	0.034	1.038	0.055	1.089	0.060
100bn–500bn	264	1.070***	0.026	0.949	0.036	1.028	0.047
500bn–1tn	89	1.079**	0.035	0.903	0.043**	0.975	0.065
1tn–2tn	63	1.107**	0.045	0.914	0.054	0.967	0.072
>2tn	29	1.151**	0.059	0.904	0.062	0.957	0.086
Panel E: Measures the price of physical capital alternatively as w_p = other NIE/fixed assets							
Full sample	1,380	1.263***	0.033	1.192***	0.038	1.304***	0.059
<100bn	579	1.249***	0.039	1.231***	0.049	1.240***	0.057
100bn–500bn	501	1.259***	0.034	1.174***	0.038	1.355***	0.064
500bn–1tn	150	1.237***	0.046	1.136***	0.050	1.254**	0.122
1tn–2tn	111	1.337***	0.068	1.156**	0.065	1.427***	0.161
>2tn	39	1.386***	0.088	1.169**	0.079	1.437***	0.159

Table 1.4: *continued*

Total assets (US$)	N	Standard model[d] Mean	Standard model[d] Std. Error	Augmented model, w_d^* adjusted for TBTF funding cost advantages[e] Mean	Augmented model, w_d^* adjusted for TBTF funding cost advantages[e] Std. Error	Standard model, parameterised for non-TBTF banks[f] Mean	Standard model, parameterised for non-TBTF banks[f] Std. Error
Panel F: Excludes observations from the year 2009							
Full sample	1,237	1.064***	0.014	1.028	0.020	1.014	0.020
<100bn	532	1.051***	0.017	1.044*	0.025	1.021	0.023
100bn–500bn	445	1.063***	0.015	1.022	0.020	1.014	0.022
500bn–1tn	135	1.083***	0.022	1.022	0.029	0.994	0.037
1tn–2tn	94	1.093***	0.029	0.983	0.034	1.006	0.042
>2tn	31	1.114***	0.035	0.993	0.041	1.000	0.049
Panel G: Includes observations from the period 2001 to 2007							
Full sample	958	1.052***	0.017	1.076***	0.026	1.005	0.022
<100bn	442	1.043**	0.021	1.082***	0.031	1.007	0.025
100bn–500bn	332	1.050***	0.018	1.077***	0.027	1.005	0.023
500bn–1tn	107	1.067**	0.027	1.070*	0.038	0.987	0.037
1tn–2tn	63	1.087**	0.036	1.046	0.047	1.010	0.043
>2tn	14	1.098**	0.043	1.066	0.056	1.016	0.051
Panel H: Excludes observations for Chinese banks							
Full sample	1,267	1.071***	0.015	0.988	0.022	1.002	0.021
<100bn	538	1.048***	0.017	1.011	0.027	1.002	0.023
100bn–500bn	464	1.070***	0.016	0.973	0.023	1.003	0.023
500bn–1tn	128	1.113***	0.025	0.978	0.034	0.988	0.037
1tn–2tn	99	1.123***	0.031	0.949	0.038	1.009	0.045
>2tn	38	1.152***	0.039	0.969	0.047	1.005	0.052
Panel I: Excludes observations for U.S. banks							
Full sample	1,192	1.072***	0.015	0.992	0.023	1.021	0.025
<100bn	499	1.046***	0.017	1.018	0.029	1.013	0.026
100bn–500bn	427	1.071***	0.016	0.980	0.023	1.026	0.029
500bn–1tn	141	1.109***	0.024	0.982	0.033	1.020	0.047
1tn–2tn	93	1.129***	0.032	0.938	0.038	1.043	0.055
>2tn	32	1.165***	0.043	0.944	0.049	1.044	0.067
Panel J. Specifies the cost function using a Fourier Flexible functional form							
Full sample	1,381	1.048***	0.014	0.999	0.022	1.002	0.021
<100bn	579	1.061***	0.017	1.025	0.027	1.041*	0.024
100bn–500bn	501	1.028*	0.015	1.000	0.026	1.014	0.026
500bn–1tn	150	1.016	0.021	0.935**	0.032	0.910**	0.036
1tn–2tn	112	1.085**	0.034	0.948	0.045	0.922	0.048
>2tn	39	1.130**	0.062	0.979	0.084	0.854*	0.075

(a) The results are for the estimated scale economies over the period 2001 to 2010. A value equal to one, less than one, or greater than one implies constant returns to scale, scale diseconomies, and scale economies, respectively.
(b)Total assets have been adjusted to constant year-2010 prices using country level inflation rate data.
(c) Presented results are for the mean statistic are calculated as the mean of the estimated scale economies for each point in the sample, rather than scale economies evaluated for the mean of the sample. The standard error of this mean statistic is computed via the delta method.
(d) From a standard model of bank production.
(e) From an augmented model of bank production, adjusted for TBTF funding cost advantages via the implicit subsidy measure.
(f) From a standard model of bank production, estimated for banks deemed not to be TBTF. The parameter estimates obtained for the non-TBTF banks only are applied to the full sample. TBTF status of banks is determined by the implicit subsidy measure.
***, **, and * refers to the value being significantly different from 1 at the 1 per cent, 5 per cent, and 10 per cent level, respectively.

not driven entirely by the fact that our measure of the implicit subsidy varies with the business cycle. The results show that the main conclusions are similar, but we can see that the crisis period does influence the results presented for the full sample; for bank observations with less than US$1 trillion and also for the full sample, the mean of the estimated scale economies from the augmented model are now significantly different from one.

Second, we check if banks from one country are driving our results. Chinese banks and U.S. banks are the most populous in our sample. We exclude the bank observations from each of these countries, in turn, and re-estimate (Panel H for no Chinese banks and Panel I for no U.S. banks). The conclusions from these two country robustness checks remain the same.

We also consider an alternative specification from the translog to specify the cost function: the Fourier-Flexible functional form (Panel J). This functional form includes a standard translog cost function plus Fourier trigonometric terms.[41] This alternative specification does not materially affect our results. The main difference is for the bank observation with US$500 billion to US$1 trillion. Originally these banks had statistically significant scale economies and constant returns to scale from the standard model and the augmented model, respectively. They now appear to have constant returns to scale and scale diseconomies from the standard model and the augmented model, respectively.

To summarize, the results appear to be broadly robust to a range of checks. Further research, with more advanced models of bank production, is a possible next step.

There are some similarities and some differences between the results presented here and other recent empirical studies. Our results indicate that estimated scale

[41] We include first-order and second-order Fourier trigonometric terms for the output variables only, as done by Altunbas et al. (2001). Trigonometric terms applied to the output variables allow for greater flexibility in the local identification of scale economies (Humphrey and Vale 2004). But this comes at a cost: our specification here requires estimation of 40 additional parameters.

economies exist from a standard minimum cost function that does not control for any TBTF factors. Allen and Liu (2007) find evidence of scale economies from a similar minimum cost function to our specification for their panel dataset of large Canadian banks.[42] Hughes and Mester (2011) also employ a similar minimum cost function, but from this specification they find some evidence of scale diseconomies. One reason for the difference in these findings may be due to the differences in the datasets. Hughes and Mester (2011) consider a cross-section of U.S. bank holding companies in 2007; 2 per cent of their sample comprises banks with more than US$100 billion. This paper considers a panel of the largest international commercial banks over the period from 2001 to 2010; more than half of our sample comprises bank observations with more than US$100 billion in assets. In addition, Table 1.1 suggests that banks from the Americas and also with less than US$100 billion in assets are less likely to be considered TBTF, according to the implicit subsidy measure. As such, our estimated scale economies may be more affected by TBTF factors than those of Hughes and Mester (2011).[43]

[42] Although Allen and Liu (2007) note an upward bias in their scale economies estimates for their fixed-effects estimation that assumes stationarity of the data when the data are non-stationary. We have not considered the same estimation issues here because we have only a short panel of 10 time periods; the panel of Allen and Liu (2007) is more than 80 time periods.

[43] Another difference between our methods is the variable inputs to the model. We include fewer and more aggregated variable inputs than that of Hughes and Mester (2011). Our methodology is similar to other studies that consider an international sample of banks, whereby more granular data are unavailable.

1.6. Conclusions

There are two main findings in this paper. From a standard model of bank production that does not control for any TBTF funding cost advantage, we find evidence that scale economies exist for our international sample of large banks. These results are similar to recent findings in the literature.

A potential TBTF funding cost advantage could be affecting the estimated scale economies for large banks however. To investigate this possibility, we employ a measure of the implicit subsidy which estimates the extent to which bank funding costs are lowered due to a market expectation that the state will bail out banks deemed to be TBTF. We employ two alternative methodologies to determine if TBTF factors are affecting scale economies at large banks. The objective of both methods is to uncover the underlying production technology that is unaffected by TBTF factors.

First, we estimate scale economies from an augmented model of bank production that adjusts the price of debt using the measure of the implicit subsidy. Second, we estimate scale economies from a model of bank production that is estimated only on a sample of banks that are not considered TBTF, in accordance with our implicit subsidy measure. From both methods that attempt to uncover the production technology for banks that is unaffected by TBTF, we no longer find evidence of scale economies for our sample of large banks. These results imply that estimated scale economies for large banks are affected by TBTF factors.

These conclusions are subject to some caveats. Both methods we employ have weaknesses. The first approach does not uncover the true parameters of the cost function. This is because the method employs a counterfactual estimate of the social price of debt, thereby violating the assumption that banks choose their input quantities to minimize costs with respect to the *actual* prices they face. We provide some rough evidence, however, that the magnitude of this violation

may not be serious. The second approach will only reveal the true parameters of the cost function if our method of identifying TBTF banks is accurate. Our method of identifying TBTF banks appears to perform well but it is unlikely to be perfect.

The optimal size of banks – regulated institutions – is a question of public policy. A full answer needs to balance the benefits of scale with the costs of scale due to potential increases in systemic risk and crisis costs. In this paper, we address a narrow subset of this question, via an investigation of the private benefits to banks from increased scale. We show that estimated scale economies are affected by TBTF factors. Although policies that limit the size of banks may come with economic costs in the form of forgone scale economies, our research suggests that some of the costs advantages of larger banks are due to TBTF factors rather than to true economies of scale.

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1.A. Implicit Subsidy Calculations

1.A.1. Ratings Data

Moody's issue several ratings for banks but the ones we primarily use are the Bank Financial Strength rating (BFSR) and the senior unsecured (domestic) rating. The "stand-alone" rating is the BFSR. This is issued on a different scale to other Moody's ratings. Moody's provide a BFSR "look-up" table (Table 1.5) which we use to convert these ratings to a comparable basis. This look-up table was published by Moody's in 2007, but we apply is to all of our ratings data from 2001 to 2010.

We use only Moody's ratings. Both Fitch and S&P also provide similar support

Table 1.5.: Moody's Bank Financial Strength Ratings and Baseline Risk Assessment "look-up" table

Bank Financial Strength Rating	Baseline Risk Assessment[a]
A	Aaa
A-	Aa1
B+	Aa2
B	Aa3
B-	A1
C+	A2
C	A3
C-	Baa1-Baa2
D+	Baa3-Ba1
D	Ba2
D-	Ba3
E+	B1-B3
E	Caa1-Ca

Source: Moody's Investor Service (2007)
(a) The Baseline Risk Assessment reflects what the local currency deposit rating of the bank would be without any assumed external support (Moody's 2007). In this paper we typically employ senior unsecured ratings which appear to use the same long-term rating scale as the local currency deposit ratings.

and stand-alone ratings. We do not consider these in our study. We also convert the rating's data to a year-end series. That is, if a bank is assigned several rating changes within a year, the year-end rating for that bank is based on the last observed ratings assigned for that year.

For the majority of banks, we use the senior unsecured (domestic) rating for the "support rating". Where this is unavailable, we use the senior unsecured (foreign) rating (some banks issue in primarily foreign currency debt). And finally, when this is unavailable, we use the long term rating for the bank which is typically the long term deposit (foreign) rating. We investigated the difference between the long term rating and the senior unsecured (domestic) rating for those banks that have both ratings types, and found either little or no difference between these.

We obtain ratings for the ultimate parent company. But for some banks in our sample, we use the support or stand-alone rating for one of the largest bank subsidiary instead of for the ultimate parent company (UPC). This is typically because no ratings are assigned to the UPC Moody's for these banks, but instead to their subsidiaries.

1.A.2. Funding Rate Data

To estimate the rate at which banks fund themselves we use Merrill Lynch, Pierce, Fenner & Smith Incorporated bond indices data. Table 1.6 describes the indices we use by geographic region.

However, these indexes are only on a scale of: AAA, AA, A, BBB, B and C. To capture the more granular aspect of bank ratings these are linearly interpolated to represent the full Moody's ratings scale using Table 1.7. The data used are the yearly average funding rates for each category.

We almost always observe, as expected, that the average funding rate increases as we move down the rating scale. On a limited number of occasions, we find that the average funding rate decreases as we move down the rating scale (this is often due to the fact that we use two different types of rating indices for a given

Table 1.6.: List of employed Merrill Lynch, Pierce, Fenner & Smith Incorporated Bond Indices

Index	Description	Region
EB10	EMU Corp Financial AAA	Europe
EB20	EMU Corp Financial AA	Europe
EB30	EMU Corp Financial A	Europe
EB40	EMU Corp Financial BBB	Europe
HE10	Euro High Yield BB	Europe
HE20	Euro High Yield B	Europe
HE30	Euro High Yield C	Europe
GBF1	Global Broad Mkt Financial AAA	Global
GBF2	Global Broad Mkt Financial AA	Global
GBF3	Global Broad Mkt Financial A	Global
GBF4	Global Broad Mkt Financial BBB	Global
HW10	Global High Yield BB	Global
HW20	Global High Yield B	Global
HW30	Global High Yield C	Global
UF10	Sterling Corporates Financials AAA Rated	UK
UF20	Sterling Corporates Financials AA Rated	UK
UF30	Sterling Corporates Financials A Rated	UK
UF40	Sterling Corporates Financials BBB Rated	UK
HL10	Sterling High Yield BB	UK
HL20	Sterling High Yield B	UK
HL30	Sterling High Yield C	UK
C0P1	US Corp Banks AAA	US
C0P2	US Corp Banks AA	US
C0P3	US Corp Banks A	US
C0P4	US Corp Banks BBB	US
H0A1	US High Yield BB	US
H0A2	US High Yield B	US
H0A3	US High Yield C	US

geographic region, as can illustrated by Table 1.9). In these instances, we assign an implicit subsidy of zero.

1.A.3. Rating-Sensitive Liabilities

We compute the "rating-sensitive liabilities" for each bank in each time period as total liabilities less the sum of total deposits and derivative liabilities. We obtain the total liabilities and the total deposits data from S&P Capital IQ data. We supplement these data with derivatives liabilities data obtained from a combination of SNL and banks' published accounts.

Table 1.7.: Moody's ratings and Indices ratings mapping

Moody's ratings	Bond indices ratings
Aaa-Aa1	$= 1/2 \times (AAA + AA)$
Aa2	AA
Aa3	$= 2/3 \times AA + 1/3 \times A$
A1	$= 1/3 \times AA + 2/3 \times A$
A2	A
A3	$= 2/3 \times A + 1/3 \times BBB$
Baa1	$= 1/3 \times A + 2/3 \times BBB$
Baa1-Baa2	$= 1/2 \times (Baa1 + Baa2)$
Baa2	BBB
Baa3	$= 2/3 \times BBB + 1/3 \times BB$
Baa3-Ba1	$= 1/2 \times (Baa3 + Ba1)$
Ba1	$= 1/3 \times BBB + 2/3 \times BB$
Ba2	BB
Ba3	$= 1/2 \times (BB + B)$
B1-B3	B
Caa1-Ca	C

1.A.4. Calculating the Implicit Subsidy

Using the methodology of Haldane (2010), we compute the implicit subsidy as: the reduced funding cost due to TBTF, multiplied by the amount of liabilities which are sensitive to a bank's credit rating. The necessary steps are described in Section 1.3.

1.A.5. Caveats to the Data

BFSRs are intended to reflect a bank's stand-alone financial strength but do not have a one to one mapping with specific credit instruments. In other words, the BFSR is applied to the whole bank not to individual bonds. Moody's issues subordinated debt ratings, which are sometimes rated lower than the bank's BFSR rating. The calculations we have done assume that all rating-sensitive liabilities are funded at the Senior Unsecured (domestic) rating. The methodology should

perhaps be refined to reflect the use of subordinated debt in banks' balance sheets. However, given that banks issue little subordinated debt this should not have a large impact on the results.

1.B. Summary Statistics for Cost Function Variables

Table 1.8.: Definitions and data sources of variables used in the minimum cost functions

Symbol	Variable name	Calculation	Data sources
Dependent variable			
C	Total costs	Interest expenses + Non-interest expenses	Primarily S&P Capital IQ, supplemented with some data from Bloomberg and banks' published accounts.
Variable input prices			
w_d	Price of debt	Interest expenses/ (Short term debt + Long term debt + Total deposits)	
w_d^*	Social price of debt	(Interest expenses + Implicit subsidy)/ (Short term debt + Long term debt + Total deposits)	
w_l	Price of labour	Personnel expenses/Total assets	
w_p	Price of physical capital	(Non-interest expenses – Personnel expenses)/ Total assets	
Variable output quantities			
y_1	Liquid assets	Cash and equivalents	
y_2	Securities	Total investments (includes securities, trading asset securities and mortgage backed securities)	
y_3	Loans	Net loans (includes loans given to banks and customers, financial leases and total portfolio loans, and deducts allowance for loan losses and other adjustments	
y_4	Other non-loan financial assets	Total other assets	
y_5	Off-balance sheet activities	Non-interest income – Service charge of deposits	
Fixed netput quantities			
z_1	Equity capital	Total equity + Allowance for loan losses	
z_2	Asset quality	Non-performing loans	
Environmental variables			
m_1	Economic growth	Real GDP growth	IMF, International Financial Statistics, World Economic Outlook Database, April 2011
m_2	Interest rates	Nominal Interest rates	IMF, International Financial Statistics
m_3	Development	GDP per capita	IMF, International Financial Statistics and IMF, World Economic Outlook Database, April 2011
m_4	Financial intermediation	Domestic credit provided by the banking sector as a per cent of GDP	World Bank, World Development Indicators. Several missing values are linearly interpolated.
m_5	Banking sector concentration	Proportion of total assets held by the three largest banks in the country	Barth, Caprio and Levine (2004, 2008), supplemented with some data primarily

Table 1.9.: Variables used in the cost functions: means and standard deviations for the period 2001 to 2010, by region (standard deviations are in parentheses)

Symbol	Variable name	Full sample	Americas	Asia and Oceania	Europe	Middle East and Africa
N	Number of bank observations	1,386	288	432	595	71
C	Total costs	15,567.9 (22,892.7)	17,146.7 (22,391.2)	8,522.4 (11,472.1)	21,080.0 (28,321.6)	6,050.7 (6,541.0)
$w_d \times 10^2$	Price of debt	3.3 (2.5)	3.6 (3.2)	2.2 (1.4)	3.7 (2.1)	5.3 (3.6)
$w_d^* \times 10^2$	Social price of debt	3.7 (2.8)	3.7 (3.2)	2.5 (1.5)	4.3 (2.8)	5.3 (3.5)
$w_l \times 10^2$	Price of labour	1.0 (0.5)	1.6 (0.6)	0.6 (0.2)	0.9 (0.4)	1.1 (0.4)
$w_p \times 10^2$	Price of physical capital	1.4 (2.3)	2.1 (1.9)	1.4 (2.6)	1.0 (1.1)	2.6 (5.7)
y_1	Liquid assets	15,227.0 (36,939.7)	13,723.5 (35,482.3)	11,434.4 (21,750.3)	19,849.8 (46,786.3)	5,869.6 (4,029.1)
y_2	Securities	138,768.0 (281,556.0)	123,420.2 (212,863.0)	69,674.8 (134,758.8)	210,663.2 (373,738.7)	21,996.8 (18,886.0)
y_3	Loans	172,934.3 (217,489.5)	143,847.2 (189,599.2)	142,724.1 (192,922.5)	225,268.6 (244,885.9)	38,681.9 (23,284.7)
y_4	Other non-loan financial assets	33,269.9 (58,908.9)	34,083.6 (57,074.2)	32,452.3 (62,150.6)	36,872.6 (60,007.2)	4,942.7 (7,044.3)
y_5	Off-balance sheet activities	5,594.5 (9,901.8)	7,491.7 (11,320.0)	3,007.4 (5,856.2)	6,890.7 (11,407.6)	2,814.5 (4,687.6)
z_1	Equity capital	22,826.3 (33,316.5)	29,259.0 (45,207.8)	17,007.7 (24,233.0)	25,764.3 (33,024.4)	7,599.0 (4,105.1)
z_2	Asset quality	4,982.4 (11,723.2)	2,528.8 (4,976.8)	5,905.9 (16,199.2)	5,972.1 (10,566.4)	1,090.4 (1,084.8)
m_1	Economic growth (per cent)	3.1 (3.8)	2.0 (2.0)	5.6 (4.3)	1.6 (2.6)	5.1 (5.8)
m_2	Interest rates (per cent)	3.5 (5.1)	4.2 (5.0)	2.7 (1.7)	2.7 (1.5)	12.1 (16.8)
m_3	Development	28,647.9 (17,462.6)	35,848.8 (13,441.7)	17,151.4 (14,696.4)	35,148.9 (15,706.9)	15,113.1 (17,177.0)
m_4	Financial intermediation	155.5 (59.7)	196.6 (49.5)	158.8 (68.2)	141.6 (43.5)	84.8 (44.9)
m_5	Banking sector concentration	0.6 (0.2)	0.5 (0.2)	0.6 (0.1)	0.6 (0.2)	0.7 (0.1)

Table 1.10.: Variables used in the cost functions: means and standard deviations for the period 2001 to 2010, by asset size (standard deviations are in parentheses)

Symbol	Variable name	<US$100 bn	US$100bn–US$500bn	US$500bn–US$1tn	US$1tn–US$2tn	> US$2tn
N	Number of bank observations	580	503	151	113	39
C	Total costs	2,893.6 (3,061.6)	11,604.2 (8,294.1)	30,593.0 (19,241.9)	57,297.2 (31,320.7)	77,024.8 (33,356.4)
$w_d \times 10^2$	Price of debt	3.1 (2.5)	3.5 (2.4)	3.4 (2.6)	2.8 (2.0)	2.8 (2.3)
$w_d^* \times 10^2$	Social price of debt	3.3 (2.5)	4.1 (3.1)	4.0 (3.0)	3.5 (2.1)	3.5 (2.2)
$w_l \times 10^2$	Price of labour	1.0 (0.6)	1.0 (0.6)	0.8 (0.4)	0.8 (0.3)	0.7 (0.3)
$w_p \times 10^2$	Price of physical capital	1.5 (2.6)	1.6 (2.4)	0.9 (1.0)	1.2 (1.1)	0.8 (0.7)
y_1	Liquid assets	3,319.2 (3,221.7)	7,507.1 (9,925.0)	27,675.8 (36,060.4)	61,598.5 (66,523.3)	110,134.9 (104,569.0)
y_2	Securities	12,530.1 (8,106.2)	6,3415.0 (47,643.2)	237,136.8 (112,274.1)	570,414.4 (240,514.1)	136,2969 (431,849.9)
y_3	Loans	34,828.6 (15,252.5)	132,632.1 (65,816.3)	362,939.5 (112,211.4)	602,821.3 (235,372.5)	775,663.8 (272,033.1)
y_4	Other non-loan financial assets	4,409.2 (4,315.5)	20,055.7 (18,320.9)	63,200.1 (48,781.9)	151,754.2 (86,797.1)	176,113.1 (95,605.9)
y_5	Off-balance sheet activities	1,042.2 (1,859.4)	4,121.4 (5,190.4)	8,740.1 (8,378.6)	22,857.2 (15,305.7)	30,429.3 (17,298.2)
z_1	Equity capital	5,155.1 (2,837.2)	15,953.4 (8,455.7)	38,520.3 (18,540.7)	87,028.4 (38,940.5)	128,728.7 (58,799.1)
z_2	Asset quality	1,119.2 (1,419.3)	2,994.5 (5,409.1)	15,021.3 (24,843.3)	14,830.0 (15,686.1)	20,981.0 (14,519.2)
m_1	Economic growth (per cent)	3.8 (3.9)	2.8 (3.6)	2.8 (3.9)	2.2 (3.8)	1.0 (3.1)
m_2	Interest rates (per cent)	4.1 (7.2)	3.4 (3.0)	2.7 (1.5)	2.0 (1.5)	2.5 (2.0)
m_3	Development	22,427.0 (17,587.5)	32,080.9 (16,765.6)	32,406.9 (15,061.1)	36,059.4 (14,324.2)	41,161.5 (7,653.0)
m_4	Financial intermediation	147.1 (65.2)	153.9 (52.2)	162.3 (49.0)	187.8 (64.0)	183.0 (50.3)
m_5	Banking sector concentration	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)	0.6 (0.1)

2. The Real Effects of Zombie Lending in Europe[1]

Chapter Abstract

Around 10 per cent of European firms were in receipt of subsidized bank loans following the peak of the European sovereign debt crisis in 2011 (Acharya et al., 2015). To what extent did such forbearance lending contribute to the economic stagnation in Europe that commenced during this period? We address this question by developing a quantitative model in which forbearance lending and firm defaults arise endogenously. Lenders also face information asymmetry because they do not know firm quality with certainty. The model provides a good approximation to key Euro Area firm statistics over the period 2011 to 2014. We evaluate the impact of forbearance lending by considering a counterfactual scenario in which firms have the option to default but no longer have access to loan forbearance. In the absence of forbearance lending, we find that average firm sales growth, investment and productivity are higher than in the benchmark scenario with forbearance lending. A key driver of this result is that there is a larger proportion of high-quality firms in our counterfactual scenario;

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in the benchmark scenario forbearance lending prevents low-quality firms from defaulting more quickly, which is a drag on average sales growth, investment and productivity. These findings suggest that forbearance lending practices may have contributed to the recent economic stagnation across the Euro Area. However, we show that these results only hold when lenders face information asymmetry.

2.1. Introduction

Forbearance lending occurs when a lender supports an otherwise insolvent borrower. There are a many forms of forbearance lending such as relaxing the original loan terms or "evergreening", which involves extending further credit. Japanese banks engaged in extensive forbearance lending to firms during the 1990s (see, e.g., Sekine, Kobayashi and Saita 2003, Peek and Rosengren 2005, Cabellero, Hoshi, and Kashyap 2008). More recently, evidence of widespread forbearance lending to European firms has emerged (Bank of England, 2012). Acharya et al. (2015) estimate that as many as 12 per cent of European firms were in receipt of subsidized bank loans in 2014.

To what extent did these forbearance lending practices contribute to the Japanese "lost decade" and the economic stagnation currently affecting Europe? In this paper we address this question by developing a quantitative model to evaluate the impact of forbearance lending on firm dynamics and performance. Among others, we consider its influence on the average sales growth, investment, productivity, and entry and liquidation decisions of firms.

We focus our attention on the European economy after the onset of the sovereign debt crisis in 2010, a period marked by higher levels of forbearance lending. According to Acharya et al. (2015), the core reason for such extensive levels of

forbearance lending during this period relates to the weak capital position of European banks. Specifically, the Outright Monetary Transaction program launched by the European Central Bank in 2012 bolstered the value of European sovereign bonds, and therefore indirectly recapitalized European banks due to their large holdings of these bonds. But Acharya et al. (2015) argue that European banks nonetheless remained weak, giving rise to "zombie lending" incentives, i.e., weakly capitalized banks faced incentives to forbear on loans to troubled firms in order to avoid the realization of losses on their own balance sheets.

In line with the literature on forbearance lending in Japan, Acharya et al. (2015) argue that forbearance lending represents a misallocation of credit that has adversely impacted the economic recovery in Europe. In particular, forbearance lending is said to suppress creative destruction because it facilitates the continued operation of otherwise nonviable firms (Caballero, Hoshi and Kashyap 2008). As such, forbearance lending constrains lending to new firms because bank credit remains tied up in support of so-called "zombie firms". Moreover, overall productivity may be lower because the distribution of firms includes a subset of zombie firms with poor prospects. Following this reasoning, it is therefore entirely possible that forbearance lending to inefficient firms has hampered the economic recovery in Europe in recent years.

However, there are also potential benefits associated with forbearance lending. Fukuda and Nakamura (2011) document for the Japanese case that the eventual bankruptcy of firms who benefited from forbearance lending was rare and that most of these firms recovered in the 2000s. They argue that if these zombie firms were truly inefficient, the forbearance lending they received would not prevent their ultimate insolvency. Their results suggest rather that banks forbear on loans to firms with good long-term prospects, thereby helping these firms survive a period of weak demand. Hence, to the extent that banks can tell low-quality and high-quality firms apart, forbearance lending may be beneficial for economic

performance.

In short, depending on how the costs of forbearance, in terms of refinancing low-quality firms, weigh up against its benefits, in terms of refinancing high-quality firms experiencing a sequence of negative shocks, forbearance lending can influence overall economic performance either positively or negatively. A core aim of this study is to illuminate how the trade-off between these beneficial and adverse mechanisms operates, focusing on the Euro Area in the post-crisis period.[2]

To this end, we go beyond previous work in this field by developing a rich structural model to study the overall consequences of forbearance lending. Most of the existing literature, by contrast, focuses on the costs related to forbearance lending. Peek and Rosengren (2005), for instance, find that troubled Japanese firms were more likely to receive additional bank loans. And Cabellero et al. (2008) and Acharya et al. (2015) both find that congestion caused by the presence of zombie firms harmed the performance of non-zombies in Japan and Europe, respectively. Crucially, however, and unlike the structural model we outline in this study, the reduced form analyses in these earlier studies cannot directly assess the trade-offs associated with forbearance lending. Therefore, they cannot draw definitive conclusions about the overall impact of forbearance lending on economic performance.

Our vehicle of analysis is a stochastic dynamic firm equilibrium model, which features endogenous default and endogenous forbearance lending. A main contribution of this study is that we incorporate information asymmetry about the quality of firms into our firm equilibrium model. In our model, firms can obtain a loan from a lender to be used for production and they subsequently have the

[2]In addition to this main trade-off, there is also a second-level trade-off noted by Caballero et al. (2008), arising from the fact that it is unknown whether the costs of forbearance lending, in terms of productivity loss, can outweigh any additional costs that would result from firm insolvencies, like employment losses and a reduced supply capacity.

option to default in each period. The lender observes overall firm productivity but does not know whether this productivity draw belongs to a "low-quality" or "high-quality" firm. These two types of firms, low-quality and high-quality, both face stochastic shocks that differ by the mean of the productivity processes. This type of information asymmetry is similar to what lenders face in reality, whereby they observe some information about borrower quality but not a perfect signal. Our model enables us to consider the net impact of forbearance lending on firm dynamics and performance by examining how the costs of forbearance lending, due to credit misallocations from lenders incorrectly assessing a firm to be high-quality, and its benefits, due to refinancing high-quality firms experiencing a sequence of negative shocks, balance out. Apart from the firm-type information asymmetry, the model and firm default options are similar to those of Corbae and D'Erasmo (2015), Senkal (2014) and Tamayo (2015), who consider the impact of U.S. bankruptcy laws on firm dynamics.[3]

There are two different types of forbearance lending incorporated into our model. First, it takes place in the form of a renegotiation over an *ex post* reduction to the outstanding loan repayment; the extent of the reduction is determined endogenously in a Nash bargaining game. Second, there is "evergreening" because firms continue to have access to credit even in the period that they choose forbearance lending in the form of loan renegotiation. Lenders offer firm-specific loan schedules, based on a prediction of liquidation risk, forbearance risk, as well as "firm-type risk". Firm-type risk describes the risk lenders face due to the information asymmetry. Lenders assess firm-type risk based on the observed overall productivity and information about the productivity distributions of each firm-type. We evaluate firm dynamics and performance by considering the average sales growth, leverage, investment, productivity, as well as entry and exit

[3]The model of Tamayo (2015) also offers similar firm default choices, but features a different type of information asymmetry, with the lender being unable to observe any form of firm productivity but having the option to engage in various types of monitoring.

decisions of firms.

We calibrate our model using Euro Area firm-level statistics over the period 2011 to 2014, primarily obtained through the Amadeus Database. The calibrated model provides a good match to these key statistics, including the prevalence of forbearance lending practices and firm defaults. We next use the calibrated model to consider the quantitative impact of forbearance lending on firm dynamics and performance. To do this, we conduct a counterfactual exercise in which firms have the option to default but no longer have access to any form of loan forbearance.[4]

We find that average firm sales growth is around 14 per cent higher, or 0.27 percentage points higher, in our counterfactual scenario as compared with the benchmark scenario fitted to the Euro Area. We also find that average investment and productivity are higher. A key driver of these results is that there is a larger proportion of high-quality firms in our counterfactual scenario; the forbearance lending that is present in the benchmark scenario prevents low-quality firms from defaulting, which lowers the average sales growth, investment and productivity.

The reason that only low-quality firms access forbearance lending in our benchmark model relates to the information asymmetry. The fact that lenders cannot perfectly predict firm quality will mean that the interest rate schedule is more (less) favorable than otherwise for a low- (high-) quality firm. In turn, the relatively lower (higher) interest rate schedule makes forbearance lending *ex ante* a more (less) valuable choice for low- (high-) quality firms. The end result is that the vast majority of firms in receipt of forbearance lending are low-quality. Therefore, the costs of forbearance lending, due to allocating credit to low-quality firms, dominate any potential benefits in our model. These findings suggest that forbearance lending practices may have contributed to the recent economic stagnation across the Euro Area. That said, we show that these results only hold

[4]Tamayo (2015) conducts a similar counterfactual exercise to examine the impact of different US bankruptcy options.

when lenders face information asymmetry.

While we are the first to study the quantitative impact of forbearance lending in Europe, it is worthwhile to note that there are already a few other studies that have attempted to systematically model the influence of forbearance lending in Japan. First, Caballero et al. (2008) outline a simple and stylized model of entry and exit to consider the impact of zombies on firm creation and productivity. Our model extends this work by incorporating a much richer firm problem, as well as a lender's problem that includes defaultable loans. Therefore, our model can be matched to data to provide quantitative, rather than qualitative, insights. Kwan et al. (2015), in turn, estimate the impact of forbearance lending on aggregate output for Japan, based on a counterfactual scenario that applies the distribution of factor-input wedges estimated for non-zombies to all firms. We build on this research by incorporating a role for lending, loan financing, firm default and therefore actual forbearance lending. These are all factors which are likely to influence firms' equilibrium behavior and input choices. Finally, whereas these previous studies focus only on the potential costs of forbearance lending, our work explicitly models the aforementioned trade-off associated with forbearance lending. This makes it possible to gain more advanced insights.

This study furthermore relates to several papers that consider the impact of regulatory forbearance on output (see, e.g., Dekle and Kletzer 2004, Barseghyan 2010). This literature is distinct from our paper however, because it focuses on the forbearance policies adopted by bank supervisors towards banks when deciding whether to address concerns about a bank's lack of transparency, or accumulation of non-performing loans and delayed government bank bailouts. In this paper, we instead focus on forbearance practices that take place when a bank lends to a firm, which are also known to have occurred in Japan (see, for e.g., Caballero et al. 2008) and Europe (see, e.g., Acharya et al. 2015).

The remainder of this paper is structured as follows. Section 2.2 outlines the

model environment. Section 2.3 describes the recursive equilibrium of the model. Section 2.4 discusses the model calibration and analyzes the model equilibrium. Section 2.5 quantitatively evaluates the impact of forbearance lending on firm dynamics and performance. Section 2.6 concludes.

2.2. The Model Economy

This section sets out a discrete-time, quantitative model for our study of forbearance lending, which builds on several other firm equilibrium models. The model and default options are similar to those of Arellano, Bai and Zhang (2012), Corbae and D'Erasmo (2015), Senkal (2014) and Tamayo (2015), and our description of the model in Section 2.2 and Section 2.3 largely follows these previous studies. Nevertheless, there are several differences between this model and the aforementioned studies. Aside from the fact that we employ this model to study forbearance lending rather than U.S. bankruptcy laws or financial development, the most important point of departure is that we incorporate in our model a role for information asymmetry about firm-type.

2.2.1. Firms and technology

Entrepreneurs are infinitely lived. They have access to a pool of risky projects of mass one, which are referred to as firms. Each entrepreneur owns at most one firm. An entrepreneur that owns firm j chooses physical capital k_{jt+1} and a new one-period loan contract $(l_{jt+1}, l_{R,jt+1})$ to maximize the expected present value of all current and future dividends:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[d_{jt} \left(1 + \gamma I_{\{d_{jt}<0\}} \right) \right], \tag{2.1}$$

where $\beta \in (0,1)$ is the discount factor of all firms, γ is a proportional cost of equity issuance, and d_{jt} is the dividend function given by:

$$d_{jt} = y_{jt} - k_{jt+1} + (1-\delta) k_{jt} - l_{R,jt} + l_{jt+1} - \frac{\phi i_{jt}^2}{2k_{jt}} - \chi_c \tag{2.2}$$

where y_{jt} is output produced by the firm, $\delta \in (0,1)$ is the depreciation rate for

physical capital, $k_{jt+1} - (1-\delta) k_{jt}$ is investment i_{jt}, $l_{R,jt}$ is the loan repayment on the previous period's loan l_{jt}, $\phi i_{jt}^2 / (2k_{jt})$ are capital adjustment costs, and χ_c is a fixed cost of operation that firms must pay to produce. The price of output is normalized to one. Firms produce output according to a decreasing returns to scale production technology $y_{jt} = z_{jt} k_{jt}^{\alpha}$, where z_{jt} is an idiosyncratic productivity process. The probability distribution of firm j's productivity z_{jt} is conditional on the previous realization z_{jt-1} and follows a Markov process given by $f(z_{jt}, z_{jt-1})$.

We assume that firm productivity is a log-normal AR(1) process: $\ln(z_{jt}) = \mu_j (1-\varphi) + \varphi \ln(z_{jt-1}) + \epsilon$, with $|\varphi| < 1$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. There are two firm types j, which differ according to the permanent productivity parameter μ_j.[5] "Low-quality" firms have a permanent productivity μ_b and "high-quality" firms have a permanent productivity μ_g, such that $\mu_b < \mu_g$. This firm-type distinction is important for our consideration of forbearance lending. We distinguish between forbearance lending to a low-quality firm and forbearance lending a high-quality firm that is experiencing a negatives series of shocks.

One way to describe the dividend function in Equation (2.2) is that firm j uses both internal and external funds in order to obtain profits, as well as to finance investment and capital adjustment costs. The internal funds consist of the firm's output net of the debt repayment, $y_{jt} - l_{R,jt}$. The firm obtains external funds by obtaining a one-period loan from a lender each period, l_{jt+1}. When there are negative dividends, $d_{jt} < 0$, the entrepreneur can obtain resources from equity holders by paying a proportional cost γ.

An idle entrepreneur will start a new firm if he receives a project opportunity. Entrants start with zero capital and debt, and decide on the future optimal capital and a future loan before they know their future productivity. Their future

[5] This formulation of permanent productivity is similar to that of Arellano, Bai and Zhang (2012). They define a productivity process for firm j such that $z_{jt} = \mu_j \cdot \varepsilon_{jt}$, where the firm draws its permanent productivity μ_j from a Pareto distribution $\Pr(x) = cx^{-c-1}$ and ε_{jt} is a stochastic component from a mean-zero log-normal AR(1) process.

productivity is drawn from the stationary probability distribution $g(z_{t+1})$ derived from $f(z_{jt+1}, z_{jt})$, for which permanent productivity μ_j is drawn from a Bernoulli distribution with $\Pr(\mu_j = \mu_b) = \Pr(\mu_j = \mu_g) = 0.5$. The mass of all risky projects available to both entrants and operating firms is always equal to one. Thus, if an operating entrepreneur decides to liquidate its firm, a new risky project becomes available for a new entrepreneur to start a firm.

2.2.2. Lenders

Competitive lenders face an information asymmetry because they observe z_{jt} but not μ_j. This implies that lenders do not know with certainty whether a firm is low-quality or high-quality, and we refer to this as "firm-type risk". This type of information asymmetry is the main point of departure from similar models in the literature.

More formally, lenders are risk-neutral and can borrow or lend as much as needed from international capital markets at a constant interest rate $r > 0$. We denote $\Omega(k_{jt+1}, z_{jt})$ as the set of firm-specific loan schedules available to a firm with next period capital k_{jt+1} and productivity z_{jt}; each contract $(l_{jt+1}, l_{R,jt+1}) \in \Omega(k_{jt+1}, z_{jt})$ maps a current one-period loan l_{jt+1} to a next period repayment amount $l_{R,jt+1}$.

An entrepreneur has the option to default each period. Similar to Corbae and D'Erasmo (2015), there are two default options:[6]

1. **Liquidation**. Firm j liquidates its assets at a firesale discount $\chi_d < 1$ and so $\chi_d k_{jt}$ is the firesale firm recovery value. The entrepreneur receives $\max\{\chi_d k_{jt} - l_{R,jt}, 0\}$; the lender receives $\min\{\chi_d k_{jt}, l_{R,jt}\}$.

[6] In Corbae and D'Erasmo (2015), the two default options are modeled similarly but refer to Chapter 7 liquidation and Chapter 11 reorganization, rather than to liquidation and loan forbearance, respectively.

2. **Loan forbearance**. Loan forbearance takes the form of post-default renegotiation over the outstanding loan amount. Here the lender and the entrepreneur bargain over the loan repayment fraction $\psi\left(k_{jt}, l_{R,jt}, z_{jt}, \mu_j\right)$ in a Nash bargaining game. The repayment $\psi\left(k_{jt}, l_{R,jt}, z_{jt}, \mu_j\right)$ is restricted to the interval $[0,1]$. The entrepreneur repays the reduced loan amount $\psi l_{R,jt}$ in the default period, as well as a renegotiating cost proportional to its capital stock $\chi_f k_{jt}$. The entrepreneur continues to operate and to have access to new loan finance in the default period.

Lenders offer a firm-specific loan schedule $\Omega\left(k_{jt+1}, z_{jt}\right)$ such that they break even in expected value on each loan. The loan schedule incorporates firm-specific liquidation risk and forbearance risk. The loan schedule also incorporates the firm-type risk, which accounts for the information asymmetry but still ensures that the zero expected profit condition will hold. The lenders' problem is outlined formally in Section 2.3.5.

2.2.3. Timing

At the beginning of time t, the model timing is as follows:

1. Productivity z_{jt} is realized, and the state space for incumbent firm j is $\{k_{jt}, l_{R,jt}, z_{jt}, \mu_j\}$
2. Entrepreneurs choose from the following options for their incumbent firm j:

    a) to continue operating and repay the full loan amount $l_{R,jt}$. The en-

trepreneur chooses physical capital k_{jt+1} and a new loan contract $(l_{jt+1}, l_{R,jt+1})$.

b) to default on the full loan amount owing, $l_{R,jt}$, and liquidate the firm. Here the entrepreneur receives the liquidation value $\max\{\chi_d k_{jt} - l_{R,jt}, 0\}$.

c) to obtain loan forbearance by renegotiating over the outstanding loan amount, $l_{R,jt}$. The entrepreneur bargains with the lender over the loan repayment fraction$\psi(k_{jt}, l_{R,jt}, z_{jt}, \mu_j)$. When the entrepreneur and the lender agree on the repayment fraction, the firm repays $\psi(k_{jt}, l_{R,jt}, z_{jt}, \mu_j) l_{R,jt}$. It chooses physical capital k_{jt+1}, and continues to have access to new loan finance in the default period.

3. Idle entrepreneurs make an entry decision about whether to start a firm or not. Their initial productivity is drawn from the stationary distribution $g(z_{t+1})$.

2.3. Recursive Equilibrium

In this section, we define a stationary recursive equilibrium for the model. For all variables, we drop the time and firm subscripts for ease of exposition and employ the notation: $x_{jt-1} = x^{-}$, $x_{jt} = x$ and $x_{jt+1} = x'$. We denote the optimal policy rules for the entrepreneur for capital and loans as $k'(s)$ and $l'_R(s)$, respectively, for the states $s = (k, l_R, z, \mu)$. Given the states $s = (k, l_R, z, \mu)$, the equilibrium is determined by the policy rules for the entrepreneur, $k'(s)$ and $l'_R(s)$, and the loan schedule for loan contracts, $\Omega(k', z)$. And given any loan schedule for loan contracts, $\Omega(k', z)$, and debt recovery schedule, $\psi(s)$, the entrepreneur solves its firm optimization problem. Note that the entrepreneur solves its firm optimization problem with perfect information about all states $s = (k, l_R, z, \mu)$, but the lender prices loans based on a subset of all states that excludes knowledge of μ.

2.3.1. The Firm's Problem

The firm chooses whether to default or repay its loan in order to maximize the present value of current and future profits, given the productivity shock z, the permanent productivity μ, the initial capital k and the loan repayment amount l_R. Recall there are two firm types, low-quality and high-quality, which differ by their permanent productivity μ. Their permanent productivity μ also represents the mean of their log-normal shock process z.

If the entrepreneur chooses to default, it can either liquidate the firm or receive forbearance lending by renegotiating the repayment fraction of the original loan. Alternatively, the entrepreneur can choose to repay the loan and continue operating. If the entrepreneur chooses to continue operating, the firm must also determine its new level of capital k' and a new loan contract (l', l'_R). The loan

schedule offered for new borrowing $\Omega(k', z)$ depends on the firm's choice of k' and on the state z but not on permanent productivity μ, which is understood by the firm. The value function for a firm that has the option to default and that starts the current period with capital k, a loan repayment l_R and productivity z is:

$$V(k, l_R, z, \mu) = \max_{\{c,d,f\}} \{V_c(k, l_R, z, \mu), V_d(k, l_R), V_f(k, l_R, z, \mu)\}, \tag{2.3}$$

where $V_c(k, l_R, z, \mu)$ is the value function if the entrepreneur does not default and continues to operate; $V_d(k, l_R, z, \mu)$ is the value function if the entrepreneur defaults and liquidates the firm; and $V_f(k, l_R, z, \mu)$ is the value function for forbearance lending when the entrepreneur defaults and renegotiates with the lender about the repayment fraction of the original loan.

The decision to default or repay the loan is a period-by-period decision. The value function conditional on the firm not defaulting and continuing to operate is:

$$\begin{aligned} V_c(k, l_R, z, \mu) = & \max_{k', (l', l'_R) \in \Omega} d_c \left(1 + \gamma I_{\{d_c < 0\}}\right) \\ & + \beta \int_{z'} V(k', l'_R, z', \mu) f(z', z) dz', \end{aligned} \tag{2.4}$$

where $d_c = zk^{\alpha} - k' + (1-\delta)k - l_R + l' - \frac{\phi i^2}{2k} - \chi_c$ are the dividends for a continuing firm, and γ is the proportional equity issuance cost. Here the entrepreneur chooses the optimal k' and (l', l'_R) to maximize the present value of current and future dividends for the firm.

When the entrepreneur defaults on the loan and liquidates the firm, the value function is:

$$V_d(k, l_R) = \max\{\chi_d k - l_R, 0\}, \tag{2.5}$$

If the entrepreneur decides to default and obtain loan forbearance, the firm must

repay a reduced fraction $\psi(k, l_R, z, \mu)$ of the unpaid loan repayment amount l_R. The recovery rate $\psi(k, l_R, z, \mu)$ is determined endogenously in a Nash bargaining game explained in the next section. In the period of default, the reduced loan is repaid and the firm continues to have access to new loan finance. This continued access to credit is akin to "evergreening". The value function associated with a firm that defaults but repays the agreed reduced fraction of the outstanding loan is:

$$\begin{aligned} V_f(k, l_R, z, \mu) = & \max_{k', (l', l'_R) \in \Omega} d_f \left(1 + \gamma I_{\{d_f < 0\}}\right) \\ & + \beta \int_{z'} V(k', l'_R, z', \mu) f(z', z) \, dz', \end{aligned} \tag{2.6}$$

where $d_f = zk^\alpha - k' + (1-\delta)k - \psi(k, l_R, z, \mu) l_R + l' - \frac{\phi I^2}{2K} - \chi_c - \chi_f k$ are the dividends for a firm with forbearance lending, γ is the proportional equity issuance cost, and ψ is the fraction of the unpaid loan repayment amount l_R.

2.3.2. Default Policies

An entrepreneur's default policy can be characterized by a continuing set, a liquidation set and a forbearance lending set. The continuing set, $C(k, l_R, \mu)$, is the set of z's for which continued operation is optimal when capital is k and the loan contract is (l, l_R), such that:

$$C(k, l_R, \mu) = \left\{ z \in Z \; : \; V_c(k, l_R, z, \mu) \geq \max_{\{d,f\}} \{V_d(k, l_R), V_f(k, l_R, z, \mu)\} \right\}. \tag{2.7}$$

The liquidation set $D(k, l_R, \mu)$, is the set of z's for which loan default and liquidation is optimal when capital is k and the loan contract is (l, l_R), such that:

$$D(k, l_R, \mu) = \left\{ z \in Z \; : \; V_d(k, l_R) > \max_{\{c,f\}} \{V_c(k, l_R, z, \mu), V_f(k, l_R, z, \mu)\} \right\}, \tag{2.8}$$

And finally, the forbearance lending set, $F(k, l_R, \mu)$, is the set of productivity shocks z's for which loan default and renegotiation is optimal when capital is k and the loan contract is (l, l_R), such that:

$$F(k, l_R, \mu) = \left\{ z \in Z \ : \ V_f(k, l_R, z, \mu) > \max_{\{c,d\}} \{V_c(k, l_R, z, \mu), V_d(k, l_R)\} \right\}. \quad (2.9)$$

These three sets that comprise an entrepreneur's default policy are mutually exclusive. That is, for example, $C(k, l_R, \mu) = \tilde{D}(k, l_R, \mu) \bigcup \tilde{F}(k, l_R, \mu)$.

2.3.3. Entrants

When an idle entrepreneur receives a project opportunity, he will attempt to start a new firm. Entrants choose their optimal capital and loan before they know their future productivity. Entrants' future productivity is drawn from the stationary distribution $g(z')$ derived from $f(z', z)$, for which permanent productivity μ is drawn from a Bernoulli distribution with $\Pr(\mu = \mu_b) = \Pr(\mu = \mu_g) = 0.5$. The value function associated with a potential entrant is given by:

$$V_e = \max_{k', \left(l', l'_R\right) \in \Omega} d_e \left(1 + \gamma I_{\{d_c < 0\}}\right) + \int_{z'} V(k', l'_R, z', \mu) \, g(z') \, dz', \quad (2.10)$$

where $d_e = -k' + l'$, and we assume that the equity issuance costs are the same for the initial period as for continuing firms.

2.3.4. The Forbearance Problem

Our discussion of the forbearance lending problem, and parts of the lender's problem in Section 2.3.5, draws on that of Yue (2010), who studies sovereign default and debt renegotiation. Forbearance lending takes the form of a generalized Nash bargaining game regarding the fraction $\psi(k, l_R, z, \mu)$ of the outstanding loan re-

payment l_R. Here the value of the defaulted loan repayment amount l_R is reduced to $\psi(k, l_R, z, \mu) l_R$. The value of such an agreement to the firm is described by Equation (2.6), which is the present value of all future expected profits of forbearance when the loan recovery rate is $\psi(k, l_R, z, \mu)$. The lender gets the value of the reduced loan repayment $\psi(k, l_R, z, \mu) l_R$.

The threat point of the Nash bargaining game is that the firm is liquidated such that the entrepreneur receives the liquidation value $V_d(k, l_R, z, \mu)$ and the lender receives the firesale recovery value $\min\{\chi_d k, l_{R,}\}$.

We let $\triangle^f(p; k, l_R, z, \mu)$ denote the firm's surplus in the Nash bargaining agreement, which is the difference between the value of accepting the loan recovery rate p and the value of rejecting it, given the firm's capital k, the loan repayment amount l_R, the firm's productivity z, and the firm permanent productivity μ. The firm's surplus is:

$$\triangle^f(p; k, l_R, z, \mu) = V_f(p; k, l_R, z, \mu) - V_d(k, l_R) \tag{2.11}$$

We let $\triangle^b(p; k, l_R)$ denote the risk-neutral lender's surplus in the Nash bargaining agreement, which is the present vale of the recovered loan repayment. The lender's surplus is:

$$\triangle^b(p; k, l_R) = p l_R - \min\{\chi_d k, l_R\} \tag{2.12}$$

The lender can extract loan repayments up to the full amount of a firm's cost of default when it has all of the bargaining power. Alternatively, the firm can obtain a complete reduction of its loan when it has all of the bargaining power. We consider the general case and assume that the borrower has bargaining power θ and the lender has bargaining power $(1-\theta)$. For any capital stock k, loan repayment amount l_R, and productivity shock z, we define the bargaining power

set as $\Theta \subset [0,1]$ for $\theta \in \Theta$ in order to ensure that the renegotiation surplus has a unique optimum.

Given the capital stock k, loan repayment amount l_R, and productivity shock z, the loan recovery rate $\psi(k, l_R, z, \mu)$ solves the following bargaining problem:

$$\begin{aligned} \psi(k, l_R, z, \mu) = \quad & \arg\max_{p \in [0,1]} \left[\triangle^f(p; k, l_R, z, \mu)\right]^{\theta} \left[\triangle^b(p; k, l_R)\right]^{1-\theta} \\ \text{s.t.} \quad & \triangle^f(p; k, l_R, z, \mu) \geq 0, \\ & \triangle^b(p; k, l_R) \geq 0. \end{aligned} \tag{2.13}$$

2.3.5. The Lender's Problem

The representative lender offers a loan schedule $\Omega(k', z)$ to maximize expected profits π_b, which are given by:

$$\begin{aligned} \pi_b(k', l'_R, z) = -l' + \quad & \textstyle\sum_{j=b,g} \Pr(\mu = \mu_j | z) \\ & \times \left\{ \tfrac{1}{1+r} \left[1 - \rho_f(k', l'_R, z, \mu_j) - \rho_d(k', l'_R, z, \mu_j)\right] l'_R \right. \\ & - \tfrac{1}{1+r} \left(\rho_f(k', l'_R, z, \mu_j) \cdot \gamma(k', l'_R, z, \mu_j)\right) l'_R \\ & \left. - \tfrac{1}{1+r} \rho_d(k', l'_R, z, \mu_j) \min\left\{\chi_d k', l'_R\right\} \right\} - \xi \end{aligned} \tag{2.14}$$

where $\Pr(\mu = \mu_j | z)$ is the probability that a firm has permanent productivity μ_j given it has observed productivity z, $\rho_d(k', l'_R, z, \mu)$ is the expected probability of liquidation for a firm with capital stock k', a loan repayment amount l'_R, in state z, and with permanent productivity μ, $\rho_f(k', l'_R, z, \mu)$ is the expected probability of forbearance, and $\gamma(k', l'_R, z, \mu)$ is the expected recovery rate, given by the expected proportion of the loans that the creditors can recover, conditional on forbearance. The lender must pay a fixed cost for each loan, ξ, as in Arellano et al. (2012). The first term on the right-hand side of Equation (2.14) represents the resources that the lender spends today. The remaining three terms on the right-

hand side comprise the expected loan repayment amount l'_R, discounted by the risk-free rate and accounting for liquidation risk, forbearance risk, and firm-type risk.

The equilibrium loan schedule $\Omega(k', z)$ comprises all loan contracts (l', l'_R) that allow the lender to break even in expected values, accounting for both the liquidation risk, the forbearance risk and the firm-type risk that the lender faces, and is described by:

$$\begin{aligned} l' = \textstyle\sum_{j=b,g} \Pr(\mu = \mu_j | z) \quad & \Big\{ \tfrac{1}{1+r} \left[1 - \rho_f(k', l'_R, z, \mu_j) - \rho_d(k', l'_R, z, \mu_j) \right] l'_R \\ & - \tfrac{1}{1+r} \left(\rho_f(k', l'_R, z, \mu_j) \cdot \gamma(k', l'_R, z, \mu_j) \right) l'_R \\ & - \tfrac{1}{1+r} \rho_d(k', l'_R, z, \mu_j) \min\{\chi_d k', l'_R\} \Big\} - \xi \end{aligned} \tag{2.15}$$

where the probability of liquidation, $\rho_d(k', l'_R, z, \mu)$, the probability of forbearance, $\rho_f(k', l'_R, z, \mu)$, the expected recovery rate, $\gamma(k', l'_R, z, \mu)$, and the probability that a firm has permanent productivity μ_j given z, $\Pr(\mu = \mu_j | z)$, are endogenous to the model. The effective interest rate for a loan contract (l', l'_R) is $r_L = l'_R/l' - 1$. The zero profit assumption and the fact that $0 \leq \rho_d \leq 1$, $0 \leq \rho_f \leq 1$ and $0 \leq \gamma \leq 1$ imply that the gross firm effective interest rate lies in the interval $[(1+r), \infty)$.

In equilibrium, the loan schedule $\Omega(k', z)$ must be consistent with the firm's optimization and with expected zero profits of the lender, such that the loan schedule correctly assesses the probability of liquidation, the probability of forbearance of firms, and the probability of firm-type (i.e. the probability of being a low- or a high-quality firm).

As noted by Yue (2010), the first term in Equation (2.15) shows that both liquidation risk ρ_d and forbearance risk ρ_f have a first-order effect on the loan schedule because they enter Equation (2.15) linearly. And the second term shows that the loan recovery rate γ affects the debt schedule through its combined effect with forbearance risk. Additionally, the loan recovery rate has an indirect impact on the *ex ante* liquidation risk, because it affects the second moment of the loan

schedule.

The firm-type risk also has an effect on the loan schedule. Because lenders cannot perfectly identify a firm's permanent productivity, high-quality firms will face a higher cost of borrowing but lower quality firms will face a lower cost of borrowing, both in comparison to a situation of perfect information. And these differences in the cost of borrowing will in turn influence the decision rules of firms.

2.3.5.1. Liquidation Risk

The liquidation probabilities $\rho_d\left(k', l'_R, z, \mu\right)$ are related to the liquidation sets $D\left(k', l'_R, \mu\right)$ as follows:

$$\rho_d\left(k', l'_R, z, \mu\right) = \int_{D\left(k', l'_R, \mu\right)} f\left(z', z\right) dz'. \tag{2.16}$$

This implies that when the liquidation sets are empty, $D\left(k', l'_R, \mu\right) = \emptyset$, the equilibrium liquidation probabilities $\rho_d\left(k', l'_R, z, \mu\right)$ equal zero. This is because with capital k' and loan repayment amount l'_R, a firm will not liquidate for any realization of the productivity shocks. The liquidation probabilities $\rho_d\left(k', l'_R, z, \mu\right)$ equal one when $D\left(k', l'_R, \mu\right) = Z$.

2.3.5.2. Forbearance Risk

Similarly, the forbearance lending probabilities $\rho_f\left(k', l'_R, z, \mu\right)$ are related to the forbearance lending sets $F\left(k', l'_R, \mu\right)$ as follows:

$$\rho_f\left(k', l'_R, z, \mu\right) = \int_{F\left(k', l'_R, \mu\right)} f\left(z', z\right) dz'. \tag{2.17}$$

This similarly implies that when forbearance sets are empty, $F\left(k', l'_R, \mu\right) = \emptyset$, the equilibrium forbearance probabilities $\rho_f\left(k', l'_R, z, \mu\right)$ equal zero. This is because

with capital k' and loan repayment amount l'_R, a firm not choose to renegotiate their loan for any realization of the productivity shocks. The forbearance probabilities $\rho_f\left(k', l'_R, z, \mu\right)$ equal one when $F\left(k', l'_R, \mu\right) = Z$.

The expected recovery rate $\gamma\left(k', l'_R, z, \mu\right)$ is determined by:

$$\gamma\left(k', l'_R, z, \mu\right) = \frac{\int_{F\left(k', l'_R, \mu\right)} \psi\left(s'\right) f\left(z', z\right) dz'}{\rho_f\left(k', l'_R, z, \mu\right)} \tag{2.18}$$

The numerator of Equation (2.18) is the proportion of the loan that the lender can expect to recover. The denominator of Equation (2.18) is the forbearance probability.

2.3.5.3. Firm-type Risk

We now consider the firm-type risk, which is a quantification of the information asymmetry faced by the lender. This is necessary for the zero profits condition. The probability that a firm has permanent productivity μ_j given z, $\Pr\left(\mu = \mu_b | z\right)$, can be determined using Bayes' Rule as follows:

$$\Pr\left(\mu = \mu_b | z\right) = \frac{\Pr(z|\mu=\mu_b)\Pr(\mu=\mu_b)}{\Pr(z|\mu=\mu_b)\Pr(\mu=\mu_b)+\Pr(z|\mu=\mu_g)\Pr(\mu=\mu_g)} \tag{2.19}$$

$\Pr\left(\mu = \mu_b\right)$ in Equation (2.19) is given by the cross-sectional stationary distributions of firms $\Gamma\left(s\right)$ such that $\Pr\left(\mu = \mu_b\right) = \int \Gamma\left(k, l_R, z, \mu_b\right) d\left(k \times l_R \times z\right)$.

$\Pr\left(z | \mu = \mu_b\right)$ in Equation (2.19) is also given by information from the cross-sectional stationary distributions of firms $\Gamma\left(s\right)$ and our assumption that the firm productivity process is log-normally distributed. The initial firm productivity process is distributed such that $\ln\left(z\right) \sim \mathcal{N}\left(\mu, \sigma_\varphi^2\right)$ for $\sigma_\varphi^2 = \frac{\sigma_\epsilon^2}{1-\varphi^2}$. The *conditional* cross-sectional distribution of the firm productivity process for $\ln\left(z\right)$ given $\mu = \mu_b$ depends on the cross-sectional distributions of firms $\Gamma\left(s\right)$. We can compute the mean of the conditional cross-sectional distribution of the firm

productivity process for $\ln(z)$ given $\mu = \mu_b$ as:

$$E(\ln(z)|\mu = \mu_b) = \sum_i \ln(z_i) p_i \tag{2.20}$$

where the probability of a given z_i is $p_i = \frac{\int \Gamma(k, l_R, z_i, \mu_b) d(k \times l_R)}{\Pr(\mu = \mu_b)}$.[7] The variance of the process is:

$$Var(\ln(z)|\mu = \mu_b) = \sum_i (\ln(z_i) - E(\ln(z)|\mu = \mu_b))^2 p_i. \tag{2.21}$$

Combined with our initial assumptions about the firm productivity process being log-normal, these results imply that the *conditional* cross-sectional distribution of the firm productivity process is $\ln(z)|\mu = \mu_b \sim \mathcal{N}(E(\ln(z)|\mu = \mu_b), Var(\ln(z)|\mu = \mu_b))$. And so we can compute $\Pr(z|\mu = \mu_b)$ as:

$$\Pr(z|\mu = \mu_b) = 2 \times \Phi\left(-\left|\frac{\ln(z) - E(\ln(z)|\mu = \mu_b)}{\sqrt{Var(\ln(z)|\mu = \mu_b)}}\right|\right) \tag{2.22}$$

where Φ is the standard normal cumulative distribution function. Expressions for $\Pr(\mu = \mu_g)$, $\Pr(z|\mu = \mu_g)$ and $\Pr(\mu = \mu_g|z)$ are obtained similarly. In equilibrium, the probabilities $\Pr(\mu = \mu_b|z)$ are consistent with the firm's decision rules, because they are based on the cross-sectional stationary distributions of firms $\Gamma(s)$, which is determined by the firm's decision rules. This means that the lender can price the firm-type risk such that the loan schedules are consistent with expected zero profits.

[7] In theory, $\ln(z)$ is a continuous random variable. Here we compute the empirical conditional mean and variance based on the discretized shock process, and so are using standard methods normally applied to compute the mean and variance of a discrete random variable.

2.3.6. The Cross-Sectional Distribution of Firms

The law of motion for the cross-sectional distribution of firms $\Gamma(s)$ is:

$$\begin{aligned}\Gamma(s') = & \int \rho_d(s) Q_e(s') g(z') \Gamma(s) d(k \times l_R \times z \times \mu) \\ & + \int_{C(k', l'_R, \mu)} (1 - \rho_d(s)) Q_c(s, s') f(z', z) \Gamma(s) d(k \times l_R \times z \times \mu) \\ & + \int_{F(k', l'_R, \mu)} (1 - \rho_d(s)) Q_f(s, s') f(z', z) \Gamma(s) d(k \times l_R \times z \times \mu)\end{aligned} \tag{2.23}$$

where $C(k', l'_R, \mu)$ is the continuing set, $F(k', l'_R, \mu)$ is the forbearance lending set, $\rho_d(k', l'_R, z, \mu)$ is the liquidation probability, and $Q_c(.)$ denotes a transition function for continuing firms, mapping the current states into future states, given by:

$$Q_c(s, s') = \begin{cases} 1 & \text{if } l'_R(s) = l'_R, k'(s) = k' \\ 0 & \text{otherwise} \end{cases} \tag{2.24}$$

and $l'_R(s)$ and $k'(s)$ are the optimal policy rules for firms. Similarly, $Q_f(s')$ is 1 if the optimal choice for forbearance lending firms is (k', l'_R) and 0 otherwise. And $Q_e(s')$ is 1 if entrants' optimal choice is (k', l'_R) and 0 otherwise.

If an existing firm liquidates, a new project z drawn from the stationary distribution $g(z)$ becomes available to an entrant entrepreneur such that the mass of risky projects is equal to one.

2.3.7. Stationary Recursive Equilibrium

Here we define a stationary recursive equilibrium for the economy. Let $s = \{k, l_R, z, \mu\}$ be the aggregate states for the economy.

Definition 1. The stationary recursive equilibrium for this economy is a set of policy rules for (i) the firm's value function $V^*(s)$, capital holdings $k'^*(s)$, loan contracts $(l'^*(s), l'^*_R(s))$, and the default policy, where the default policy is comprised by the operating sets $C^*(k, l_R, \mu)$, liquidation sets $D^*(k, l_R, \mu)$, and

forbearance lending sets $F^*(k, l_R, \mu)$; (ii) the recovery rate $\psi^*(s)$; (iii) the loan schedules $\Omega^*(k', z)$ for the loan contracts; and (iv) the cross-sectional distribution of firms $\Gamma^*(s)$ such that:

1. Given the loan schedule $\Omega^*(k', z)$ and the loan recovery rate $\psi^*(s)$: the value function $V^*(s)$, the policy rules $k'^*(s)$ and $(l'^*(s), l_R'^*(s))$, operating sets $C^*(k, l_R, \mu)$, liquidation sets $D^*(k, l_R, \mu)$, and forbearance lending sets $F^*(k, l_R, \mu)$ are consistent with the firm's optimization problem in Equation(2.3).

2. Given the loan schedule $\Omega^*(k', z)$ and value function $V^*(s)$: the loan recovery rate $\psi^*(s)$ solves the forbearance problem in Equation (2.13).

3. Given the loan recovery rate $\psi^*(s)$ and the cross-sectional distribution of firms $\Gamma^*(s)$: the equilibrium loan schedules $\Omega^*(k', z)$ satisfy the lender's expected zero profit condition, and also the liquidation probability $\rho_d^*(k', l_R', z, \mu)$, the forbearance probability $\rho_F^*(k', l_R', z, \mu)$ and the expected recovery rate $\gamma^*(k', l_R', z, \mu)$ are consistent with the firm's default policy and renegotiation agreement.

4. The cross-sectional distribution of firms $\Gamma^*(s)$ is a stationary measure of firms consistent with the firm decision rules and the law of motion for the stochastic variables.

2.4. Quantitative Analysis

2.4.1. Calibration

To consider the quantitative implications of the model, we set a model period to be one year and calibrate the model to match Euro Area data over the period 2011 to 2014. During this period, there was a high prevalence of forbearance lending (Acharya et al., 2015) and economic stagnation. Table 2.1 provides a summary of definitions that we use to compute key variables from our model.

As previously noted, we assume that firm productivity is a log-normal AR(1) process: $\ln(z_{jt}) = \mu_j(1-\varphi) + \varphi \ln(z_{t-1}) + \epsilon$, with $|\varphi| < 1$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. There are two firm types j, which differ according to the permanent productivity parameter μ_j. Low-quality firms have a permanent productivity μ_b and high-quality firms have a permanent productivity μ_g, such that $\mu_b < \mu_g$. Entrant firms draw their initial permanent productivity μ_j is drawn from a Bernoulli distribution with $\Pr(\mu_j = \mu_b) = \Pr(\mu_j = \mu_g) = 0.5$. We use the procedure of Tauchen (1986) to discretize the stochastic shock into a 10-state Markov chain.

The model comprises 15 parameters to be calibrated, which are summarized in Table 2.2. We first select the 11 "Calibrated Parameters" in Table 2.2 independently of the model equilibrium. To start with, the firm discount rate β is

Table 2.1.: Model Definitions for Key Variables

Variable	*Model Definition*
Assets	k
Loan repayment	l_R
Leverage	l_R/k
Loan interest rate	$l'_R/l' - 1$
Investment rate	$(k' - (1-\delta)k)/k^-$
Sales	zk^α
Sales growth	$\left(zk^\alpha - z^-(k^-)^\alpha\right)/z^-(k^-)^\alpha$
Working capital	$(k - l_R)/k^-$

Table 2.2.: Benchmark Parameters

Calibrated Parameters		*Value*
Firm discount rate	β	0.96
Risk-free interest rate	r	0.01
Capital depreciation rate	δ	0.16
Returns to scale	α	0.65
Equity issuance cost	γ	0.30
Capital loss in liquidation	χ_d	0.40
Firm bargaining power	θ	0.40
Autocorrelation of stochastic shock	φ	0.9
Standard deviation of stochastic shock	σ_ϵ	0.118
Low-quality firm permanent productivity	μ_b	0
High-quality firm permanent productivity	μ_g	0.448
Parameters Estimated with SMM		*Value*
Capital adjustment cost	ϕ	0.15
Lender credit cost	ξ	7.25
Fixed operating cost	χ_c	10.75
Renegotiation cost	χ_f	0.175

set to 0.96, which is standard for an annual RBC model according to Arellano et al. (2012). The risk-free interest rate r is set to 0.01, which is equal to the average interest rate of one-year Euro Area government bonds for the period 2011 to 2014.

We next use a sample of Euro Area firms over the period 2011 to 2014 to estimate several other parameters. Our data source here is the Amadeus database, and a full description of these data is contained in Appendix 2.B. The capital depreciation rate δ is set to 16 per cent per year, which equals the average depreciation rate for our sample. The returns to scale parameter α is set to 0.65, which implies decreasing returns to scale in production, similar as in the Arellano et al. (2015) study based on European firms. The equity issuance cost γ is set to 0.30, following Cooley and Quadrini (2001). The capital loss in liquidation χ_d and the firm bargaining power are both set to 0.40, which coincides with the estimates of Ramsey and Shapiro (2001) for the capital loss in liquidation. The autocorrelation φ and standard deviation σ of the stochastic shock are set to 0.90 and 0.118, respectively, which follow Corbae and D'Erasmo (2015).

Table 2.3.: Statistical Moments in the Euro Area data and in the Benchmark Model

Targeted Moments	*Data*	*Benchmark*
Firm liquidation rate	3.44%	4.45%
Firm forbearance rate	7.5%	6.79%
Average of sales growth	5.86%	2.00%
Standard deviation of sales growth	16.62%	19.54%
Average of leverage	66.46%	68.69%
Non-targeted Moments	*Data*	*Benchmark*
Standard deviation of leverage	21.70%	268.59%
Average of working capital	23.73%	29.99%
Std. dev. of working capital	21.68%	257.72%

Notes: The column under Data reports the statistical moments for the Euro Area, from 2011 to 2014. The column under Benchmark reports the model statistics under the benchmark calibration, in which firms have access to forbearance lending. All moments are calculated over a one-year period.

Finally, we use our sample of Euro Area firms to set the value of the low and high permanent productivity shocks, μ_b and μ_g. To do this, we first divide our sample into low-quality firms and high-quality firms based on the definition of Acharya et al. (2015). This involves computing for each firm the average interest coverage ratio over the period 2009 to 2011, defined as the ratio of interest expenses to EBITDA. A firm is then categorized as low-quality if its three-year average interest coverage ratio is below the country median and otherwise the firm is considered high-quality. Using these categories, we find the average yearly return on assets for high-quality firms over the period 2011 to 2014 to be around 57 per cent higher than for low-quality firms. Thus, we set μ_b to zero and μ_g to 0.448, such that the average productivity for high-quality firms is around 57 per cent higher than for low-quality firms.

Subsequently, we estimate the remaining four parameters in Table 2.2 by using the simulated method of moments (SMM) to target a set of five moment conditions from the data. More precisely,

$$\hat{\Theta} = \arg\min_{\Theta} \left[m^d - m^s(\Theta)\right]' W \left[m^d - m^s(\Theta)\right] \tag{2.25}$$

where W is a weighting matrix, $\Theta = (\phi, \xi, \chi_c, \chi_r)$ are the four parameters to be estimated, m^d are the five targeted moments from the data summarized in the "Data" column of Table 2.3 and discussed below, and $m^s(\Theta)$ are the five simulated moments from the model at parameters Θ.

Our first target moment is the firm liquidation rate. An estimate for the yearly average of this moment over the period 2011 to 2014 is 3.44 per cent, according to the default rate by value of European corporates (including non-rated coporates) of Standard & Poor's Rating Services (2014, 2016).

Our second target moment is the firm forbearance rate. The yearly average value of this moment over the period 2011 to 2014 is approximately 7.5 per cent, according to estimates of Archarya et al. (2015). These estimates are based on the asset-weighted proportion of European firms that are classified as "zombie firms".[8] Their sample of firms comprises all privately and publicly traded firms from all EU counties.

Our remaining three target moments are similar to several moments of Arellano et al. (2012) for their firm equilibrium model: the average and standard deviation of sales growth, and the average of leverage. We obtain these moments from our sample of Euro Area firms over the period 2011 to 2014. A description of how we compute each data moment is also contained in Appendix 2.B.

All of the estimated parameters affect all of the target moments in the model, although some parameters affect some moments more directly. In particular, χ_c is useful to match the firm liquidation rate; χ_f is useful to match the firm forbearance lending rate; ϕ and χ_c is useful to match the average and standard deviation of sales growth; and ξ is useful to match the average of leverage.

We assess the quantitative performance of the model in Table 2.3 by comparing the moments from the Euro Area data in the "Data" column with those produced

[8]There are three criteria to classify a firm as a "zombie firm", one being that they estimate the firm is in receipt of subsidized bank credit.

by the model in the "Benchmark" column. Overall, the simulated method of moments estimates a set of four parameter values that produce model moments that are close to the five targeted moments, although it under-predicts the average of sales growth. We also consider how the simulated model can match several non-targeted moments in Table 2.3. The model provides a good match to the working capital as observed in the data. Conversely, the model greatly overestimates the standard deviation of leverage and working capital as observed in the data. This is a general feature of models that include loan renegotiation, because there is a large difference between the leverage of firms that engage in loan renegotiation versus those that do not. By contrast, models with liquidation only are able to match the standard deviation of leverage rather well (see, e.g., Arellano et al., 2012).

2.4.2. Equilibrium Loan Schedules and Firm Decisions

Here we consider the equilibrium default policies, loan schedules and policy functions for the calibrated model. We first consider firm liquidation risk. Figure 2.1 plots the liquidation probabilities as a function of the capital choice k'. Panel (A) of Figure 2.1 plots the liquidation probabilities for a high-quality firm (i.e. with permanent productivity μ_g) and a low-quality firm (i.e. with permanent productivity μ_b) when there is a normal stochastic shock ε_m and the loan repayment choice l'_R equals the average equilibrium choice for all firms (i.e. across both the low-quality and high-quality firms). The horizontal axis is scaled by the average equilibrium capital $\bar{k}$ for all firms.

For both types of firms, the liquidation probability is lower for a firm with more capital k, because more capital makes liquidation less valuable. Similarly, the liquidation probability is lower for the high-quality firm than for the low-quality firm because liquidation is less valuable for the former. For high capital and all

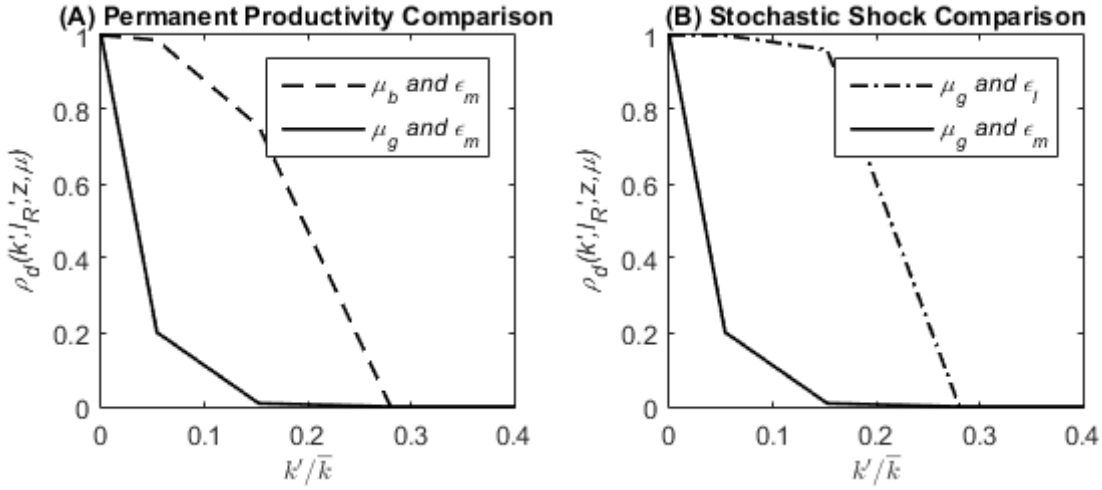


Figure 2.1.: Liquidation Probabilities

Note: Panel (A) plots the liquidation probabilities as a function of the capital choice k' for two firms, one "high-quality" firm (i.e. with permanent productivity μ_g) and one "low-quality" firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the loan repayment choice l'_R equals the average equilibrium choice for all firms. Panel (B) plots the liquidation probabilities as a function of the capital choice k' for two firms with a low stochastic shock ε_l and a normal stochastic shock ε_m when both firms are high-quality (i.e. with permanent productivityμ_g) and the loan repayment choice l'_R equals the average equilibrium choice for all firms. The horizontal axes for capital choice are scaled by the average equilibrium capital $\bar{k}$.

but the worst stochastic shocks, the liquidation probability is close to zero for high-quality firms.

Panel (B) of Figure 2.1 plots the liquidation probabilities for two firms with a low stochastic shock ε_l and a normal stochastic shock ε_m when both firms are high-quality (i.e. with permanent productivityμ_g) and the loan repayment choice l'_R equals the average equilibrium choice for all firms. The liquidation probability is lower for the normal (or around the medium) stochastic shock ε_m than the low stochastic shock ε_l because liquidation is less valuable for that firm. In general, liquidation is more valuable, and so liquidation risk is higher, for lower stochastic shocks.

We next consider the firm forbearance lending risk. Figure 1.A plots the forbearance lending probabilities as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital $\bar{k}$). Panel (A) of Figure 1.A plots the forbearance lending probabilities for two firms with low capital k_l and high capital k_h,

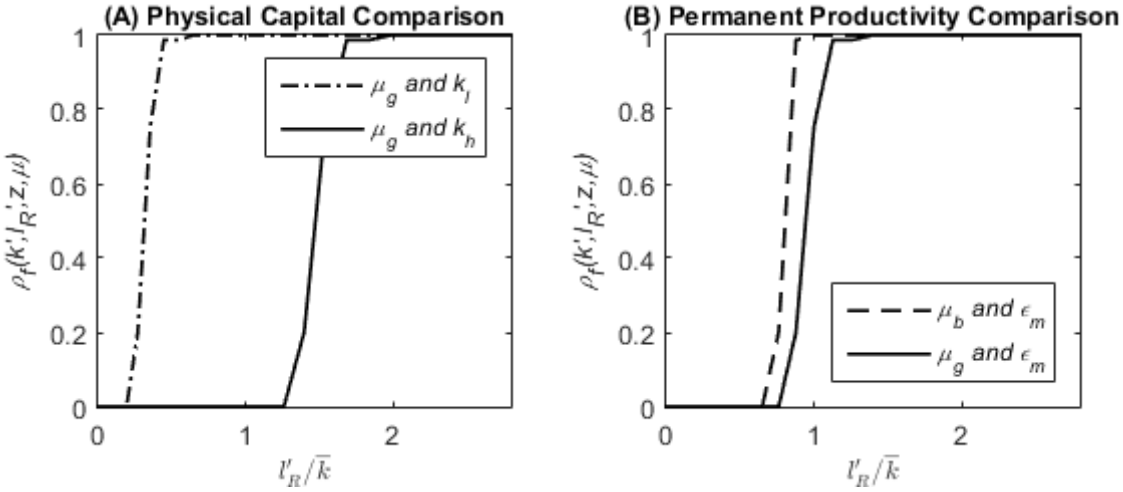


Figure 2.2.: Forbearance Lending Probabilities

Note: Panel (A) plots the forbearance lending probabilities as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital, $\bar{k}$) for two firms with low capital k_l and high capital k_h, when both firms are high-quality (i.e. with permanent productivityμ_g), face a normal stochastic shock ε_m and the capital choice k' is equal to the average equilibrium capital, $\bar{k}$. Panel (B) plots the forbearance lending probabilities as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital $\bar{k}$) for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the capital choice k' equals the median value. The horizontal axes for the loan repayment choice l'_R are scaled by the average equilibrium capital $\bar{k}$.

when both firms are high-quality (i.e. with permanent productivityμ_g), they face a normal stochastic shock ε_m and the capital choice k' is equal to the average equilibrium capital $\bar{k}$. The forbearance lending probability is higher for firms with lower levels of physical capital. The forbearance lending probability also higher for firms with larger loan repayment choices.

Panel (B) of Figure 1.A plots the forbearance lending probabilities for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the capital choice k' equals the average equilibrium capital $\bar{k}$. The forbearance lending probability is greater for low-quality firms than for high-quality firms. The high-quality firms are less likely to choose forbearance lending, even if the loan renegotiation may generate some loan reduction. The same trend

holds when both types of firms face either a low stochastic shock or a normal stochastic shock, i.e. the forbearance lending probability is higher for low-quality firms than for high-quality firms. Although not depicted here, the forbearance lending probability is higher for lower stochastic shocks, holding all else equal. As with liquidation, forbearance lending is more valuable for low-quality firms, and for firms subject to lower stochastic shocks, as well as for firms with larger repayment choices.

Prior to a consideration of the equilibrium loan schedule, we consider the equilibrium loan recovery rate for forbearance lending. Panel (A) of Figure 2.3 plots the equilibrium recovery rates as a function of the outstanding loan repayment l_R (scaled by the average equilibrium capital $\bar{k}$) for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and with capital k equal to the average equilibrium capital, $\bar{k}$.

A firm with a small loan repayment will receive no reduction to its loan. Subsequently, the loan recovery rate decreases as the loan repayment size increases. The loan recovery rate is also higher for high-quality firms than for low-quality firms, all else equal. Similarly, and although not depicted here, the loan recovery rate is higher for firms with a more favorable stochastic shock. For the same loan size, a firm that obtains loan forbearance with a more favorable stochastic shock needs to pay back a higher proportion of the loan.

We now consider the equilibrium loan schedules that arise due to liquidation risk, forbearance risk and firm-type risk. Panel (B) of Figure 2.3 plots the effective interest rate $(l'_R/l' - 1)$ for every contract (l', l'_R) as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital, $\bar{k}$) for the same two firms as in Panel (A). The plot shows that low-quality firms attract higher interest rates. This is because the liquidation risk is higher for a low-quality firm, but also due to the lower recovery rate. In general, a higher loan

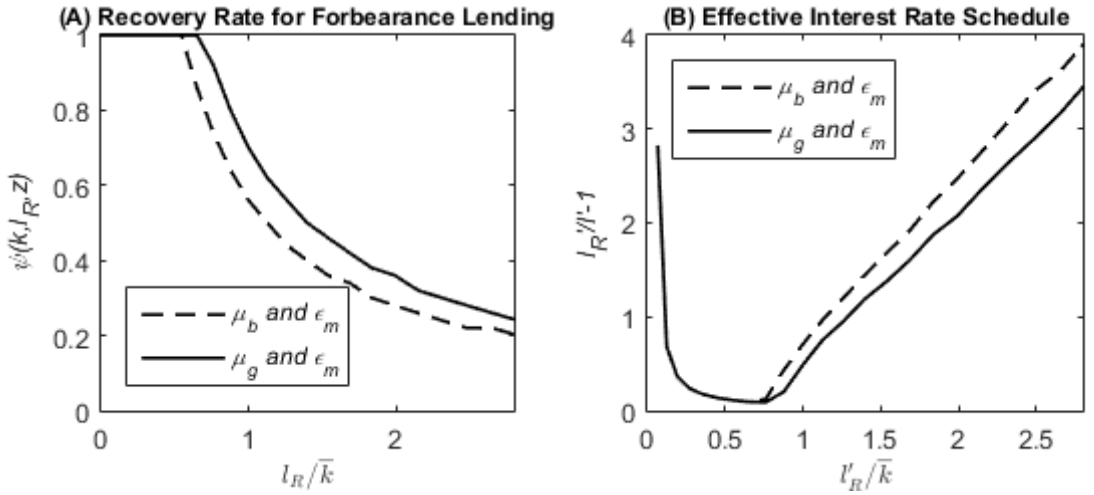


Figure 2.3.: Recovery Rate and Effective Interest Rate Schedule
Note: Panel (A) plots the equilibrium recovery rates. Panel (B) plots the effective interest rate $(l'_R/l' - 1)$ for every contract (l', l'_R). Both plots are as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital $\bar{k}$) and for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the capital choice k' is equal to the average equilibrium capital $\bar{k}$. The horizontal axes are scaled by the average equilibrium capital $\bar{k}$.

reduction, as is the case for a either low-quality firms or a firm experiencing a bad stochastic shock, can increase a firm's *ex ante* forbearance incentive. But the lender anticipates this when pricing the loan schedule, which in turn offsets forbearance incentives. We also note that the effective interest rate increases with loan repayment size. Yet, small loans also face a high effective interest rate due to the fixed cost of lending.

Our next discussion of firm dynamics draws on that of Arellano et al. (2012). To consider firm dynamics, we examine the policy rules. Figure 2.4 plots the decision rules as a function of initial capital k for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a high stochastic shock ε_h and the loan repayment l_R equals the average equilibrium choice for all firms. Panel (A) plots the optimal capital choice k'. Panel (B) plots the optimal loan choice relative to the capital choice l'/k'.

Figure 2.4 shows that with higher initial capital, the firm chooses a larger

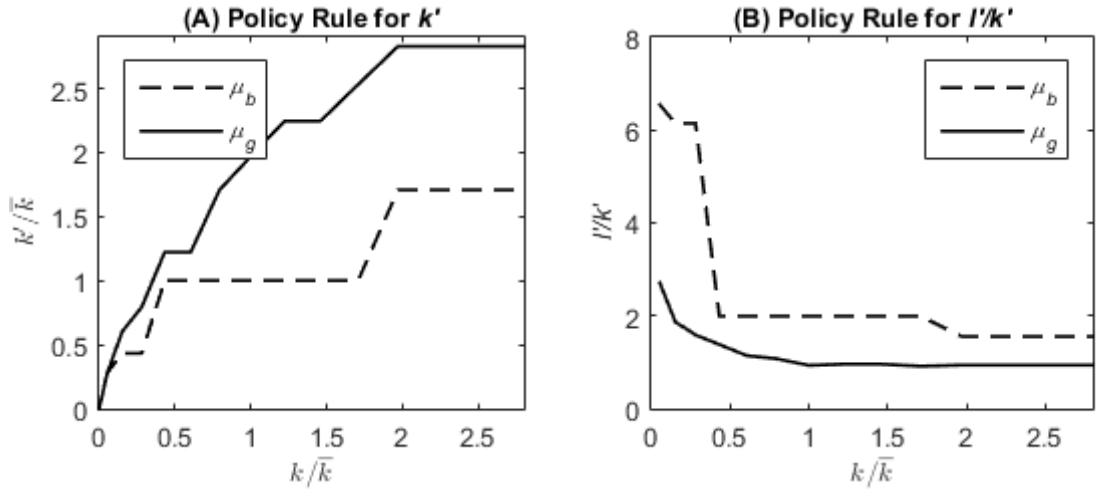


Figure 2.4.: Policy Rules

Note: Panel (A) plots the optimal capital choice k'. Panel (B) plots the optimal loan choice relative to the capital choice l'/k'. All plots as a function of initial capital k for two firms, one high-quality firm (i.e. with permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a high stochastic shock ε_h and the loan repayment l_R equals the average equilibrium choice for all firms. The horizontal axes and vertical axis of Panel (A) are scaled by the average equilibrium capital $\bar{k}$.

future capital stock and a smaller future loan. The smaller loan choice is due to a "precautionary motive"; the firm does not find it optimal to fully utilize its borrowing opportunities, because large loans increase liquidation risk and forbearance risk, as well as the risk of costly equity issuance (Arellano et al., 2012). With lower levels of capital, the firm decreases its capital and increases its leverage (Panel (B)).

Loan contracts also influence the way in which firms respond to stochastic shocks. Related to this, Arellano et al. (2012) note that when firms experience a sequence of low shocks, they will reduce their size in order to avoid equity issuance costs, and increase their loan financing, thus pushing up their leverage and their effective interest rate schedules. Conversely, when they experience a sequence of good shocks, they will enlarge their size and reduce their loan financing, which lowers their effective interest rate schedules. Additionally, low-quality firms tend to be smaller and more levered than high-quality firms because their liquidation risk is higher, so they have more incentives to reduce scale their in order to avoid equity

issuance costs.

2.4.3. Benchmark Model Results

We now consider the statistical moments for the benchmark model, which were already reported in Table 2.3. More detailed results are reported in Table 2.4. All model moments are computed from a simulation of the model economy with 1,000 firms over 500 periods.[9] Statistics for all firms in Column (1) are based on any firm operating in a period. The continuing firm statistics in Column (2) are based on firms that have existed for more than three periods and currently do not receive to loan forbearance. The forbearance firm statistics in Column (3) are based on firms that have existed for more than three periods and currently receive forbearance loans. The liquidating firm statistics in Column (4) are based on firm statistics in the period preceding firm liquidation. The entrants firm statistics in Column (5) are based on firms that have existed for three periods or less.

We first consider the continuing firms in Column (2) of Table 2.4. Most of these firms are high-quality firms (i.e. with permanent productivity μ_g). While high-quality firms comprise around half of all firm liquidations, they are more likely to make a successful entry. This is because high-quality firms are more likely to have higher overall productivity, which makes these firms better able to enter and not immediately (or soon after) liquidate. This differential in successful entry by firm-type results in almost all of continuing firms being high-quality. These continuing firms tend to be larger with lower leverage due to the aforementioned precautionary motives.

We next consider the firms in receipt of forbearance lending in Column (3) of Table 2.4. Only 0.13 per cent of firms that receive forbearance lending are high-quality firms. The reason that the majority of firms in receipt of forbearance

[9] In fact, we simulate the model over 750 periods, and disregard the first 250 periods as the model burn-in.

Table 2.4.: Quantitative Model Results by Operating Status

	(1) *All Firms*	(2) *Continuing*	(3) *Forbearance*	(4) *Liquidating*	(5) *Entrants*
Average of:					
Sales growth	2.00 %	1.07 %	-0.74 %	-10.75 %	15.18 %
Leverage	68.69 %	12.37 %	770.34%	250.86 %	149.26 %
Investment	18.98 %	17.65 %	14.17%	-38.82 %	38.40 %
Capital	126.52	139.32	64.42	43.26	27.62
Loan repayment	54.06	40.29	268.11	59.28	38.78
Firm age	46.72	52.89	12.76	22.47	2.37
Overall productivity	1.74	1.79	1.41	0.98	1.63
Proportion of firms:					
In given category	100.00 %	88.77 %	6.79 %	4.45 %	4.45 %
High-quality, i.e. $\mu = \mu_g$	90.28 %	99.65 %	0.13 %	50.02 %	54.69 %

Note: Column (1) reports the model statistics for all firms operating with age greater than one. Column (2) reports the model statistics for continuing firms, defined as any firm that has existed for more than three periods and does not currently receive loan forbearance. Column (3) reports the model statistics for forbearance firms, defined as any firm that has existed for more than three periods and currently receives loan forbearance. Column (4) reports the model statistics for liquidating firms, based on the firm statistics in the period preceding the firm liquidation. Column (5) reports the model statistics for entrant firms, defined as any firm that has existed for less than three periods. All model statistics are for the benchmark calibration, in which firms have access to forbearance lending.

lending are low-quality (i.e. with permanent productivity μ_b) relates to the information asymmetry. Specifically, *ceteris paribus* low-quality firms face a higher effective interest rate schedule than high-quality firms due to their higher liquidation and forbearance risk, and lower recovery rates (Figure 2.3). But the difference between the interest rate schedules of the high-quality firms and low-quality firms is not very large. This is because the lender cannot perfectly predict whether a given firm is high-quality of low-quality, but assigns a probability to a firm being low or high-quality. The end result is that the lender will offer relatively similar interest rate schedules to both types of firms, whereby the interest rate schedule is more (less) favorable for low (high) quality firms than it would have been under perfect information.[10] The relatively lower (higher) effective interest

[10]To expand on this, when a high-quality firm facing a lower stochastic shock has the same overall productivity as a low-quality firm experiencing a higher stochastic shock, the lender will offer both firms the same interest rate schedule. But if a high-quality firm and a low-quality firm both experience the *same* stochastic shock, the overall productivity of the high

rate schedule makes forbearance lending *ex ante* a more (less) valuable choice for low-quality firms. As such, the majority of firms in receipt of forbearance lending are low-quality.

The fact low-quality firms have lower overall productivity, on average, also increases their likelihood of loan forbearance. This is because firms facing lower overall productivity, due to a bad stochastic shock or being low-quality or both, are more likely to opt for forbearance lending arrangements as continuing is less valuable to them. The low overall productivity is consistent with the high level of leverage observed for the forbearance firms: as mentioned above, when faced with a sequence of bad shocks, firms will reduce their scale in order to avoid costly equity issuance, and increase their loan financing, thereby pushing up their leverage and effective interest rates.

There are two factors that explain why firms in receipt of forbearance lending have lower sales growth. First, these firms are often experiencing a sequence of bad shocks, and this itself will lower sales growth. Second, these firms reduce their scale in response to the sequence of bad shocks, which further contributes to lower sales growth.

We now consider the liquidating firms in Column (4) of Table 2.4. These firms are equally likely to be high-quality or low-quality firms, although the path to liquidation differs by firm-type. high-quality firms tend to liquidate after being in the market for some time; their liquidation occurs after they experience a sequence of bad stochastic shocks at some point. Low-quality firms, on the other hand, often liquidate quite quickly, after a few periods only. Alternatively, low-quality firms survive for around 12 years due to their access to forbearance lending, but at some point they also experience a sequence of shocks that makes liquidation

productivity firm will be higher, and so the interest rate schedule will be more favorable for this firm. But it will still be less favorable than in the perfect information world, because the lender will still assign some probability to the high-quality firm being low-quality. The size of this probability will depend on the overall productivity, where lower values are assigned a higher probability of being low-quality firm.

a more valuable option than forbearance lending. For both firm-types, firms have high leverage and negative sales growth in the period before they liquidate, which is as we would expect for any firm experiencing a sequence of bad stochastic shocks.

Finally, we consider the entrant firms in Column (5) of Table 2.4. These firms are smaller and have higher sales growth rates, which is consistent with the findings of Arellano et al. (2012) for firm entrants.

In summary, the evidence in Table 2.4 suggests that the nearly all firms in receipt of forbearance lending are low-quality. This is consistent with the empirical evidence of Acharya et al. (2015), who find that low-quality firms are more likely to be in receipt of subsidized loans. In the next section we quantify the impact of this forbearance lending on firm dynamics and performance.

2.5. The Quantitative Impact of Forbearance Lending

We consider the quantitative affects of forbearance lending by conducting two counterfactual experiments. We first consider a counterfactual experiment in which the possibility of forbearance lending is shut down and so firms can only choose between continuing or default.[11] This experiment aims to show how forbearance lending practices affect firm dynamics and performance. We next consider the impact of information asymmetry by considering a counterfactual experiment in which the lender can identify firm-type. Below we outline each counterfactual scenario more formally and consider the results of each experiment in turn.

2.5.1. No Forbearance Lending Scenario

For the first experiment of no forbearance lending, the value function of a firm that has the option to default and that starts the current period with capital k, a loan repayment l_R and productivity z is:

$$V\left(k, l_R, z, \mu\right) = \max_{\{c,d\}} \left\{V_c\left(k, l_R, z, \mu\right), V_d\left(k, l_R\right)\right\}, \tag{2.26}$$

where $V_c\left(k, l_R, z, \mu\right)$ is the value function if the entrepreneur does not default and continues to operate, as defined by Equation (2.4); and $V_d\left(k, l_R\right)$ is the value function if the entrepreneur defaults and liquidates the firm, as defined by Equation (2.5). Thus, the key departure from the benchmark model is that the value associated with forbearance,$V_f\left(k, l_R, z, \mu\right)$, no longer enters the value function as an option.

[11] Tamayo (2015) conducts a similar counterfactual exercise to examine the impact of different US bankruptcy options.

Similar to the problem above, an idle entrepreneur will attempt to start a new firm when she receives a project opportunity, which occurs when another entrepreneur liquidates their firm. The entrant problem is defined by Equation (2.10).

In this scenario, the equilibrium loan schedule $\Omega(k', z)$ that comprises all loan contracts (l', l'_R) allowing the lender to break even in expected values, and accounting for the liquidation risk that the lender faces, is described by:

$$l' = \sum_{j=b,g} \Pr(\mu = \mu_j | z) \quad \begin{Bmatrix} \frac{1}{1+r+\xi} \left[1 - \rho_f(k', l'_R, z, \mu_j) - \rho_d(k', l'_R, z, \mu_j)\right] l'_R \\ - \frac{1}{1+r+\xi} \rho_d(k', l'_R, z, \mu_j) \min\{\chi_d k', l'_R\} \end{Bmatrix} \tag{2.27}$$

Table 2.5 presents the statistical moments (originally used as part of the estimation of several parameters of the benchmark model) for the Euro Area data, the benchmark model, and for the counterfactual experiments. The statistical moments for the counterfactual experiment of no forbearance are contained in Column (3) of Table 2.5. Table 2.6 provides a more granular breakdown of the results by firm-type. On the basis of these results, we can conclude that with no forbearance lending, firm liquidation is higher, sales growth is higher, and leverage is lower. We discuss these points in more detail below.

First, we consider the liquidation rate. Figure 2.5 plots the liquidation probabilities as a function of the capital choice k' for two firms, one high-quality firm (i.e. with high permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the loan repayment choice l'_R equals the average equilibrium choice for all firms in the benchmark model. Panel (A) is for the benchmark model and Panel (B) is for the counterfactual experiment without forbearance lending. Panel (C) will be discussed below in Section 2.5.2.

Table 2.5 shows that the liquidation rate is around 7 per cent higher in the counterfactual experiment with no forbearance lending. Similarly, Figure 2.5 shows that the liquidation risk is higher for otherwise identical firms. But the

Table 2.5.: Statistical Moments in the Euro Area data, in the Benchmark Model, and for the Counterfactual Experiments

	(1)	(2)	(3)	(4)
Targeted Moments	*Data*	*Benchmark*	*No Forbearance*	*Perfect Information*
Firm liquidation rate	3.44%	4.45%	4.76%	5.14%
Firm forbearance rate	7.5%	6.79%	0.00%	0.03%
Average of sales growth	5.86%	2.00%	2.27%	3.92%
Std. dev. of sales growth	16.62%	19.54%	19.40%	24.03%
Average of leverage	66.46%	68.69%	18.55%	13.10%
Non-targeted Moments	*Data*	*Benchmark*	*No Forbearance*	*Perfect Information*
Std. dev. of leverage	21.70%	268.59%	41.48%	31.65%
Average of working capital	23.73%	29.99%	78.21%	91.14%
Std. dev. of working capital	21.68%	257.72%	54.68%	50.91%

Note: The column under Data reports the statistical moments for the Euro Area, from 2011 to 2014. The column under Benchmark reports the model statistics under the benchmark calibration, in which firms have access to forbearance lending. The column under No Forbearance reports the model statistics for the counterfactual experiment in which firms no longer have access to forbearance lending. The column under Perfect Information reports the model statistics for the counterfactual experiment in which there is no information asymmetry and so lenders can observe firm-type. All moments are calculated over a one-year period.

liquidation rate in this counterfactual experiment is not significantly higher than for the benchmark model; that is, it does not increase to the same extent that forbearance lending occurs in the benchmark scenario. This is because in the absence of forbearance lending, firms make different equilibrium choices for their capital and loans, which diminishes the increases in their liquidation risk.

Next we consider the equilibrium loan schedules that arise in the counterfactual scenario of no forbearance lending. Figure 2.6 plots the effective interest rate $(l'_R/l' - 1)$ for every contract (l', l'_R) as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital $\bar{k}$ for the benchmark model) for two firms, one high-quality firm and one low-quality firm, when both firms face a normal stochastic shock ε_m and the capital choice k' is equal to the average equilibrium capital $\bar{k}$ for the benchmark model. Panel (A) is for the benchmark model and Panel (B) is for the counterfactual experiment without forbearance lending. We will return to Panel (C) below in Section 2.5.2.

The equilibrium loan schedule is higher, on average, in the counterfactual exper-

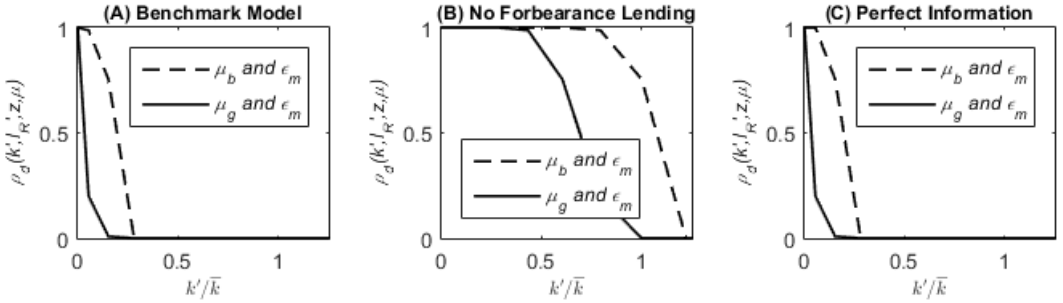


Figure 2.5.: Liquidation Probabilities

Note: Panel (A) is for the benchmark model with forbearance lending. Panel (B) is for the counterfactual experiment with no forbearance lending. Panel (C) is for the counterfactual scenario with perfect information. All figures plot the liquidation probabilities as a function of the capital choice k' for two firms, one high-quality firm (i.e. with high permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the loan repayment choice l'_R equals the average equilibrium choice for all firms in the benchmark model. The horizontal axes for capital choice are scaled by the average equilibrium capital $\bar{k}$.

iment than for the benchmark model. This is partly due to the higher liquidation risk in the counterfactual scenario (see Figure 2.5). But the more significant factor is the absence of forbearance lending. Forbearance lending risk is priced into the effective loan schedule but it can contribute to more favorable borrowing rates than pure liquidation risk, because the lender is able to recuperate a much larger proportion of the loan repayment than in the instance of liquidation.

The results for the loan schedule also relate to our observations for overall average leverage. Table 2.5 shows that overall average leverage is around 73 per cent lower in the counterfactual experiment without forbearance lending. Once more, this is due to the removal of the option for forbearance lending. The high leverage of low-quality firms in receipt of forbearance lending was driving up the average leverage in the benchmark model. Additionally, the higher loan schedule in the counterfactual scenario of Panel (B) in Figure 2.6 also disincentivizes firms to take on high levels of leverage.

Table 2.5 also shows that overall average sales growth is around 14 per cent higher in the counterfactual experiment without forbearance lending. The removal of the option of forbearance lending is a key driver of this result. Without

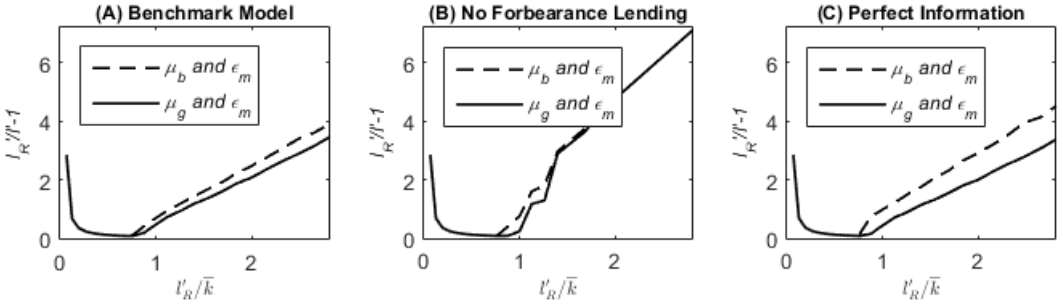


Figure 2.6.: Effective Interest Rate Schedules

Note: Panel (A) is for the benchmark model with forbearance lending. Panel (B) is for the counterfactual experiment with no forbearance lending. Panel (C) is for the counterfactual scenario with perfect information. All figures plot the effective interest rate $(l'_R/l'-1)$ for every contract (l', l'_R). Both plots are as a function of the loan repayment choice l'_R (scaled by the average equilibrium capital $\bar{k}$) and for two firms, one high-quality firm (i.e. with high permanent productivity μ_g) and one low-quality firm (i.e. with permanent productivity μ_b), when there is a normal stochastic shock ε_m and the capital choice k' is equal to the average equilibrium capital $\bar{k}$. The horizontal axes are scaled by the average equilibrium capital $\bar{k}$.

access to forbearance lending, the low-quality firms default soon after they enter. As such, the overall proportion of high-quality firms is higher in the counterfactual scenario, i.e. 96.94 per cent of all firms are high-quality versus 90.28 per cent in the benchmark model. The consequence of a higher proportion of high-quality firms is that average sales growth is higher. Low-quality firms in receipt of forbearance lending are no longer lowering the overall average sales growth, as in the benchmark model.

Similarly, average investment is around 4 per cent higher in the counterfactual exercise, as can be seen in Table 2.6, and the average overall productivity of firms is also a little higher. Again, this is due to the removal of the option for forbearance lending, and the resulting reduction in the proportion of low-quality firms.

It is worth noting that we do not find evidence of congestion effects in our model, as documented by Acharya et al. (2015) for European firms and Caballero et al. (2008) for Japanese firms. This is based on the fact that in Column (2) of Table 2.6, the average sales growth, investment and productivity are not significantly different between the benchmark model and counterfactual scenario for continuing

firms.

2.5.2. Perfect Information Scenario

We now consider the counterfactual experiment of perfect information. With perfect information, the firm problem remains identical to the baseline scenario but the equilibrium loan schedule changes because the lender can perfectly identify firm type. The equilibrium loan schedule $\Omega(k', z)$ that comprises all loan contracts (l', l'_R) allowing the lender to break even in expected value is:

$$\begin{aligned} l' = \; & \tfrac{1}{1+r}\left[1 - \rho_f\left(k', l'_R, z, \mu\right) - \rho_d\left(k', l'_R, z, \mu\right)\right] l'_R \\ & - \tfrac{1}{1+r}\left(\rho_f\left(k', l'_R, z, \mu\right) \cdot \gamma\left(k', l'_R, z, \mu\right)\right) l'_R \\ & - \tfrac{1}{1+r}\rho_d\left(k', l'_R, z, \mu\right) \min\left\{\chi_d k', l'_R\right\} - \xi \end{aligned} \tag{2.28}$$

Overall, Table 2.5 and Table 2.6 demonstrate that firm liquidation is higher, forbearance lending rates are lower, sales growth is higher, and leverage is lower under perfect information. We discuss these results in more detail below.

We first consider the liquidation rate under perfect information. Table 2.5 shows that the liquidation rate is about 16 per cent higher in the counterfactual experiment with perfect information than in the benchmark scenario. The higher liquidation rate is mainly driven by higher defaults of entrant firms, as can be seen by the lower average age of liquidating firms in Table 2.6 (i.e. 19.47 versus 22.47). In particular, low-quality firms now often liquidate after just one period. Under perfect information, lenders can properly discriminate between low-quality and high-quality firms when pricing loan schedules. The higher loan schedules for low-quality firms reduce their relative value of continuing or forbearance lending. Liquidating is typically the most valuable option for these firms.

Table 2.6.: Quantitative Model Results for Counterfactual Experiments

	(1) *All Firms*	(2) *Continuing*	(3) *Forbearance*	(4) *Liquidating*	(5) *Entrants*
Panel A: Benchmark Model					
Average of:					
Sales growth	2.00 %	1.07 %	-0.74 %	-10.75 %	15.18 %
Leverage	68.69 %	12.37 %	770.34%	250.86 %	149.26 %
Investment	18.98 %	17.65 %	14.17%	-38.82 %	38.40 %
Capital	126.52	139.32	64.42	43.26	27.62
Loan repayment	54.06	40.29	268.11	59.28	38.78
Firm age	46.72	52.89	12.76	22.47	2.37
Overall productivity	1.74	1.79	1.41	0.98	1.63
Proportion of firms:					
In given category	100.00 %	88.77 %	6.79 %	4.45 %	4.45 %
High-quality, i.e. $\mu = \mu_g$	90.28 %	99.65 %	0.13 %	50.02 %	54.69 %
Panel B: Counterfactual experiment with no forbearance					
Average of:					
Sales growth	2.27 %	1.03 %	n.a.	-3.34 %	18.36 %
Leverage	18.55 %	18.60 %	n.a.	17.59 %	17.95 %
Investment	19.69 %	17.59 %	n.a.	-17.77 %	46.84 %
Capital	134.54	142.68	n.a.	44.00	28.77
Loan repayment	54.28	57.76	n.a.	9.90	9.01
Firm age	50.00	53.68	n.a.	21.12	2.30
Overall productivity	1.76	1.79	n.a.	1.05	1.47
Proportion of firms:					
In given category	100.00 %	95.24 %	n.a.	4.76 %	4.76 %
High-quality, i.e. $\mu = \mu_g$	96.94 %	99.79 %	n.a.	49.69 %	59.89 %
Panel C: Counterfactual experiment with no information asymmetry					
Average of:					
Sales growth	3.92 %	1.87 %	-28.67 %	-5.56 %	109.44 %
Leverage	13.10 %	13.47 %	93.53 %	00.01 %	6.78 %
Investment	25.41 %	19.30 %	-38.65%	-32.74 %	352.33 %
Capital	133.96	138.74	262.93	27.05	24.34
Loan repayment	42.68	44.30	243.75	0.01	2.92
Firm age	51.98	54.00	41.45	19.47	2.50
Overall productivity	1.79	1.79	1.46	0.99	1.82
Proportion of firms:					
In given category	100.00 %	94.83 %	0.03 %	5.14 %	5.14 %
High-quality, i.e. $\mu = \mu_g$	99.98 %	100.00 %	100.00 %	49.99 %	99.59 %

Note: Column (1) reports the model statistics for all firms operating with age greater than one. Column (2) reports the model statistics for continuing firms, defined as any firm that has existed for more than three periods and does not currently receive to loan forbearance. Column (3) reports the model statistics for forbearance firms, defined as any firm that has existed for more than three periods and currently receives loan forbearance. Column (4) reports the model statistics for liquidating firms, based on the firm statistics in the period preceding the firm liquidation. Column (5) reports the model statistics for entrant firms, defined as any firm that has existed for less than three periods.

Next we consider the equilibrium loan schedules that arise in the counterfactual scenario of perfect information. Panel (C) of Figure 2.6 is the equilibrium loan schedule for the counterfactual experiment with perfect information. Compared with Panel (A), the loan schedule for the high- (low-) quality firms is more (less) favorable under perfect information. This is because the lender can now perfectly identify firm-type and so more accurately price liquidation risk and forbearance risk. The information asymmetry had the effect of narrowing the gap between the loan schedules of the high-quality and low-quality firms.

The loan schedules under perfect information lead to very different outcomes for the type of firms that obtain loan forbearance, as shown in Table 2.6. With information asymmetry, almost exclusively low-quality firms obtained forbearance lending. As previously mentioned, this was because the loan schedule under information asymmetry was more favorable for low-quality firms, which therefore incentivized these firms to choose this option. With perfect information, only high-quality firms obtain forbearance lending. Loan schedules under perfect information are priced such that low-quality firms never find it optimal to choose forbearance lending. Yet, Table 2.5 also shows that the overall forbearance rate is much lower in the counterfactual experiment with perfect information. For the given calibration, firms rarely find it optimal to choose forbearance lending under perfect information.[12]

Table 2.6 shows that average sales growth across all firms is around 96 per cent higher in the counterfactual experiment with perfect information than in the benchmark scenario, and also higher than in the counterfactual experiment with no forbearance lending. With perfect information, low-quality firms face high loan schedules because they have higher liquidation risk and forbearance risk.

[12]Under alternative calibrations, in particular with a much lower cost of forbearance lending parameter χ_f, the model with perfect information can generate higher levels of forbearance lending than observed for this experiment. The result that primarily high-quality firms access forbearance lending under perfect information holds when there are higher rates of forbearance lending.

This contributes to these firms liquidating shortly after they enter. This results in the overall proportion of high-quality firms being 99.98 per cent under perfect information, which is higher than in both the benchmark and the counterfactual scenario of no forbearance lending. Once more, the consequence of a higher proportion of high-quality firms is that overall average sales growth is higher. For similar reasons, average investment and average productivity are also higher in the counterfactual scenario with perfect information.

2.6. Conclusions

This study examines the relationship between forbearance lending, firm dynamics and firm performance. To do so, we develop a firm equilibrium model that features endogenous default and endogenous forbearance lending. Lenders face information asymmetry because they do not know with certainty whether they are lending to a "low-quality" or "high-quality" firm. Our model enables us to consider the net impact of forbearance lending on firm performance by examining how the costs of forbearance lending, due to credit misallocations from lenders incorrectly assessing a lender to be high-quality, and its benefits, due to refinancing high-quality firms experiencing a negative sequence of shocks, balance out. We fit our model to the Euro Area economy over the period 2011 to 2014, which represents a period of economic stagnation and higher levels of forbearance lending.

To examine the impact of forbearance lending, we conduct a counterfactual exercise in which firms still have the option to liquidate but no longer have access to any form of loan forbearance. In the absence of forbearance lending, we find that firm sales growth is around 14 per cent higher, or 0.27 percentage points higher, than in the benchmark scenario fitted to the Euro Area. We also find investment and average productivity to be higher in our counterfactual exercise. A key driver of this result is that there is a larger proportion of high-quality firms in our counterfactual scenario; the forbearance lending present in the benchmark model prevents low-quality firms from defaulting more quickly. We find that low-quality firms are most likely to receive forbearance lending in our benchmark model. These low-quality firms, kept alive via forbearance lending, lower the average sales growth, investment and productivity across all firms.

The fact that the overwhelming majority of firms in receipt of forbearance lending in our model are of low-quality is consistent with the empirical evidence of

Acharya et al. (2015), who find that low-quality firms are more likely to be in receipt of subsidized loans. Our results extend their empirical findings by quantifying the impact of forbearance lending on various measures of firm performance. That said, we do not find evidence of congestion effects in our model, as documented by Acharya et al. (2015) for European firms and Caballero et al. (2008) for Japanese firms.

In an additional counterfactual exercise with perfect information, we also show that only high-quality firms access forbearance lending. In this scenario, lenders know firm-type and this leads to an even higher proportion of high-quality firms among all firms. As such, sales growth, investment and productivity are higher than in the benchmark model with information asymmetry.

Our model does not include any role for the potential increased unemployment associated with higher default rates that may occur in the absence of forbearance lending. However, we do not find that default rates increase significantly in the absence of forbearance lending, which suggests a smaller role for this potential offsetting channel. We stress that in reality, we do expect lenders to face information asymmetry. Therefore, our results suggest that the costs of forbearance lending associated with the misallocation of credit to low-quality firms most likely outweigh any benefits. From this perspective, forbearance lending may have contributed to the economic stagnation observed for the Euro Area since the onset of the sovereign debt crisis.

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2.A. Computational Algorithm

We first set grids on the state space of the aggregate states of the economy, $s = \{k, l_R, z, \mu\}$. The productivity shock, z, is discretized into 10-state Markov chain, following the method of Tauchen (1986). The state space of the loan repayment amount l_R and capital k are each discretized into a grid of 15 and 25 points, respectively, between 0 and 400. The loan repayment amount grid and the capital grid are unevenly spaced, using a similar method to Corbae and Quintin (2015). That is, every point of an equally spaced grid between 0 and $400^{2/3}$ is raised to the 3/2 power. As in Corbae and Quintin (2015), this grid contains more points closer to zero and so provides improved numerical performance for our problem.

We solve the model to find the optimal loan schedules, policy functions and default policies using the following algorithm:

1. For all aggregate states of the economy, $s = \{k, l_R, z, \mu\}$, start with an initial guess for the bank loan recovery schedule ψ^0. For all k' and z, start with an initial guess for the loan schedule Ω^{00}, in which all loan contracts (l', l'_R) have the risk-free interest rate. For the probability of firm-type given observed productivity $q^0 = \Pr(\mu = \mu_j | z)$, start with an initial guess by using $\Pr(\mu = \mu_b) = \Pr(\mu = \mu_g) = 0.5$ and $\Pr(z|\mu = \mu_b) = 2 \times \Phi\left(-\left|\frac{\ln(z)-\mu_b}{\sigma_\varphi}\right|\right)$.
2. Given the bank loan recovery schedule ψ^0 and the equilibrium loan schedule Ω^0, use value function iterations to solve for the optimal policy functions for future capital stock $k'(s)$, the new bank loan contract $(l'(s), l'_R(s))$, operating sets $C(k, l_R, \mu)$, liquidation sets $D(k, l_R, \mu)$, and forbearance sets $F(k, l_R, \mu)$. We iterate on the value function until we reach convergence for a given ψ^0 and Ω^0.

3. Given the operating sets, liquidation sets, forbearance sets and q^0: compute the new debt schedule Ω^1 such that lenders break even in expectation, and compare it to loan debt schedule of the previous iteration: Ω^0. If a convergence criterion is met, $\max\{\Omega^0 - \Omega^1\} < \varepsilon$, then assign Ω^1 to Ω^0 and move on to the step 4. Otherwise, update using a Gauss-Seidel algorithm and go back to step 2.

4. Solve the bargaining problem given the converged loan schedule Ω^0 and compute the new bank loan recovery schedule ψ^1 for all aggregate states of the economy, $s = \{k, l_R, z, \mu\}$. If the new bank loan recovery schedule ψ^1 is sufficiently close to ψ^0, stop iterating on ψ. Otherwise, go back to step 2.

5. To compute the stationary cross-sectional distribution, start with a uniform distribution as an initial guess. Then simulate the stationary cross-sectional distribution associated with the set of policy functions obtained above, and such that the mass of all projects always equals one. This implies that the mass of entrants equals the the mass of liquidations. Update q^1 based on $\Pr(\mu = \mu_b)$ and $\Pr(z|\mu = \mu_b)$ from the stationary cross-sectional distribution. If the firm-type probability given productivity q^1 is sufficiently close to q^0, stop iterating on q. Otherwise, go back to step 2.

6. Simulate the model to compute statistics from a model economy of 1,000 firms over 750 periods, using the first 250 periods as a burn-in.

2.B. Data and Parameter Estimation

We use firm-level data to estimate for three parameters in Table 2.2 independently of the model equilibrium, as well as to estimate most of the model statistics listed in Table 2.3. We obtain our firm-level data from the Amadeus database, which comprises financial data for both public and private companies in Europe. Our sample comprises all public and private Euro Area firms, excluding the financial and government sectors. We collect annual financial data for the period 2009 to 2014.

We clean the dataset in several ways. Following Arellano et al. (2012), we exclude firms in the financial and government sectors. Financial sector firms correspond to NACE Divisions 64 to 67 and government sector firms correspond to NACE Division 84. We furthermore collect data for Euro Area firms only. The sample is also restricted to those firms with a reported value for EBIT, sales, and fixed assets in at least one of the years from 2012 to 2014. These criteria leave us with around 150,000 firms in 17 countries: all Euro Area countries except for Ireland. Table 2.7 describes how we compute the parameters and model statistics.

Table 2.7.: Definitions of Parameters and Model Statistics from Firm-level Data

Calibrated Parameters	*Definition*
Depreciation	$\frac{\text{Depreciation}_t}{\text{Fixed Assets}_{t-1}}$
Interest Coverage Ratio	$\frac{\text{EBIT}_t}{\text{EBIT}_t - \text{EBT}_t}$

Model Statistics	*Definition*
Sales Growth	$\frac{\text{Sales}_t - \text{Sales}_{t-1}}{\text{Sales}_{t-1}}$
Leverage	$\frac{\text{Total Assets}_t - \text{Total Equity}_t}{\text{Total Assets}_t}$
Working Capital	$\frac{\text{Working Capital}_t}{\text{Total Assets}_{t-1}}$
Return on Assets	$\frac{\text{Net Income}_t}{\text{Total Assets}_{t-1}}$
Investment	$\frac{\text{Fixed Assets}_t - \text{Fixed Assets}_{t-1} + \text{Depreciation}_{t-1}}{\text{Fixed Assets}_{t-1}}$

Note: Each variable is windsorized at the 5 per cent level. The model statistics are computed for each firm in each year from 2011 to 2014. We first take the mean and standard deviation of each statistic in each year. The model statistics are then calculated as the mean of the yearly mean (for the mean of the model statistic) or the mean of the yearly standard deviation (for the standard deviation of the model statistic) over the period 2011 to 2014.

3. Bank Capital and Risk-taking: Evidence from Misconduct Provisions[1]

Chapter Abstract

This study introduces a novel way to identify the causal effect of bank capital on risk-taking. We use provisions for misconduct issues as an instrument for bank capital. Misconduct provisions can adversely affect bank capital via their negative impact on retained earnings, and we find evidence of this for UK banks. We also find strong support for our assumption that misconduct provisions are otherwise unrelated to asset risk-taking, due to the institutional framework around, and the timing of, these penalties. We facilitate our analysis with a unique UK panel dataset of bank-level information from published accounts, merged with loan-level data on all regulated UK mortgages. Our main finding is that a negative shock to bank capital leads to an increase in risk-taking, as measured by detailed information on mortgage underwriting standards.

[1]This paper is co-authored with Christian Schnittker and Rhiannon Sowerbutts.

3.1. Introduction

The financial crisis of 2008 brought to the fore arguments in favor of increased bank capital regulation and macroprudential policies. Almost one decade later, macroprudential tools are at the fingertips of policymakers, yet our understanding of their transmission mechanisms remains in its infancy. This paper considers the impact of bank capital on risk-taking, thereby shedding light on this important topic.

Our study introduces a novel way to isolate the causal effect of bank capital on risk-taking. This type of analysis faces a major identification challenge, which has not previously been addressed in the literature, because changes in bank capital and changes in risk-taking form an endogenous relationship. We overcome this identification challenge by using provisions for misconduct fines and customer redress payments as an instrument for bank capital.

There are two necessary conditions for misconduct provisions to qualify as a valid instrument. First, we require misconduct provisions to have a significant effect on bank capital. Recent misconduct provisions have plagued many of the largest banks in the world, and their magnitude has been substantial. These misconduct provisions affect the numerator of bank capital ratios by way of a simple accounting identity. Misconduct provisions reduce retained earnings, which normally contribute to Common Equity Tier 1 capital, and thereby reduce potential capital contributions. Of course, banks can in theory simultaneously change their risk-weighted assets, the denominator for bank capital ratios, thereby limiting any impact. However, we find that there is a significant and negative correlation between misconduct provisions and bank capital ratios, even after controlling for a wide range of factors.

We also require that misconduct provisions are not correlated with risk-taking, or any other factors that independently influence risk-taking, except via their impact on bank capital. The institutional framework that determines misconduct fines, as well as the timing of these penalties, provides a strong case for this. Misconduct fines and customer redress payments occur because a bank has breached the rules, manipulated markets, or engaged in some other kind of misconduct; they are not issued due to prudential concerns relating to a bank's *asset* risk. To be sure, one could argue that if a bank is more likely to commit some kind of misconduct, then it is also more likely to take on asset risk. But even if that were the case, these misconduct provisions do not relate to the current activities or financial position of the bank, but rather to previous misconduct that has since ceased. For example, in the case of provisions for Payment Protection Insurance (PPI) claims, which account for around half of all misconduct provisions in our sample, these often relate to policies that were sold more than a decade prior.

Given the strong effect of misconduct provisions on bank capital, and the plausible assumption that misconduct provisions are not otherwise related to risk-taking, we use misconduct provisions as an instrument to estimate the effect of bank capital on risk-taking. To perform our analysis, we construct a unique UK panel dataset. Our dataset merges bank-level information from published accounts with loan-level data on all regulated UK mortgages. These data cover the period from 2010 to 2015, which coincides with the time that misconduct provisions became more prevalent. Our dataset facilitates a rich analysis of risk-taking in the UK mortgage market. We consider the following loan-specific measures of risk: the loan-to-value (LTV) ratio, the loan-to-income (LTI) ratio, the payment-to-income (PTI) ratio, and whether the borrower has previous loan non-performance.

Previous studies that examine the relationship between bank capital and risk-taking rely on bank-level balance sheet measures of risk (see, for example, Shieves and Dahl, 1992, Jacques and Nigro, 1997, Aggarwal and Jacques, 1998, Aggarwal

and Jacques, 2001, and Rime, 2001). We are the first study to consider the causal impact of changes in bank capital on risk-taking by utilizing granular loan-level information about lending standards. As such, our dataset allows us to disentangle changes in the demand for loans from changes in supply. We control for changes in the loan demand of risky borrowers by including detailed borrower characteristics in our empirical specifications. Additionally, we control for changes in loan demand by merging our loan-level data with granular regional house price index data.[2] Given that housing supply has low price elasticity in the UK (Caldera and Johansson, 2013), and that the majority of house purchases are mortgage-financed (Council of Mortgage Lenders, 2015), changes in house prices act as a proxy for changes in overall demand for mortgage credit. This study therefore adds to a growing literature that uses loan-level data to help control for loan demand, which helps to better address various questions relating to bank behaviors (see, for example, Jimenez et al., 2012, Jimenez et al., 2013, Ionnidou et al. 2015).

In sum, our empirical specification controls for endogeneity, loan demand factors, borrower characteristics, loan characteristics, bank characteristics, and other features that may influence the riskiness of mortgage credit. Hence, we can use this specification to test our hypotheses about the causal impact of bank capital on risk-taking. This is very much an empirical task, given the contradictory conclusions that arise in the theoretical literature. One main strand of the literature claims that insured, value-maximizing banks will *decrease* risk-taking when they have higher capital (see, for example, Kareken and Wallace, 1978, Buser, Chen and Kane, 1981, Furlong and Keeley, 1989, Keeley, 1990). However, another main strand of the literature makes the opposite prediction that increasing capital ratio requirements - in the absence of appropriate risk weights and assuming banks are fully liable - may lead to an *increase* in risk-taking (see, for example, Kahane,

[2]This advances on the approach of Uluc and Wieladek (2015), who use granular regional time dummy variables for a similar purpose.

1997, Koehn and Santomero, 1980, Kim and Santomero, 1988).

Our results support the first stand of the theoretical literature. We find that a negative shock to bank capital causes an increase in risk-taking, as measured by the lending standards in the UK mortgage market. More specifically, we find that a decrease in bank capital will lead to an increase in the LTV ratio, the LTI ratio, the PTI ratio, and the likelihood of making a loan to a borrower with previous loan non-performance, holding all else equal.

One of the main contributions of this study is our identification strategy, which enables us to isolate the casual impact of an exogenous change to bank capital on risk-taking. We therefore extend previous empirical research that has examined the relationship between bank capital and risk-taking by using a simultaneous equations approach, with mixed findings (see, for example, Shieves and Dahl, 1992, Jacques and Nigro, 1997, Aggarwal and Jarcques, 1998, Aggarwal and Jacques, 2001, Rime, 2001, and Altunbus et al., 2007).

We also build on the literature that considers the impact of bank capital on bank lending (see, for example, Bernanke and Lown, 1991, Peek and Rosengren, 1995a, Peek and Rosengren, 1995b, Gabacorta and Mistrulli, 2004), as well as the literature on the impact of bank capital requirements on bank lending (see, for example, Francis and Osbourn, 2012, Aiyer et al., 2014, Bridges et al., 2014, Uluc and Wieladek, 2015). While these studies provide useful findings about the impact of bank capital on the *quantity* of lending, we provide new insights about the transmission mechanisms of changes in bank capital on the *quality* of lending.

Our results first and foremost provide insights about how banks will respond to individual capital shocks. But they can potentially also provide valuable insights about the wider effects of capital policies and macroprudential policies. If we assume that banks will respond in a similar way to that observed for the exogenous individual capital shocks, our results imply that higher capital requirements - in

the form of minimum capital ratios, countercyclical capital buffers, or systemic risk buffers - are likely to reduce the incentives for excessive risk-taking.

The paper is organized as follows. In Section 3.2, we outline the theory to motivate our hypotheses on bank capital and risk-taking. Section 3.3 describes the data and empirical strategy. Section 3.4 assesses the suitability of misconduct provisions as an instrument for bank capital. Section 3.5 presents our empirical results on the impact of bank capital on risk-taking. Section 3.6 concludes.

3.2. The Theory of Bank Capital and Risk-taking

The aim of this section is to review the theories that make predictions about the impact of bank capital on risk-taking, and to use these insights to derive our hypotheses. We consider two main strands of the literature, which provide contrasting conclusions.

The first strand of the literature considers the impact of bank capital on the asset risk and insolvency risk for insured and value-maximizing banks. In the absence of any market imperfections, Modigliani and Miller (1958) show that a bank's value is independent of its capital structure. Kareken and Wallace (1978) consider the impact of two market imperfections in the form of bankruptcy costs and deposit insurance. They show that when bankruptcy costs are introduced, unregulated banks will choose a level of risk such that bankruptcy does not occur. But when an additional market imperfection is introduced in the form of a fixed-rate deposit insurance scheme, they show that banks will be incentivised to increase risk-taking because depositors will no longer be incentivised to monitor banks. Furlong and Keeley (1989) build on the work of Karaken and Wallace (1978), as well as Merton (1977) and others, to show that a value-maximizing bank's incentives to increase asset risk will fall as its capital increases. And herein lies the main finding from this first stand of the literature. As such, our first hypothesis is:

H1A. *A decrease in bank capital will lead to an* ***increase*** *in a bank's risk-taking, as measured by their mortgage lending standards.*

The second strand of the literature considers the impact of bank capital on the asset risk and insolvency risk for insured and utility-maximizing banks. The main contributions to this second literature are Kahane (1977) and Koehn and Santomero (1980). Kahane (1977) shows that a combination of minimum capital

ratios and asset portfolio constraints is required to prevent a utility maximizing bank from reaching excessive risk levels. Koehn and Santomero (1980) find that a utility-maximizing bank will respond to an increase in capital ratio requirements by increasing asset risk. This result stems from the idea that the bank will treat leverage and asset risk as substitutes, and so the bank will seek to adjust asset risk when faced with a restriction to leverage in order to achieve its desired total level of risk. As a consequence, the insolvency of some banks - depending on the risk aversion of the bank - may increase rather than decrease when capital requirements are introduced. Kim and Santomero (1988) extend this work to show that appropriately chosen risk-related capital regulation can limit the insolvency. Overall, these findings contradict the main conclusions from the first strand of the literature, and give rise to our second hypothesis:

H1B. *A decrease in bank capital will lead to a* ***decrease*** *in a bank's risk-taking, as measured by their mortgage lending standards.*

Both strands of the literature are subject to several criticisms. The first strand of the literature makes the undesirable assumption that markets are complete, which implies that banks would be indifferent about their asset risk and capital ratios, were it not for bankruptcy costs (Rochet, 1992). The second strand of the literature accounts for incomplete markets, but it does not account for the option value of the deposit insurance subsidy (Keeley and Furlong, 1990). Moreover, it makes other unrealistic assumptions, such as banks being fully liable (Rochet, 1992). Given the limitations associated with both strands of the literature, in addition to the contradictory conclusions, the impact of bank capital on risk-taking is a topic that is worthwhile to consider empirically, and we do so in this paper.

3.3. Data and Methodology

We construct a unique panel dataset that merges bank-level information from published accounts, including information about misconduct provisions, with loan-level administrative data on all regulated UK mortgages over the period from 2010 to 2015. We also include granular regional house price inflation measures and some policy controls. The mortgage data allow us to link information about individual loans and borrowers with information about individual banks. This linking facilitates a rich analysis of the impact of bank capital on risk-taking, as measured by lending standards.

3.3.1. Data

Misconduct Provisions and Bank-level Data

Our sample comprises the 22 largest lenders by mortgage market share in the UK, representing around 96 per cent of all UK mortgage lending over the period from 2010 to 2015. Lenders include both banks and building societies, referred to hereafter simply as 'banks'. We hand-collect our bank-level data from published accounts. These data are semi-annual and include our misconduct provisions data, as well as information about capital ratios and other bank-level variables (e.g. total assets, liquid assets, return-on-assets and non-performing loans).

We collect our data at the consolidated group level because strategic decisions about capital management and lending are typically made at the group level (Bridges et al., 2014). This also holds for misconduct provisions, which are generally made at the group level. There are a few exceptions whereby we do not collect data for the ultimate parent company, however. For example, Tesco Bank is included in our sample and we collect corresponding data for Tesco Personal Fi-

nance Group Limited (the bank) rather than the ultimate parent company Tesco Plc (the food retailer).

Our sample of UK banks offers a useful setting for the question at hand because a number of UK banks, along with other major global banks internationally, have been involved in various misconduct cases. A well-known example is the Libor scandal, which was described by some commentators as the biggest financial scandal in history; four UK banks were initially accused of collusion in manipulating the London interbank offered rate.[3] Additionally, smaller banks and building societies in the UK have been affected by misconduct provisions due to customer redress payments relating to the mis-selling of Payment Protection Insurance (PPI). While the Libor scandal and other similar cases primarily affected the major global banks, customer redress payments related to PPI have affected the UK banking system more broadly.

Beyond the aforementioned Libor manipulation and PPI claims, our data include provisions relating to the following broad range of misconduct issues: Euribor manipulation, foreign exchange market manipulation, money laundering, violations of the US Consumer Credit Act, and US residential mortgage-backed security miss-selling.

We collect data on *provisions* for misconduct fines and customer redress payments, rather than actual fines data, because provisions data are more timely. Misconduct fines can take years to be finalized, following long-ago initial conversations between a bank and the regulator. By contrast, banks are legally required in accord with the International Accounting Standards to make provisions in the period they become aware of any potential misconduct fine or pending customer redress payments. Moreover, banks are required to make a reliable estimate for the size of their pending obligation. We expect banks to adjust their risk-taking

[3] http://www.wsj.com/articles/civil-antitrust-lawsuits-reinstated-against-16-banks-in-libor-case-1464022330

in the period they are subject to a bank capital shock, thus misconduct provisions are the most suitable measure for our analysis.

We limit our bank-level data collection to the period from 2010 to 2015. The start date of our sample coincides with a change in the institutional setting. Namely, a new penalties regime for determining financial penalties in enforcement cases was introduced on 6 March 2010, and this regime has seen a considerable increase in the provisions relating to misconduct fines. Additionally, new rules for selling PPI were introduced on 1 December 2010 and applied retrospectively, leading to large misconduct provisions to pay for customer compensation over the miss-selling of PPI. We discuss the institutional setting in more detail in Section 3.4, when we assess the suitability of misconduct provisions as an instrument for bank capital.

Mortgage Data and Measures of Risk-taking

We obtain loan-level data from the Product Sales Database (PSD). The PSD is a regulatory database of all new mortgages in the UK, which is collected on a quarterly basis by the FCA starting from April 2005. It comprises all regulated mortgages, and so excludes other unregulated products such as buy-to-let mortgages.

For each loan, we have detailed information about the mortgage contract, including the loan value, the property value, the date the mortgage was made, the mortgage term, the mortgage type (e.g. first-time buyer, home mover, re-mortgagor), and the repayment type (e.g. fixed interest rate, variable interest rate). We also have information about the borrower associated with each loan, including: age, employment status, income, whether the borrower has an impaired repayment history, and the postcode of the home address of the mortgagor. The postcode information enables us to merge the PSD with granular information on house price inflation, as discussed in the next sub-section. Finally, we have informa-

tion about the lender for each loan. This enables us to merge the PSD with our bank-level data.

The loan-level variables allow us to control for, among others, changes in demand for mortgages from risky borrowers.[4] This is an advantage of our loan-level analysis, as an analysis of lending standards at the portfolio level may fail to detect offsetting shifts in loan-level and borrower characteristics.

The PSD is collected from banks at the individual entity level rather than the bank group level. We therefore consolidate these data so that they correspond to our misconduct provisions and bank-level data, which are at the bank group level. We do so by considering all constituent entities for a given banking group. For example, for the Royal Bank of Scotland Banking Group, we include seven bank entities (The Royal Bank of Scotland Plc, National Westminster Bank Plc, National Westminster Home Loans, Ulster Bank Ltd, Coutts & Company, Adam & Company Plc).

The PSD facilitates a rich analysis of risk-taking in the UK mortgage market. In particular, we consider the following loan-level measures of risk: the loan-to-value (LTV) ratio, the loan-to-income (LTI) ratio, the payment-to-income (PTI) ratio, and whether the borrower has previous loan non-performance (IMPAIRED).

The LTV ratio is one of most important measures of bank risk-taking. In the UK, banks offer quoted interest rates for mortgages that are largely based on LTV buckets. The quoted rate for a given LTV bucket will have a large impact on market share, and thus banks actively target LTV ratios for new mortgage lending flows.

The LTI ratio and PTI ratio are also important in terms of general lending stan-

[4] Similarly, Ionnidou et al. (2015) use borrower characterisics to control for changes in loan demand of risky borrowers in their study of monetary policy and risk-taking.

dards, but these loan features are generally less actively targeted by UK banks. Finally, we include IMPAIRED, which is another important measure of bank risk-taking because banks may actively change their policy on whether they lend to borrowers with a past history of non-performance. The impairment history can thus be a factor that determines whether or not a borrower qualifies for certain mortgage products.

House Price Inflation Data

We supplement our dataset with regional house price data taken from the Price Paid Dataset (PPD). The PPD includes information about all completed residential property transactions for the UK, and is collected and published by the Land Registry. We use average house price data, which are computed on a monthly basis for 380 regions, to a compute regional half-yearly measure of house price inflation. We also use the 2011 Census data on small areas and postcodes to match our house price data with the PSD mortgage data.

Our regional house price inflation measure separate risk-taking related to mortgage credit supply from that related to changes in the demand for mortgage credit from risky borrowers. This is because house price supply has relatively low price elasticity in the UK[5] and the majority of residential purchases are mortgage-financed.[6] As such, changes in house prices provide a proxy for changes in the overall demand for mortgage credit.

Policy Data

We also control for relevant policy changes that may have affected lending standards during our sample period. Namely, we control for the UK government's

[5]Caldera and Johansson (2013) estimate the long-run price elasticity of new housing supply to be around 0.4 for Great Britain.

[6]Around two thirds of all housing transactions are mortgage-financed (Council of Mortgage Lenders, 2015).

Help-to-Buy (HTB) scheme and the Bank of England's Funding for Lending Scheme (FLS).

The HTB scheme was designed to lower the equity required for a home purchase. Thus, the HTB scheme may increase LTV ratios because these borrowers have an effective government guarantee for the initial part of their mortgage. The PSD however does not have a variable that explicitly states whether a borrower was a HTB participant. We therefore create a dummy variable that takes the value one if a borrower meets the conditions for the HTB scheme. These conditions are: the mortgage must be extended by a lender involved in the HTB scheme; the LTV ratio of the mortgage must be in the interval (90,95); the mortgage is granted from 2014 onward; the property value is less than £600,000; the mortgage cannot be an interest-only or offset mortgage; and finally, the LTI ratio of the mortgage is required to be less than 4.5. Our dummy variable assumes all eligible mortgagors participate in the HTB scheme because, the scheme lowers a borrower's mortgage costs, and so it is reasonable to assume a good participation rate.

The FLS was designed to encourage bank lending, and therefore may have influenced lending standards in the UK mortgage market during its implementation. The FLS initially supported both lending to businesses and households, but was subsequently restricted to business lending from 2014 onward. We include the FLS drawings of a bank, scaled by total assets, as an additional policy control variable.

3.3.2. Empirical Strategy

Here we outline the empirical model that we use to evaluate the effect of bank capital on risk-taking. We estimate the following two-stage panel data model:

$$\begin{aligned} \text{CAPITAL}_{j,t} &= a_0 + a_1 \text{MISCONDUCT}_{j,t} + \mathbf{a_2 BANK}_{j,t} + \mathbf{a_3 LOAN}_{i,j,t} \\ &\quad + a_4 \text{HPI}_{i,j,t} + \mathbf{a_5 POLICY}_{i,j,t} + a_{6,t} + u_{i,j,t} \end{aligned} \tag{3.1}$$

$$\begin{aligned} \text{RISK}_{i,j,t} &= b_0 + b_1 \text{CAP}\hat{\text{I}}\text{TAL}_{j,t} + \mathbf{b_2 BANK}_{j,t} + \mathbf{b_3 LOAN}_{i,j,t} \\ &\quad + b_4 \text{HPI}_{i,j,t} + \mathbf{b_5 POLICY}_{i,j,t} + b_{6,t} + e_{i,j,t} \end{aligned} \tag{3.2}$$

Each observation in our dataset corresponds to a mortgage made to borrower i by bank j in period t. We observe banks over time, and in each period the mortgages made by each bank to new borrowers. Therefore, our bank-level information has a panel data structure, but the mortgage-level information has a pooled cross-sectional data structure.

RISK is a measure of bank risk-taking and our dependent variable. We consider the following four measures for RISK: the loan-to-value (LTV) ratio, the loan-to-income (LTI) ratio, the payment-to-income (PTI) ratio, and a dummy variable that takes on the value one if the borrower does not have a standard credit history, and zero otherwise (IMPAIRED). For the first three dependent variables, we estimate a two-stage least squares (2SLS) model. For the last binary dependent variable, we estimate an instrumental variable probit model.

CAPITAL is the ratio of Common Equity Tier 1 capital to risk-weighted assets. This is our key variable of interest in the second equation of our 2SLS panel data model, and the coefficient estimate of this variable will indicate the impact of bank capital on risk-taking. MISCONDUCT is the ratio of a bank's misconduct provisions to their adjusted total assets, where the adjusted total assets are total assets less derivative assets. MISCONDUCT is utilized as an instrumental variable for CAPITAL in the first equation of our two-stage model. We discuss the appropriateness of MISCONDUCT as an instrumental variable in Section 3.4.

BANK is a vector of variables that capture bank characteristics that could influence risk-taking. We include several variables to reflect the financial health of the bank. LIQUIDITY is the ratio of cash and balances at central banks to adjusted total assets. NPL is the non-performing loans ratio. These two measures

should be related to the bank's ability to extend new mortgage credit. Similarly, we include ROA, a bank's return on assets, calculated as the ratio of net profits (before tax and misconduct provisions) to adjusted total assets.[7] LN(ASSETS) is the natural log of adjusted total assets, and it is included to control for potential too-big-to-fail factors relating to risk-taking, as done by Ioannidou et al. (2015).

LOAN is a vector of variables that capture loan-level and borrower characteristics that could influence risk-taking. These variables control for changes in the demand for mortgage credit from borrowers. TERM indicates the length of the mortgage term. REPAYMENT is a set of fixed effects for the repayment type, for e.g. if the loan is "capital and interest". RATE is a set of fixed effects for the rate type, for example if the loan has a fixed rate.

The other variables in **LOAN** relate more directly to the borrower, and the affordability of the mortgage. AGE is the borrower's age. TYPE is a set of fixed effects for the borrower type, for example if the borrower is a first-time borrower. We include IMPAIRED for all specifications except where IMPAIRED is the left-hand side risk measure. VERIFIED is a dummy variable that takes on the value one if the borrower's income has been verified, and zero otherwise. Finally, EMPLOYMENT is a set of fixed effects for employment status.

HPI is our regional house price inflation measure used to control for demand factors. **POLICY** is a vector of policy-related variables that could influence risk-taking, namely HTB and FLS. HTB is a dummy variable for the help-to-buy scheme, which takes on a value of one if the borrower was eligible for the help-to-buy scheme and zero otherwise. FLS is a variable that reflects the Funding for Lending drawings of a given bank, which we scale by adjusted total assets.

Finally, we include a set of half-yearly time fixed effects, $a_{6,t}$ and $b_{6,t}$, to account

[7] We consider net profits before tax and misconduct provisions, because net profits after misconduct provisions are strongly collinear with misconduct provisions. For some banks, the negative correlation between misconduct provisions and net profits after misconduct provisions is more than 80 per cent.

for unobservable bank-invariant characteristics, including macro-economic conditions. These time fixed effects further absorb all banking sector-wide factors relating to changes in the definition of capital and capital requirements. This is relevant for our setting because we consider the Basel III Common Equity Tier 1 ratio for our analysis of bank capital, but prior to 2014 the broadly equivalent Basel II measure was the "Core Tier 1 ratio". These two capital ratios are similar but have some differences in their definitions. Thus, in 2014 there is a step change in this ratio affecting all banks, and this change is absorbed by the time fixed effects.

The time fixed effects also absorb the effects of other banking sector-wide regulatory factors, such as changes to the minimum capital requirements and standards, as well as newer macroprudential regulations such as the countercyclical capital buffer and LTI restrictions. Finally, these time fixed effects will capture changes in the level of competitiveness of the banking sector, which is likely to influence lending standards.

We are primarily interested in the coefficient estimates for MISCONDUCT in Equation 3.1 and for CAPITAL in Equation 3.2. For Equation 3.1, we require the coefficient estimate for MISCONDUCT (a_1) to be significant in order for MISCONDUCT to be a valid instrument. We expect the sign of a_1 to be negative, as discussed in the next section. For Equation 3.2, the coefficient estimate for CAPITAL (b_1) directly tests our core hypotheses. Hypothesis **H1A** implies $b_1 < 0$. That is, that a decrease in the bank capital ratio will lead to an *increase* in a bank's risk-taking. Hypothesis **H1B** implies $b_1 > 0$. That is, that a decrease in the bank capital ratio will lead to a *decrease* in a bank's risk-taking.

Table 3.1 describes all variables included in our models, and Table 3.2 presents the corresponding summary statistics. Most summary statistics are computed at the loan-level, but we compute the summary statistics for the bank-level variables on the bank panel only and un-weighted by the amount of loans in each period.

Although the total possible number of bank-half year observations is 264, we report summary statistics for the 227 clusters that are ultimately employed for our empirical specification. Of the 37 bank-half year clusters that are missing from our analysis, 26 clusters are excluded due to missing bank-level information. In these cases, the bank-level information is missing due to either no publicly available half-yearly reports, or key variables in our empirical specification that are not reported within a given half-yearly report. The remaining 11 clusters are excluded due to missing loan-level information. We also have a different number of mortgage-half year observations for the summary statistics for some of the loan-level variables due to missing loan-level information.

Table 3.1.: Definitions and Data Sources of Variables in Empirical Model

This table describes all variables included in our empirical model. Adj. total assets are total assets less derivative assets.

Variable Name	Variable Description	Data Sources
Dependent Variables		
LTV	Loan-to-value ratio of a mortgage	FCA's Product Sales Database
LTI	Loan-to-income ratio of a mortgage	
PTI	Repayment-to-income ratio of a mortgage	
IMPAIRED	Takes the value 1 if the borrower has any credit history impairment, 0 otherwise	
Bank-level Variables		
MISCONDUCT	Misconduct provisions/Adj. total assets	Banks' published accounts
CAPITAL	Capital ratio, calculated as: Common equity tier 1 capital/Risk-weighted assets	
LN(ASSETS)	Log of adj. total assets	
LIQUIDITY	Liquidity ratio, calculated as: Cash & balances at central banks/Adj. total assets	
NPL	Non-performing loans ratio	
ROA	Return on assets, calculated as: Net profits (before tax and misconduct provisions) /Adj. total assets	
Loan-level and Borrower Variables		
RATE	Mortgage rate type. Categories: fixed; discount; trackers; capped; standard variable rate; other	FCA's Product Sales Database
REPAYMENT	Repayment type. Categories: capital & interest; interest only (endowment); interest only (pension); interest only (other); mix of capital & interest & interest only; unknown; other	
TERM	Remaining years until mortgage maturity	
TYPE	Borrower type. Categories: business; first-time buyer; home mover; remortgagor; social tenant	
VERIFIED	Takes the value 1 if the borrower had their income verified, 0 otherwise	
EMPLOYMENT	Employment status. Categories: employed; self-employed; retired; other	
AGE	Age of the borrower	
HPI	6 month house price inflation for local authority (at local authority level, not individual loan-level)	Land Registry's Price Paid Dataset
Policy Variables		
HTB	Takes the value 1 if the borrower is eligible to participate in the Help-to-Buy scheme, 0 otherwise	Authors' calculations
FLS	Calculated as: Bank drawings from the Funding for Lending Scheme/Adj. total assets	Bank of England

Table 3.2.: Summary statistics

For all variables included in the empirical specifications, this table provides their mean, standard deviation, 5th percentile, median, and 95th percentile. The number of mortgage-half year observations is 4,589,174. The number of bank-half year observations is 227. The number of region-half year observations is 4,560. Statistics for bank-level variables are computed for the bank-panel rather than weighted by the amount of loans in the loan-level data. Bank-type is a dummy variable, which takes the value one for a bank and zero for a building society. We do not provide summary statistics for several variables in our empirical specification, including RATE, REPAYMENT, TYPE and EMPLOYMENT because these are multi-category variables. Information about these variables is available upon request.

Variable name	Unit	Mean	Std. dev.	5th %tile	50th %tile	95th %tile
Dependent Variables						
LTV	%	63.60	22.33	19.63	70.00	90.00
LTI	-	2.93	1.89	0.98	2.91	4.71
PTI	%	9.55	5.97	2.35	9.00	18.30
IMPAIRED	0/1	0.0029	0.053	0	0	0
Bank-level Variables						
MISCONDUCT	%	0.080	0.19	0.00	0.0093	0.36
CAPITAL	%	13.65	4.13	8.98	12.80	22.50
LN(ASSETS)	£bn	11.27	2.16	8.30	10.66	14.81
LIQUIDITY	%	7.02	4.23	0.72	6.40	14.36
NPL	%	4.18	12.80	0.38	2.52	11.32
ROA	%	0.22	0.37	-0.39	0.23	0.80
BANK-TYPE	0/1	0.47	0.50	0	0	1
Loan-level and Borrower Variables						
TERM	Years	22.09	8.12	8	23	35
VERIFIED	0/1	0.80	0.40	0	1	1
AGE	Years	39.11	10.21	25	38	57
HPI	%	1.72	3.39	-3.64	1.62	7.42
Policy Variables						
HTB	0/1	0.027	0.16	0	0	0
FLS	%	0.27	1.10	0.00	0.00	1.97

3.4. Misconduct Provisions as an Instrument for Bank Capital

Estimating the impact of bank capital on risk-taking is challenging due to simultaneity. The issue of simultaneity arises because asset risk - such as the LTV ratio of a mortgage - has a direct effect on the denominator of capital ratios, the risk weighted assets.[8] Additionally, theory suggests that bank capital and risk-taking are jointly determined. If risk-weights are imperfect, then banks will jointly choose a level of capital and risk that is consistent with their overall desired level of risk (Kim and Santomero, 1988). Given this simultaneity, we require an instrument that influences bank capital but is otherwise unrelated to risk-taking, in order to isolate the causal effect of bank capital on risk-taking. We propose misconduct provisions as such an instrument, and evaluate the merits of this instrument below.[9]

3.4.1. Do Misconduct Provisions meet the Exclusion Restriction?

For misconduct provisions to qualify as a valid instrument for bank capital, they should have no effect on risk-taking, as well as other factors that independently influence risk-taking, except through their impact on bank capital. That is, our instrument must satisfy the exclusion restriction. Are misconduct provisions indeed unrelated to risk-taking? The institutional setting, as well as the timing

[8] For the standardized approach of Basel II, the risk weight of a mortgage with an LTV less than 80 is 35 per cent, and otherwise 75 per cent on the balance of a loan for a LTV ratio above 80. For the Internal Ratings Based (IRB) approach of Basel II, the risk weight is determined by a formula that is based on the probability of default, loss given default and exposure at default of the mortgage. The IRB approach is used by the larger banks in our sample, which conduct the majority of mortgage lending. And the Basel II requirements are most relevant for our study because they came into force in early 2008.

[9] Instrumental variable techniques also solve any problems that may exist regarding measurement error of bank capital.

and nature of the misconduct provisions included in our sample, provide a strong case for this.

The Financial Conduct Authority (FCA) is responsible for consumer protection and the maintenance of market integrity in the UK, and is therefore responsible for issuing misconduct fines relating to a broad range of activities. The Financial Services Authority (FSA), which preceded the FCA, introduced in March 2010 a new penalties regime for determining financial penalties in enforcement cases. This new regime, which the FCA continues to apply, has seen a considerable increase in the provisions relating to misconduct fines and customer redress payments. The regime aims to create a consistent and transparent framework for determining financial penalties in enforcement cases, and the approach is based on the principles of "disgorgement, discipline and deterrence" (FSA, 2009).

The penalty policy of the FCA clearly states that financial penalties are imposed because a bank has engaged in some kind of misconduct; they are not imposed due to prudential concerns relating to a bank's *asset* risk-taking. Moreover, financial penalties are made in respect of misconduct - and the associated profits - for activities that have since ceased, implying that the associated misconduct provisions are unrelated to current bank profits or other characteristics.

These arguments are well illustrated by the type of misconduct provisions included in our sample. More than half of all misconduct provisions included in our sample are for Payment Protection Insurance (PPI) claims.[10] Provisions for PPI claims occur because a bank has *previously* miss-sold the insurance product, not because they are currently engaged in asset risk-taking. One might of course argue that a bank that miss-sells more PPI may also make more high-risk loans. But even if this were the case, provisions for PPI claims do not relate to a bank's current activities but rather to claims for policies often sold more than 10 years

[10]PPI claims are customer redress payments, not financial penalties. But customer redress payments are similar to financial penalties; they occur because a bank has previously miss-sold a product and must therefore provide customer compensation.

prior, as noted by Barclays in their 2012 Q1 trading statement. Some banks in fact no longer write PPI: Lloyds Banking Group ceased writing any new PPI, as noted in their 2010 half yearly report, prior to their first provision for PPI claims in 2011.

Other significant misconduct provisions included in our sample relate to market manipulation. The main cases concern the manipulation of Libor, Euribor and foreign exchange markets. It is difficult to argue that a bank that engages in the manipulation of markets is also more likely to take on asset risk; market manipulation and asset risk are two different forms of risk-taking. But even if one does not accept this line of argument, it remains the case that provisions for market manipulation do not relate to a bank's current activities, and therefore to their current risk-taking. These instances of market manipulation had long ceased by the time the involved banks provisioned for potential fines. For example, the manipulation of Libor is believed to have ceased around 2008 and no later than 2009, whereas banks did not make provisions for the associated fines until 2012 or later. During this time, the three major UK banks in receipt of fines relating to Libor manipulation have undergone changes to their executives and boards, as well as changes in response to the aftermath of the financial crisis. To the extent that one believes that market manipulation and asset risk-taking are related, it is unlikely that a bank's misconduct many years prior could be considered a direct indicator of their asset risk-taking in 2012.

3.4.2. Do Misconduct Provisions affect Bank Capital?

A second requirement for misconduct provisions to qualify as a valid instrument is that these provisions have a significant effect on bank capital. That is, we require the instrument to be very significant in our first-stage analysis. One would expect this to be the case *ex ante* because misconduct provisions affect the

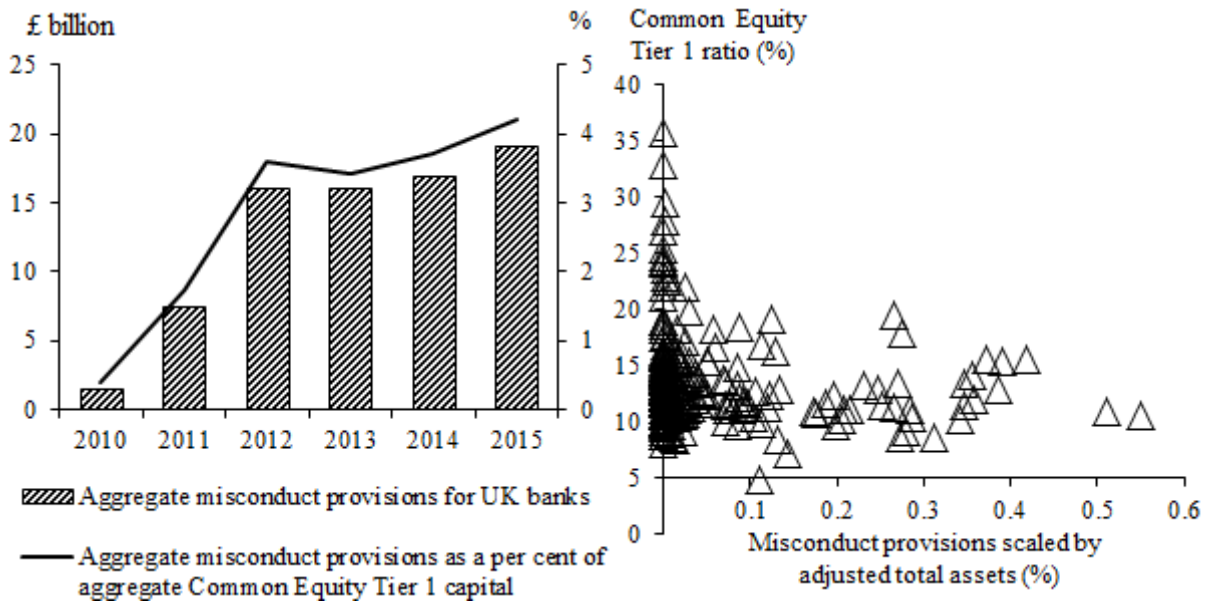


Figure 3.1.: The Effect of Misconduct Provisions on Bank Capital
The left panel plots the aggregate misconduct provisions for the 22 UK banks in our sample, as well as the ratio of the aggregate misconduct provisions to the aggregate Common Equity Tier 1 capital, over the period 2010 to 2015. The right panel is a scatter plot of misconduct provisions (scaled by adjusted total assets) and the Common Equity Tier 1 ratio for the 22 UK banks in our sample. The scatter plot does not display the following (CET1 ratio, Misconduct provisions) outlying observations: (13.95, 0.68), (16.20, 0.78), (12.84, 1.01), (13.29, 1.21), (12.06, 1.82).

numerator of the bank capital ratio by way of an accounting identity. Namely, misconduct provisions reduce retained earnings, which would otherwise contribute to Common Equity Tier 1 (CET1) capital, and therefore reduce potential capital contributions.

All of the UK banks in our sample have made misconduct provisions during our sample period, and the magnitude of these provisions has often been substantial. The left panel of Figure 3.1 plots the aggregate misconduct provisions for the 22 UK banks in our sample, as well as the ratio of the aggregate misconduct provisions to the aggregate CET1 capital, over the period 2010 to 2015. Aggregate misconduct provisions peaked in 2015 at around £19 billion, and were by then equivalent to around 4 per cent of aggregate CET1 capital. The aggregate CET1 ratio (CET1 capital scaled by risk-weighted assets) was 12.7 for our sample in 2014. Thus, holding all else equal, these misconduct provisions would reduce the

CET1 ratio from 12.7 in 2014 to 12.1 in 2015.

Of course, all else is not equal, and there are many other moving parts that can affect the CET1 ratio. For example, banks can simultaneously adjust their risk-weighted assets, the denominator of a bank's capital ratio, thereby mitigating any impact from misconduct provisions on their capital ratios. Nonetheless, we find a significant and negative correlation between misconduct provisions and bank capital ratios, even after controlling for a wide range of relevant factors. The right panel of Figure 3.1 is a scatter plot of misconduct provisions (scaled by adjusted total assets) and the CET1 ratio for the 22 UK banks in our sample. The plot suggests there is a negative and nonlinear relationship between the scaled misconduct provisions and the CET1 ratio for our sample.

Table 3.3 considers the impact of misconduct provisions on bank capital more systematically. This table presents the results of the first stage of our analysis, and a more comprehensive version of these results that includes the coefficient estimates for all control variables can be found in Table 3.8 in Appendix 3.A. We regress bank capital (CAPITAL) on misconduct provisions scaled by adjusted total assets (MISCONDUCT), as outlined by Equation 3.1. We also include all control variables that will enter Equation 3.2 in our first-stage regression, because failure to do so can result in inconsistent two-stage estimators.

Prior to a discussion of the the estimates for the proposed instrument, MISCONDUCT, it is worth noting that the coefficient estimates for all control variables appear sensible, as reported in Table 3.8in Appendix 3.A. Of most interest, an increase in bank size and an increase in non-performing loans are both associated with a decrease in bank capital, holding all else equal.

Column (1) of Table 3.3 presents the results of the specification outlined by Equation 3.1, where standard errors are heteroskedasticity-robust and clustered by bank-half year group. These results suggest that MISCONDUCT has a nega-

Table 3.3.: Misconduct provisions as an instrument for bank capital

The table presents coefficient estimates for Equation 3.1, the first-stage regression of the CET1 ratio (CAPITAL) on misconduct provisions scaled by adjusted total assets (MISCONDUCT) and the relevant control variables. Column (1) presents the baseline results, with MISCONDUCT as an instrument. Column (2) presents results that include an additional bank-type dummy variable, which takes the value one for a bank and zero for a building society. Column (3) presents the results that include bank fixed effects in addition to the bank control variables. Column (4) and Column (5) present the results from a similar specification to that presented in Column (1) and Column (2), respectively, but include MISCONDUCT^2 as an additional instrument. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and the standard errors of the coefficient estimates are in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	(1)	(2)	(3)	(4)	(5)
Instrument					
MISCONDUCT	-3.64***	-3.69***	-1.48	-5.30**	-4.38*
	(1.23)	(1.18)	(0.99)	(2.61)	(2.46)
MISCONDUCT^2				1.57	0.66
				(1.52)	(1.38)
Control variables					
BANK CONTROLS	√	√	√	√	√
LOAN CONTROLS	√	√	√	√	√
HPI	√	√	√	√	√
POLICY CONTROLS	√	√	√	√	√
TIME FIXED EFFECTS	√	√	√	√	√
BANK FIXED EFFECTS	×	×	√	×	×
BANK-TYPE FIXED EFFECTS	×	√	×	×	√
Model statistics					
Number of clusters	227	227	227	227	227
Number of observations	4,589,174	4,589,174	4,589,174	4,589,174	4,589,174
F-statistic for instrument	8.82***	9.85***	2.20	5.82***	8.56***

tive impact on CAPITAL, and the coefficient estimate is significant at the 1 per cent level. Specifically, an increase of one standard deviation in scaled misconduct provisions (equivalent to a 0.19 percentage points increase) will lead to a 0.69 percentage point decrease in the CET1 ratio, holding all else equal.

We also examine additional diagnostics to assess the strength of our identification strategy. We first consider the F-statistic for the null hypothesis that the coefficient estimate of MISCONDUCT is equal to zero. The F-statistic is 8.82, while Straiger and Stock (1997) suggest as a "rule of thumb" that this should be greater than 10 in order to be considered a strong instrument. Applying the more precise critical values of Stock and Yogo (2005), this corresponds to a 5 per

cent level test that the maximum size is no more than 20 per cent, meaning that the maximum 2SLS size distortion is no more than 15 per cent.[11]

Caution is however required when considering this F-statistic and the Stock and Yogo (2005) critical values for our particular setting. This is because the "rule of thumb" and the Stock and Yogo (2005) critical values are valid only for i.i.d. errors, whereas we employ cluster-robust standard errors. The Stock and Yogo (2005) critical values are therefore likely to be inappropriate in this instance, given that it is unlikely that the thousands of mortgages made by the same bank in the same period are i.i.d. Nonetheless, we are able to draw on two alternative tests in our second-stage analysis, which are cluster-robust test statistics and robust in the presence of weak instruments. Namely, we consider the Anderson-Rubin test and the Stock-Wright S statistic in Section 3.5, which both provide strong support for our specifications. Given that these test statistics are cluster-robust and robust in the presence of weak instruments, their results dominate the first-stage inferences from the F-statistic about instrument strength.

Table 3.3 also considers some additional specifications for Equation 3.1. Column (2) presents the results of this specification with an additional bank-type dummy variable, which takes the value one for a bank and zero for a building society. These results are similar to those for our baseline specification in Column (1), in terms of the magnitude, sign and significance of MISCONDUCT.

Column (3) presents the results of the specification outlined by Equation 3.1 with bank fixed effects included in addition to the bank control variables. The results suggest that MISCONDUCT is not a valid instrument in this alternative specification, as indicated by the insignificant coefficient estimate.

The reason that MISCONDUCT is no longer a valid instrument for CAPITAL

[11] That is, one is rejecting a test statistic at the 15 per cent level rather than the 5 per cent level.

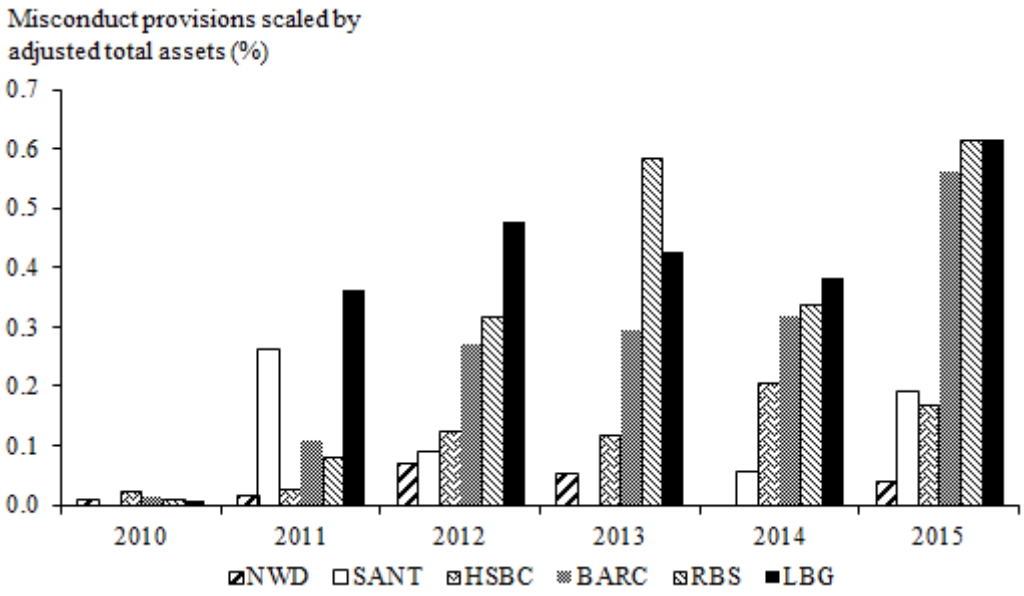


Figure 3.2.: Misconduct provisions for the largest six UK banks
The figure shows misconduct provisions (scaled by adjusted total assets) for the largest six UK banks in our sample, over the period 2010 to 2015.

when bank fixed effects are included is that there is insufficient variation left in MISCONDUCT, after having controlled for both bank fixed effects and time fixed effects. Figure 3.2 plots the scaled misconduct provisions for the largest six UK banks in our sample, over the period 2010 to 2015. This figure shows that there is considerable persistence in misconduct provisions for each bank. That is, banks that have higher misconduct provisions in a given year tend to have higher misconduct provisions in other years also, with the relative ranking of misconduct provisions among banks remaining fairly stable across the years.

We also examine the persistence of misconduct provisions more formally by considering the Spearman's rank correlation coefficient across different years for all banks in our sample. The results are summarized in Table 3.11 in Appendix 3.B. The Spearman's rank correlation coefficient is on average about 80 per cent across all pairwise year combinations (including non-successive year combinations) from 2011 to 2015, which suggests that the relative position of misconduct provisions (scaled by total assets) is largely stable across the years for our sample of banks. In sum, we cannot include bank fixed effects in our specification because this

would render our inferences invalid.

Column (4) presents the results from a similar specification to that presented in Column (1), but includes the square of MISCONDUCT as an additional instrument. That is, we estimate the following model:

$$\begin{aligned} \text{CAPITAL}_{j,t} &= a_0 + a_1 \text{MISCONDUCT}_{j,t} + a_2 \text{MISCONDUCT}_{j,t}^2 + \mathbf{a_3 BANK}_{j,t} \\ &\quad + \mathbf{a_4 LOAN}_{i,j,t} + a_5 \text{HPI}_{i,j,t} + \mathbf{a_6 POLICY}_{i,j,t} + a_{7,t} + u_{i,j,t} \end{aligned} \tag{3.3}$$

We include the additional squared term of MISCONDUCT, because the scatter plot depicted in the right panel of Figure 3.1 suggests that scaled misconduct provisions and the CET1 ratio have a negative but nonlinear relationship. The F-statistic for the two instruments is 5.82, which is below the critical values of Stock and Yogo (2005). But, as mentioned earlier, these critical values are not valid for our setting and the literature currently provides no alternatives. And we show in Section 3.5 that the Anderson-Rubin Wald statistic and the Stock-Wright S statistic provide strong support for this specification. Given the support from Figure 3.1, combined with evidence from the Anderson-Rubin Wald statistic and the Stock-Wright S statistic in the next section, we use the specification from Equation 3.3, with the associated results in Column (4) of Table 3.3, as our baseline model. We also report the results from the specification with only MISCONDUCT as an instrument as a robustness exercise.

Finally, Column (5) presents the results of the specification outlined by Equation 3.3 with the additional bank-type dummy variable. These results are similar to those for our baseline specification in Column (4).

3.5. The Effect of Bank Capital on Risk-taking

3.5.1. Naive Results for the Impact of Bank Capital on Risk-taking

We now examine the effect of bank capital on risk-taking. Prior to a discussion of our main results, we present the "naive" results from a specification that does not account for the endogeneity between the variables RISK and CAPITAL. The coefficient estimates of these results will therefore be biased. These results serve as benchmark for our main results. Table 3.4 presents coefficient estimates for the regression of RISK on CAPITAL and the other relevant control variables, where we employ the variable CAPITAL rather than the instrumented version of CAPITAL. Table 3.9 in Appendix A is a comprehensive version of Table 3.4, which includes the coefficient estimates of all variables and not just of the main variable of interest, CAPITAL. The results from the naive specification suggest a negative relationship between bank capital and our measures of risk-taking, i.e., they support hypothesis **H1A**.

In Column (1) of Table 3.4 we present the results for the first measure of RISK, the LTV ratio. The LTV is an actively targeted measures of risk-taking for the UK mortgage market. The OLS results suggest a negative relationship between bank capital and the LTV ratio, which is significant at the 1 per cent level. This result is also economically significant, and a 4.13 percentage point (i.e. one standard deviation) decrease in Common Equity Tier 1 capital is on average associated with a 0.74 percentage point increase in the LTV ratio.

In Column (2) and Column (3) of Table 3.4 we present the results for the LTI ratio and the PTI ratio, respectively. The LTI and PTI are also important measures of lending standards, but they are less actively targeted by banks than the

Table 3.4.: Naive Regression Results for the Impact of Bank Capital on Risk-taking

The table presents coefficient estimates for Equation 3.2, the regression of RISK on CAPITAL and the relevant control variables. For these results we employ the variable CAPITAL rather than the instrumented version of CAPITAL. The RISK measures are: LTV, LTI, PTI, and IMPAIRED, which are reported in Column (1) through to Column (4). Column (1) through to Column (3) present results estimated by ordinary least squares. Column (4) presents results estimated by a probit model. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Bank Capital				
CAPITAL	-0.18**	-0.018***	-0.074***	-0.019**
	(0.082)	(0.0037)	(0.012)	(0.0093)
Control Variables				
BANK CONTROLS	√	√	√	√
LOAN CONTROLS	√	√	√	√
HPI	√	√	√	√
POLICY CONTROLS	√	√	√	√
TIME FIXED EFFECTS	√	√	√	√
Model Statistics				
Number of clusters	227	227	227	227
Number of observations	4,589,174	4,563,024	3,253,692	4,584,637
F statistic/ Wald statistic	1,969.50***	598.59***	567.36***	1,475.92***
Centered R2/ Pseudo R2	0.40	0.11	0.27	0.021

LTV ratio. Once more, we find a negative relationship between bank capital and these two risk-taking measures, and both results are significant at the 1 per cent level. A one standard deviation decrease in Common Equity Tier 1 capital is on average associated with a 0.074 increase in the LTI ratio, and a 0.31 percentage point in the PTI ratio, holding all else constant.

In Column (4) of Table 3.4 we present the results for the final measure of RISK, whether the borrower has a history of impairment. The probit results also suggest a negative relationship between bank capital and the likelihood that a bank will issue a loan to borrowers with a history of non-performance. This result is statistically significant at the 5 per cent level.

3.5.2. Main Results for the Impact of Bank Capital on Risk-taking

Due to the likely endogeneity between bank capital and risk-taking, however, the estimates presented in Table 3.4 should be considered with caution. For this reason, we now outline our main specification to estimate the impact of bank capital on risk-taking using misconduct provisions and their square as instrumental variables for bank capital. By employing instrumental variable techniques, these models link exogenous variation in bank capital to actual variation in risk-taking.

Table 3.5 presents coefficient estimates for Equation 3.2 of our main specification, the regression of RISK on CAPITAL and the other relevant control variables, where bank capital is instrumented by both scaled misconduct provisions and its square. Table 3.10 in Appendix A is a comprehensive version of Table 3.5, which includes the coefficient estimates of all variables and not just the of main variable of interest, CAPITAL. The results in Table 3.5 confirm the findings reported in Table 3.4 to the extent that they show a negative relationship between bank capital and our measures of risk-taking. That said, the magnitude of the coefficient estimates strongly varies between Table 3.4 and Table 3.5. The coefficient estimates presented in Table 3.5 can be considered more reliable, however given that we now employ an instrument to correct for the simultaneity between the variables RISK and CAPITAL.

In Column (1) of Table 3.5 we present the results for the first measure of RISK, the LTV ratio. The 2SLS results suggest that a 4.13 percentage point decrease in Common Equity Tier 1 ratio - which is equivalent to a one standard deviation decrease - will lead to a 7.76 percentage point increase in the LTV ratio, holding all else constant, and this relationship is significant at the 5 per cent level. The more reliable coefficient estimate from the 2SLS results is much more economically significant than the biased OLS results.

Table 3.5.: Main Regression Results for the Impact of Bank Capital on Risk-taking

The table presents coefficient estimates for Equation 3.2, the second-stage regression of RISK on CAPITAL and the relevant control variables, where CAPITAL has been instrumented by MISCONDUCT and MISCONDUCT^2. The RISK measures are: LTV, LTI, PTI, and IMPAIRED, which are reported in Column (1) through to Column (4). Column (1) through to Column (3) present results estimated by two-stage least squares. Column (4) presents results estimated by an instrumental variable probit model. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Bank Capital				
CAPITAL	-1.88**	-0.069*	-0.13*	-0.14**
	(0.89)	(0.039)	(0.067)	(0.072)
Control Variables				
BANK CONTROLS	√	√	√	√
LOAN CONTROLS	√	√	√	√
HPI	√	√	√	√
POLICY CONTROLS	√	√	√	√
TIME FIXED EFFECTS	√	√	√	√
Model Statistics				
Number of clusters	227	227	227	227
Number of observations	4,589,174	4,563,024	3,253,692	4,584,637
F statistic for instrument (first stage)	5.82***	5.84***	7.73***	5.82***
Anderson-Rubin test	39.05***	9.62***	4.19	n.a.
Stock-Wright S statistic	23.37***	17.82***	9.37***	n.a.
Hansen J statistic	0.073	1.986	1.043	n.a.
p-value for Hansen J statistic	0.79	0.16	0.31	n.a.
Wald statistic	56,322.89***	20,926.22***	28,870.90***	1,343.35***
Centered R2	0.36	0.10	0.27	n.a.

In Column (2) and Column (3) of Table 3.5 we present the results for the LTI ratio and the PTI ratio, respectively. A one standard deviation decrease in Common Equity Tier 1 ratio is on average associated with a 0.28 and 0.54 increase in the LTI ratio and PTI ratio, respectively, holding all else constant. The results for the LTI ratio and the PTI ratio are both significant at the 10 per cent level. In Column (4) of Table 3.5 we present the results for the final measure of RISK, whether the borrower has a history of impairment. The instrumental variable

probit results suggest that a bank with a lower capital ratio is more likely to issue a loan to borrowers with a history of non-performance. As with the results for the LTV ratio, the results in Table 3.5 for the LTI ratio, the PTI ratio and IMPAIRED are much more economically significant than the biased results presented in Table 3.4.

We report a number of model statistics in Table 3.5, which provide support for our results regarding the impact of bank capital on risk-taking. We first consider the Anderson-Rubin test, which is a cluster-robust test statistic, and is also robust in the presence of weak instruments; the results from the Anderson-Rubin test therefore dominate the first-stage inferences about instrument strength that we discussed in Section 3.4.2. The Anderson-Rubin test examines the joint null hypothesis that both the coefficient estimate of our endogenous variable CAPITAL in Equation 3.2 is equal to zero and that our over-identifying restrictions are valid (if there is more than one instrument). We reject the null hypothesis of the Anderson-Rubin test at the 1 per cent level for our results relating to the LTV ratio and the LTI ratio in Column (1) and Column (2), respectively. We also consider the Stock-Wright S statistic, which is a generalized version of the Anderson-Rubin test with the same null hypothesis, and is similarly a cluster-robust and weak instrument-robust test. Here we can reject the null hypothesis for all relevant instances, which provides support for our results about the impact of bank capital on risk-taking reported in Column (1), Column (2) and Column (3). These test statistics do not apply to the instrumental variable probit model results of Column (4) however.

We also consider the Sargan-Hansen test. The null hypothesis of the Sargan-Hansen test is that the over-identifying restrictions are valid, which implies that the instruments satisfy the exclusion restriction and are uncorrelated with the error process in Equation 3.2. This statistic is far from rejection for the results in Column (1), Column (2) and Column (3), which provides additional confidence

that we can use both MISCONDUCT and MISCONDUCT^2 as instruments for bank capital. Once more, this test does not apply to the results in Column (4) however. Additionally, given the results of the Sargan-Hansen test, this implies that our rejection of the Anderson-Rubin and Stock-Wright S statistic above was because the coefficient estimate of CAPITAL is different from zero, rather than the over-identifying restrictions being invalid.[12]

Overall, these results provide support for our first hypothesis outlined in Section 3.2 that a decrease in bank capital will lead to an increase in a bank's risk-taking, as measured by their mortgage lending standards. Thus, these results provide support for the theoretical insights of Furlong and Keeley (1989) and Kareken and Wallace (1978).

As mentioned, a more comprehensive version of these results is reported in Table 3.10 in Appendix A, which includes the coefficient estimates for all other control variables and not just the main variable of interest. Those estimates are broadly inline with our expectations. For example, an increase in bank size - as measured by the log of adjusted total assets - is associated with a statistically significant decrease in the LTV ratio, holding all else constant. Similarly, an increase in bank size is associated with a statistically significant decrease in the proportion of loans made to impaired borrowers. These results supports the charter value hypothesis first proposed by Keeley (1990), which states that banks will reduce their risk to protect a higher charter value. More generally, these results complement our findings regarding the impact of bank capital on risk-taking.

[12]One weakness of the Anderson-Rubin test and the Stock-Write S statistics is that when there is more than one instrumental variable, there is uncertainty about whether a rejection of the null hypothesis is because the coefficient estimate of the instrumented variable is different from zero or because the over-identifying restrictions are invalid. Thus, the results of the Sargan-Hansen test here provides clarity about these results, because we cannot reject that the over-identifying restrictions are valid. Our robustness checks also include a specification with only one instrument. When there is only one instrument, a rejection of the null hypothesis implies that the coefficient estimate of the instrumented variable is different from zero. And we find this to be the case in our robustness checks.

3.5.3. Robustness Checks

The findings in this study are robust to a number of alternative modeling strategies. Table 3.6 presents the coefficient estimates for CAPITAL from the regressions of RISK on CAPITAL and the other relevant control variables in Equation 3.2, where bank capital is instrumented by MISCONDUCT, for three alternative specifications. Row (A) presents the results from a specification where bank capital is instrumented by MISCONDUCT only (i.e. without MISCONDUCT^2). The coefficient estimates for CAPITAL and their significance levels for the results in Row (A) are similar to our main results in Table 3.5, although we find that the negative relationship between the LTI ratio and bank capital is no longer statistically significant.

Row (B) presents the results from a specification where the five largest observations of MISCONDUCT are excluded.[13] These observations are significantly

[13]We exclude the following (CET1 ratio, Misconduct provisions) outliers: (13.95, 0.68), (16.20,

Table 3.6.: General Robustness Checks for the Impact of Bank Capital on Risk-taking

The table presents coefficient estimates for CAPITAL in Equation 3.2, the second-stage regression of RISK on CAPITAL and the relevant control variables, where CAPITAL has been instrumented by MISCONDUCT. The RISK measures are: LTV, LTI, PTI, and IMPAIRED, which are reported respectively in Column (1) through to Column (4). Column (1) through to Column (3) present results estimated by two-stage least squares. Column (4) presents results estimated by an instrumental variable probit model. Three robustness checks are reported. Row (A) includes and MISCONDUCT^2 as an additional instrument for CAPITAL. Row (B) excludes the 5 largest MISCONDUCT observations. Row (C) The third includes a bank-type dummy variable, which takes the value 1 for a bank and 0 for a building society. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
(A) *MISCONDUCT as only instrument*	-1.84**	-0.050	-0.10*	-0.11*
	(0.78)	(0.036)	(0.057)	(0.063)
(B) *Excluding MISCONDUCT outliers*	-1.63**	-0.10**	-0.21**	-0.15*
	(0.86)	(0.042)	(0.086)	(0.084)
(C) *Including bank-type dummy variable*	-1.88**	-0.059*	-0.12**	-0.13*
	(0.87)	(0.035)	(0.062)	(0.067)

larger than average and so could influence our overall results. Here the coefficient estimates for CAPITAL and their significance levels for the results are broadly similar to our main results in Table 3.5. Row (C) presents the results from a specification where we include a bank-type dummy variable, which takes the value one for a bank and zero for a building society. Once more, the coefficient estimates for CAPITAL and their significance levels are similar to our main results in Table 3.5. Overall, the results from the three alternative specifications in Table 3.6 provide further support for our main finding that an exogenous and negative change in bank capital will lead to an increase in risk-taking via mortgage lending standards.

In Table 3.7 we examine several alternative measures of risk-taking as the dependent variable. We first consider SIZE, which is a variable for the individual loan value, and the results are reported in Column (1). There are two different ways to interpret any results for SIZE. The theoretical literature on loan-level default finds that the probability of a loan default increases in the value of the loan (see, for example, Arellano et al., 2012, Corbae and Quintin, 2015). In this case, the size of a loan can be viewed as another measure of risk-taking, and so a negative coefficient estimate for bank capital would suggest that banks increase their risk as bank capital decreases. On the other hand, the empirical literature that uses loan-level data interprets the change in the value of the loan as a measure for a change in credit supply (see, for example, Uluc and Wieladek, 2015, Jimenez et al., 2013). According to this alternate view, a positive coefficient estimate for bank capital would imply that banks reduce their lending in response to a negative bank capital shock, which is in line with previous findings (see, for example, Bernanke and Lown, 1991, Peek and Rosengren, 1995a, Peek and Rosengren, 1995b, Gabacorta and Mistrulli, 2004). All of this said, however, we do not find any statistically significant relationship between bank capital and SIZE.[14]

0.78), (12.84, 1.01), (13.29, 1.21), (12.06, 1.82).

[14]This finding holds also when we take the log of loan value, as done by Uluc and Wieladek

Table 3.7.: Robustness Checks for the Impact of Bank Capital on Risk-taking using Alternative Risk Measures

The table presents coefficient estimates for Equation 3.2, the second-stage regression of RISK on CAPITAL and the relevant control variables, where CAPITAL has been instrumented by MISCONDUCT and MISCONDUCT^2. The RISK measures are: SIZE, LTV $\geq$ 85, LTV $\geq$ 90, and LTV $\geq$ 95, which are reported in Column (1) through to Column (4). Column (1) presents results estimated by two-stage least squares. Columns (2) through to (4) present results estimated by an instrumental variable probit model. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	SIZE	LTV $\geq$ 85	LTV $\geq$ 90	LTV $\geq$ 95
	(1)	(2)	(3)	(4)
Bank capital				
CAPITAL	2,453.37	-0.15**	-0.11	-0.048
	(3033.69)	(0.065)	(0.074)	(0.065)
Control variables				
BANK CONTROLS	√	√	√	√
LOAN CONTROLS	√	√	√	√
HPI	√	√	√	√
POLICY CONTROLS	√	√	√	√
TIME FIXED EFFECTS	√	√	√	√
Model statistics				
Number of clusters	227	227	227	227
Number of observations	4,589,242	4,467,232	4,467,232	4,589,351
F-statistic for instrument (first stage)	5.82***	n.a.	n.a.	n.a.
Anderson-Rubin test	7.71**	n.a.	n.a.	n.a.
Stock-Wright S statistic	6.52**	n.a.	n.a.	n.a.
Hansen J statistic	1.93	n.a.	n.a.	n.a.
p-value for Hansen J statistic	0.17	n.a.	n.a.	n.a.
Wald statistic	8,026.16***	1,0351.32***	8,460.09***	4,199.20***
Centered R2	0.13	n.a.	n.a.	n.a.

Next we consider several transformations of the LTV ratio as a dependent variable. We report the results of models with dummy variables for a loan with an LTV ratio equal or greater than 85, 90 and 95 as dependent variables in Columns (2), (3) and (4) of Table 3.7, respectively. The motivation for these transformations of the LTV ratio is that our main results in Table 3.5 pertain to the mean

(2015), who find that an increase in bank-specific changes to capital requirements leads to a decrease in the average individual loan value, which they interpret as a decrease in overall mortgage loan supply.

of the distribution of the LTV ratio. These results are informative about any changes to the average risk of a mortgage portfolio. But changes to the tail of the distribution of the LTV ratio might flag to more serious changes in risk-taking. We find in Table 3.7 that a decrease in bank capital leads to an increase in the probability of making a loan with an LTV ratio that is equal or greater than 85, and this is statistically significant at the 5 per cent level. Yet, we do not find a statistically significant relationship for the probability that a bank makes a loan with an LTV ratio that is equal to or greater than 90 or 95.[15] These results suggest that there is some increased risk-taking in the tail of the distribution for the LTV ratio in response to a decrease in bank capital, but this does not seem to occur in the most extreme part of the tail of this distribution.

There are finally a few caveats to our findings worth noting. In particular, we only observe how banks respond to an exogenous shock to capital by altering risk-taking via their *mortgage* lending standards. Our dataset does not include business loans, and so we cannot observe the potential effects of changes in bank capital on lending standards to corporates. Similarly, we cannot observe the potential effects on risk-taking in non-retail banking activities. Given that we find in this paper that a negative shock to bank capital leads to an increase in risk-taking, our hypothesis is that the effect of a negative shock to bank capital on these other activities might be even more pronounced. This is because these activities are in general more risky than secured lending to households. Nevertheless, these questions remain open until data on corporate lending and other banking activities are available.

Another caveat to our results is that caution is required when interpreting the findings because they only provide insights about how banks respond to idiosyn-

[15] Although when we use only MISCONDUCT as an instrument, instead of both MISCONDUCT and MISCONDUCT^2 as instruments, we do find a statistically significant relationship at the 5 per cent level for the probability that a bank makes a loan with an LTV ratio that is great than 90.

cratic bank capital shocks. We do expect that there are similarities in how banks respond to idiosyncratic bank capital shocks versus changes in individual bank capital requirements or system-wide bank capital requirements, but this does not necessarily need to be the case, and further research is required to determine the generality of our findings.

3.6. Conclusions

This paper examines the impact of changes in bank capital on risk-taking, using a unique UK panel dataset that combines bank-level information on bank capital with detailed mortgage-level information on lending standards.

One of the main contributions of this study is to determine the causal impact of bank capital on risk-taking by using misconduct provisions as an instrument for bank capital. The UK offers a useful setting to address this question because UK banks were significantly affected by misconduct provisions during the period 2010 to 2015. Our analyses demonstrate that misconduct provisions are a valid instrument. First, we show that misconduct provisions have a statistically significant and negative impact on bank capital, even after controlling for a wide range of other factors. Second, we provide strong evidence in support of the assumption that misconduct provisions are not correlated with risk-taking, except via their impact on bank capital.

Our core fining is that a negative shock to bank capital leads to an increase in risk-taking, as measured by a variety of mortgage lending standards. This is consistent with the theory that a general decline in the value of a bank charter will lead to an increase in risk-taking, as a bank will have less incentive to protect their charter value.

Our results provide insights about how banks respond to individual capital shocks. But they may also provide valuable insights about how macroprudential policies and other capital-related policies might affect bank risk-taking. If we assume that banks respond in a similar way to that observed for the exogenous individual capital shocks, our results imply that higher capital requirements - in the form of minimum capital ratios, countercyclical capital buffers, or systemic risk buffers - are likely to reduce the incentives for excessive risk-taking. Our findings suggest that in the event of a negative capital shock – such as might be experienced in a

downturn – regulators should be aware of the potential for banks to make riskier lending.

3.7. References

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3.A. Comprehensive Results Tables

Table 3.8.: Comprehensive Version of Misconduct Provisions as an Instrument for Bank Capital

The table presents coefficient estimates for Equation 3.1, the first-stage regression of the CET1 ratio (CAPITAL) on misconduct provisions scaled by adjusted total assets (MISCONDUCT) and the relevant control variables. Column (1) presents the baseline results, with MISCONDUCT as an instrument. Column (2) presents results that include an additional bank-type dummy variable, which takes the value one for a bank and zero for a building society. Column (3) presents the results that include bank fixed effects in addition to the bank control variables. Column (4) and Column (5) present the results from a similar specification to that presented in Column (1) and Column (2), respectively, but include MISCONDUCT^2 as an additional instrument. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and the standard errors of the coefficient estimates are in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	(1)	(2)	(3)	(4)	(5)
Instrument					
MISCONDUCT	-3.64***	-3.69***	-1.48	-5.30**	-4.38*
	(1.23)	(1.18)	(0.99)	(2.61)	(2.46)
MISCONDUCT^2				1.57	0.66
				(1.52)	(1.38)
Bank-level Control Variables					
LN(ASSETS)	-1.04***	-0.69***	0.25	-1.01***	-0.69**
	(0.16)	(0.27)	(1.56)	(0.17)	(0.27)
LIQUIDITY	-0.015	0.053	0.33***	-0.015	0.051
	(0.10)	(0.096)	(0.078)	(0.10)	(0.096)
NPL	-0.020***	-0.018***	-0.015***	-0.020***	-0.018***
	(0.0033)	(0.0035)	(0.0030)	(0.0034)	(0.0035)
ROA	1.03	1.10	1.45*	0.94	1.06
	(0.82)	(0.73)	(0.83)	(0.84)	(0.75)
Loan-level and Borrower Variables					
RATE (BASE = FIXED)					
DISCOUNT	-1.03**	-0.94**	0.20*	-1.03**	-0.94**
	(0.42)	(0.45)	(0.11)	(0.42)	(0.45)
TRACKER	0.27	0.20	0.0082	0.24	0.19
	(0.17)	(0.17)	(0.063)	(0.18)	(0.18)
CAPPED	-0.49	0.062	-0.18	-0.44	0.067
	(1.57)	(1.47)	(0.41)	(1.56)	(1.47)
SVR	1.00***	0.83***	-0.081	1.00***	0.83***
	(0.28)	(0.25)	(0.072)	(0.28)	(0.25)
OTHER	2.77*	2.73*	0.77***	2.70*	2.71*
	(1.56)	(1.49)	(0.25)	(1.56)	(1.49)
REPAYMENT (BASE = CAPITAL & INTEREST)					
INTEREST (ENDOWMENT)	1.16	1.19	.0046	1.21	1.21
	(1.02)	(1.01)	(0.36)	(1.03)	(1.01)
INTEREST (ISA)	-0.14	-0.079	0.29*	-0.17	-0.092
	(0.20)	(0.20)	(0.16)	(0.20)	(0.20)
INTEREST (OTHER)	-0.35***	-0.35**	0.016	-0.36***	-0.35**
	(0.12)	(0.15)	(0.048)	(0.12)	(0.15)

continued

Comprehensive Version of Misconduct Provisions as an Instrument for Bank Capital *(continued)*

	(1)	(2)	(3)	(4)	(5)
Loan-level and Borrower Variables (continued)					
REPAYMENT (BASE = CAPITAL & INTEREST) *(continued)*					
INTEREST (PENSION)	-0.33**	-0.25*	0.05	-0.33**	-0.25*
	(0.14)	(0.15)	(0.064)	(0.14)	(0.15)
MIX	-0.36**	-0.35**	-0.079	-0.36**	-0.35**
	(0.15)	(0.15)	(0.062)	(0.15)	(0.15)
UNKOWN	-3.31***	-3.79***	-0.79	-3.21***	-3.74***
	(0.88)	(0.90)	(0.31)	(0.92)	(0.93)
OTHER	-1.88***	-1.70***	-0.36	-1.87***	-1.70***
	(0.56)	(0.50)	(0.36)	(0.55)	(0.50)
TYPE (BASE = BUSINESS)					
SOCIAL TENANT	1.37***	1.17***	0.44*	1.41***	1.19***
	(0.37)	(0.37)	(0.24)	(0.37)	(0.36)
FIRST-TIME BUYER	1.05***	0.90**	0.46*	1.06***	0.91**
	(0.38)	(0.38)	(0.24)	(0.39)	(0.38)
HOME MOVER	0.95**	0.82**	0.39*	0.96**	0.83**
	(0.38)	(0.38)	(0.23)	(0.39)	(0.38)
REMORTGAGOR	1.11***	1.00***	0.44*	1.11***	1.00***
	(0.37)	(0.37)	(0.23)	(0.38)	(0.37)
UNKOWN	0.60	0.41	0.26	0.59	0.41
	(0.51)	(0.50)	(0.33)	(0.52)	(0.50)
OTHER	0.49	0.38	0.54**	0.49	0.39
	(0.34)	(0.33)	(0.23)	(0.34)	(0.33)
EMPLOYMENT (BASE = EMPLOYED)					
SELF-EMPLOYED	0.020	0.068	-0.010	0.025	0.068
	(0.075)	(0.067)	(0.020)	(0.073)	(0.067)
RETIRED	0.36**	0.38***	-0.022	0.38**	0.38***
	(0.15)	(0.15)	(0.051)	(0.15)	(0.15)
OTHER	0.66**	0.64**	-0.18	0.67**	0.64**
	(0.28)	(0.27)	(0.080)	(0.28)	(0.27)
TERM	-0.0086*	-0.0064	-0.0015	-0.0084*	-0.0064
	(0.0049)	(0.0049)	(0.0022)	(0.0049)	(0.0049)
IMPAIRED	-0.36	-0.28	0.0062	-0.33	-0.27
	(0.23)	(0.23)	(0.11)	(0.22)	(0.23)
VERIFIED	-0.55***	-0.65***	-0.11	-0.59***	-0.66***
	(0.17)	(0.19)	(0.10)	(0.18)	(0.19)
AGE	-0.0051*	-0.0044*	-0.0014	-0.0051*	-0.0044*
	(0.0030)	(0.0028)	(0.00094)	(0.0030)	(0.0028)
HPI	-1.08**	-1.10**	-0.15	-1.13**	-1.11**
	(0.48)	(0.47)	(0.20)	(0.47)	(0.46)

continued

Comprehensive Version of Misconduct Provisions as an Instrument for Bank Capital *(continued)*

	(1)	(2)	(3)	(4)	(5)
Policy Control Variables					
HTB	-0.27*	-0.26*	-0.16*	-1.13**	-0.26*
	(0.16)	(0.15)	(0.085)	(0.47)	(0.15)
FLS	-0.27	-0.36	-0.54***	-0.28	-0.36
	(0.25)	(0.25)	(0.19)	(0.26)	(0.25)
Other Control Variables					
BANK-TYPE FIXED EFFECTS	√	√	√	√	√
BANK FIXED EFFECTS	×	×	√	×	×
TIME FIXED EFFECTS	×	√	×	×	√
Model Statistics					
Number of clusters	227	227	227	227	227
Number of observations	4,589,174	4,589,174	4,589,174	4,589,174	4,589,174
F-statistic for instrument	8.82***	9.85***	2.20	5.82***	8.56***

Table 3.9.: Comprehensive Version of Naive Regression Results for the Impact of Bank Capital on Risk-taking

The table presents coefficient estimates for Equation 3.2, the regression of RISK on CAPITAL and the relevant control variables. For these results we employ the variable CAPITAL rather than the instrumented version of CAPITAL. The RISK measures are: LTV, LTI, PTI, and IMPAIRED, which are reported in Column (1) through to Column (4). Column (1) through to Column (3) present results estimated by ordinary least squares. Column (4) presents results estimated by a probit model. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Bank Capital				
CAPITAL	-0.18**	-0.018***	-0.074***	-0.019**
	(0.082)	(0.0037)	(0.012)	(0.0093)
Bank-level Control Variables				
LN(ASSETS)	-0.56***	0.024**	-0.059	-0.041
	(0.19)	(0.012)	(0.048)	(.034)
LIQUIDITY	0.11	0.012***	0.039**	-0.011
	(0.074)	(0.0042)	(0.015)	(0.0097)
NPL	0.0018	-0.000030	-0.00098	-0.0030
	(0.010)	(0.00050)	(0.0020)	(0.0019)
ROA	-3.59***	-0.26***	-0.39	0.089
	(1.20)	(0.073)	(0.26)	(0.15)
Loan-level and Borrower Variables				
RATE (BASE = FIXED)				
DISCOUNT	-0.021	-0.045	-2.19	-0.16**
	(0.70)	(0.034)	(0.19)	(0.080)
TRACKER	-2.43***	-0.15***	-3.38***	-0.14***
	(0.78)	(0.033)	(0.16)	(0.040)
CAPPED	-0.41	0.024	-2.64***	-0.38***
	(1.07)	(0.10)	(0.32)	(0.12)
SVR	-2.21***	-0.12***	-1.66***	-0.020
	(0.40)	(0.023)	(0.39)	(0.030)
OTHER	-9.14***	-0.38***	-2.37***	-0.12
	(1.90)	(0.10)	(0.50)	(0.077)
REPAYMENT (BASE = CAPITAL & INTEREST)				
INTEREST (ENDOWMENT)	-5.20***	0.21**	0.42	-0.18***
	(1.55)	(0.10)	(0.35)	(0.068)
INTEREST (ISA)	2.93***	0.55***	1.18***	0.10**
	(0.92)	(0.043)	(0.33)	(0.049)
INTEREST (OTHER)	1.62***	0.51***	1.02***	-0.14***
	(0.58)	(0.028)	(0.086)	(0.027)
INTEREST (PENSION)	3.51***	0.27***	0.041	0.062
	(1.00)	(0.042)	0.17	(0.062)
MIX	2.00***	0.40***	0.73***	-0.14***
	(0.48)	(0.021)	(0.13)	(0.031)
UNKOWN	2.19	0.44***	0.62	n.a.
	(1.78)	(0.17)	(0.44)	n.a.
OTHER	-10.09***	0.38***	0.95***	-0.27***
	(1.72)	(0.11)	(0.29)	(0.096)

continued

Comprehensive Version of Naive Regression Results for the Impact of Bank Capital on Risk-taking *(contined)*

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Loan-level and Borrower Variables (continued)				
TYPE (BASE = BUSINESS)				
SOCIAL TENANT	-13.19***	2.14	10.47	0.92***
	(2.00)	(1.54)	(8.46)	(0.26)
FIRST-TIME BUYER	-6.70***	2.59*	12.66	0.71***
	(1.90)	(1.54)	(8.46)	(0.27)
HOME MOVER	-8.95***	2.55*	11.55	0.76***
	(1.78)	(1.54)	(8.46)	(0.27)
REMORTGAGOR	-12.75***	2.46	10.74	0.72***
	(3.07)	(1.54)	(8.46)	(0.27)
UNKOWN	-9.64***	2.70*	11.63	n.a.
	(1.93)	(1.54)	(8.46)	n.a.
OTHER	-18.95***	2.19	10.38	0.72***
	(3.07)	(1.54)	(8.46)	(0.27)
EMPLOYMENT (BASE = EMPLOYED)				
SELF-EMPLOYED	-1.90	0.50***	0.64***	0.0085
	(0.17)	(0.10)	(0.12)	(0.014)
RETIRED	-11.89	0.13	0.72***	-0.12***
	(0.48)	(0.092)	(0.23)	(0.040)
OTHER	-6.76	0.19***	0.57***	0.085**
	(0.72)	(0.043)	(0.15)	(0.036)
TERM	1.07	0.077***	0.27***	0.0035***
	(0.29)	(0.0019)	(0.0083)	(.00092)
IMPAIRED	1.57	-0.024	-0.11	n.a.
	(0.38)	(0.029)	(0.13)	n.a.
VERIFIED	4.33	0.00047	0.68***	-0.055
	(0.63)	(0.038)	(0.21)	(0.055)
AGE	-0.27	0.0072***	0.013***	0.0097***
	(0.017)	(0.00096)	(0.0042)	(0.00074)
HPI	-44.82	3.40***	4.42***	-0.94***
	(2.37)	(0.16)	(0.55	(0.21)
Policy Control Variables				
HTB	-44.82	-0.23***	3.04***	0.10
	(2.37)	(0.024)	(0.18)	(0.083)
FLS	0.69	0.017	-0.14*	-0.0038
	(0.30)	(.017)	(0.078)	(0.058)
Model Statistics				
Number of clusters	227	227	227	227
Number of observations	4,589,174	4,563,024	3,253,692	4,584,637
F statistic/ Wald statistic	1,969.50***	598.59***	567.36***	1,475.92***
Centered R2/ Pseudo R2	0.40	0.11	0.27	0.021

Table 3.10.: Comprehensive Version of Main Regression Results for the Impact of Bank Capital on Risk-taking

The table presents coefficient estimates for Equation 3.2, the second-stage regression of RISK on CAPITAL and the relevant control variables, where CAPITAL has been instrumented by MISCONDUCT and MISCONDUCT^2. The RISK measures are: LTV, LTI, PTI, and IMPAIRED, which are reported in Column (1) through to Column (4). Column (1) through to Column (3) present results estimated by two-stage least squares. Column (4) presents results estimated by an instrumental variable probit model. Standard errors are heteroskedasticity-robust and clustered by bank-half year groups, and are presented in parentheses. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Bank Capital				
CAPITAL	-1.88**	-0.069*	-0.13*	-0.14**
	(0.89)	(0.039)	(0.067)	(0.072)
Bank-level Control Variables				
LN(ASSETS)	-2.44**	-0.033	-0.12	-0.18***
	(0.96)	(0.045)	(0.098)	(0.062)
LIQUIDITY	0.024	0.0091	0.037**	-0.018
	(0.16)	(0.0058)	(0.016)	(0.017)
NPL	-0.032*	-0.0011	-0.0021	-0.0054***
	(0.019)	(0.00095)	(0.0025)	(0.0020)
ROA	-2.17	-0.21**	-0.37	0.17
	(2.20)	(0.10)	(0.28)	(0.16)
Loan-level and Borrower Variables				
RATE (BASE = FIXED)				
DISCOUNT	-1.58	-0.092	-2.23***	-0.26**
	(1.36)	(0.061)	(0.20)	(0.10)
TRACKER	-1.86**	-0.13***	-3.35***	-0.094**
	(0.80)	(0.032)	(0.16)	(0.043)
CAPPED	-1.39	-0.0059	-2.68***	-0.43*
	(2.95)	(0.15)	(0.35)	(0.23)
SVR	-0.46	-0.068	-1.59***	0.11
	(1.05)	(0.045)	(0.38)	(0.086)
OTHER	-4.51	-0.24	-2.19***	0.23
	(4.30)	(0.17)	(0.55)	(0.29)
REPAYMENT (BASE = CAPITAL & INTEREST)				
INTEREST (ENDOWMENT)	-3.30	0.27**	0.49	-0.038
	(3.03)	(0.14)	(0.38)	(0.19)
INTEREST (ISA)	2.67***	0.54***	1.13***	0.074
	(0.94)	(0.047)	(0.33)	(0.059)
INTEREST (OTHER)	1.15*	0.49***	1.00***	-0.16***
	(0.68)	(0.033)	(0.088)	(0.032)
INTEREST (PENSION)	2.94***	0.25***	0.023	0.018
	(1.04)	(0.044)	(0.17)	(0.071)
MIX	1.35**	0.38***	0.70***	-0.18***
	(0.62)	(0.027)	(0.12)	(0.037)
UNKOWN	1.15	0.25	0.34	n.a.
	(0.68)	(0.24)	(0.51)	n.a.
OTHER	-13.53***	0.27*	0.84***	-0.53***
	(2.60)	(0.14)	(0.31)	.1608129

continued

Comprehensive Version of the Main Regression Results for the Impact of Bank Capital on Risk-taking *(continued)*

	LTV	LTI	PTI	IMPAIRED
	(1)	(2)	(3)	(4)
Loan-level and Borrower Variables (continued)				
TYPE (BASE = BUSINESS)				
SOCIAL TENANT	-11.09***	2.34	10.79	1.01***
	(2.40)	(1.54)	(8.47)	(0.25)
FIRST-TIME BUYER	-4.83**	2.79*	12.97	0.80***
	(2.38)	(1.54)	(8.46)	(0.25)
HOME MOVER	-7.18***	2.74*	11.86	0.83***
	(2.24)	(1.54)	(8.46)	(0.26)
REMORTGAGOR	-10.69***	2.65*	11.07	0.83***
	(2.35)	(1.54)	(8.47)	(0.26)
UNKOWN	-8.21***	2.87*	11.94	n.a.
	(2.30)	(1.54)	(8.46)	n.a.
OTHER	-18.16***	2.34	10.66	0.72***
	(3.28)	(1.53)	(8.45)	(0.25)
EMPLOYMENT (BASE = EMPLOYED)				
SELF-EMPLOYED	-1.94***	0.50***	0.64***	0.013
	(0.21)	(0.10)	(0.12)	(0.016)
RETIRED	-11.39**	0.14	0.74***	-0.074
	(0.66)	(0.095)	(0.24)	(0.059)
OTHER	-5.73***	0.23***	0.62***	0.15**
	(0.97)	(0.049)	(0.15)	(0.059)
TERM	1.06***	0.077***	0.27***	0.0026*
	(0.029)	(0.0018)	(0.0082)	(0.0015)
IMPAIRED	0.83	-0.046	-0.16	n.a.
	(0.54)	(0.031)	(0.14)	n.a.
VERIFIED	3.57***	-0.023	0.66***	-0.13**
	(0.79)	(0.044)	(0.22)	(0.059)
AGE	-0.27***	0.0069***	0.013***	0.0086***
	(0.017)	(0.00095)	(0.0042)	(0.0013)
HPI	-45.51***	3.38***	4.41***	-0.92***
	(2.57)	(0.16)	(0.56)	(0.22)
Policy Control Variables				
HTB	15.81***	-0.25***	3.03***	0.055
	(0.57)	(0.025)	(0.18)	(0.096)
FLS	0.29	-0.0039	-0.15*	-0.040
	(0.66)	(0.025)	(0.087)	(0.061)
Model Statistics				
Number of clusters	227	227	227	227
Number of observations	4,589,174	4,563,024	3,253,692	4,584,637
F statistic for instrument (first stage)	5.82***	5.84***	7.73***	5.82***
Anderson-Rubin test	39.05***	9.62***	4.19	n.a.
Stock-Wright S statistic	23.37***	17.82***	9.37***	n.a.
Hansen J statistic (*p-value*)	0.073 (0.79)	1.986 (0.16)	1.043 (0.31)	n.a.
Wald statistic	56,322.89***	20,926.22***	28,870.90***	1,343.35***
Centered R2	0.36	0.10	0.27	n.a.

3.B. Misconduct Provisions Correlations Across Years

Table 3.11.: Spearman's Rank Correlation Coefficient Across Years for Misconduct Provisions

The table presents the Spearman's rank correlation coefficient between misconduct provisions across different years (scaled by adjusted total assets) for the 22 UK banks in our sample. ***, **, and * are coefficient estimates statistically different from zero at the 1 per cent, 5 per cent and 10 per cent confidence level, respectively.

	2010	2011	2012	2013	2014	2015
2010	1					
2011	0.28	1				
2012	0.38	0.88***	1			
2013	0.46*	0.73***	0.88***	1		
2014	0.29	0.76***	0.86***	0.82***	1	
2015	0.38	0.66***	0.73***	0.68***	0.84***	1

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