Asymmetric Information and Capital Regulation in SME Lending: A Structural Model of Bank and Non-Bank Competition*

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Abstract

We develop and estimate a structural model of competition between banks and non-banks in the UK unsecured SME lending market under asymmetric information. Because risk-based capital regulation applies exclusively to banks, it ties a bank's loan capital charges directly to its internal risk assessment, creating a buffer-dependent shadow cost that enters bank loan prices. We document a novel empirical pattern in SME credit supply: bank lending behavior shifts sharply at loan-size caps corresponding to application channels, transitioning from automated online screening on small loans to human-mediated evaluation on large ones, whereas non-bank lenders exhibit no such channel segmentation. Combining loan-level originations with confidential supervisory data, we estimate lender-specific cost structures and screening precisions, allowing bank precision to vary across application channels. We find that banks screen less precisely than non-banks on smaller online loans, but overcome this disadvantage on larger loans routed through relationship managers. Counterfactual policy simulations show that tightening minimum capital requirements by 2 percentage points increases the average bank-originated loan rate by roughly 83 basis points and reduces the bank share of originations by 7.6 percentage points.

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1 Introduction

Small and medium-sized enterprises (SMEs) are central to economic activity, yet they face persistent difficulties in accessing external finance. A key friction in SME lending is asymmetric information: relative to large corporations, SMEs typically lack long and verifiable financial histories, making it costly for lenders to assess their creditworthiness. While banks have traditionally been the primary providers of SME credit, non-bank lenders — with distinct screening technologies and cost structures — have emerged as an increasingly important source of funding in recent years Buchak et al. (2018); Irani et al. (2021); Gopal and Schnabl (2022). This competitive landscape is shaped by differential regulation. In particular, banks are subject to risk-based capital requirements, which directly affect the incentives to originate risky loans, whereas non-bank lenders operate outside this regulatory framework. These institutional differences raise a fundamental question: how do capital requirements affect competition between banks and non-banks, and what are the implications for the pricing, composition, and overall availability of credit to SMEs?

In this paper, we develop and estimate a structural model of SME lending designed to quantify the effects of risk-based capital requirements on credit outcomes in equilibrium. The model incorporates asymmetric information, which is essential not only because opacity is a key feature of the SME lending market, but also because the impact of capital regulation on lending is endogenous to borrower risk, which is informed by lenders' screening outcomes. Banks form internal estimates of default risk, and the regulatory framework maps these probabilities of default into loan risk weights, which translate into bank-level capital requirements. The model also features non-bank lenders, who compete for the same borrowers but operate outside this capital framework, and it lets banks and non-banks differ in both screening precision and cost structure. We focus on unsecured SME term loans in the UK, where the absence of collateral drives high credit risk and makes these loans capital-intensive under risk-based requirements, a natural setting for this paper's question. We obtain preliminary estimates of lender-specific screening precision and costs, along with demand elasticities.

We provide the first evidence that loan application channels exert a first-order effect on competition between banks and non-banks in this setting. As loan size grows, banks become more prudent, coinciding with a shift in their application mode. On smaller loans, banks accept online applications, whereas larger loans require a more involved application through a human relationship manager. Around the loan sizes where this transition occurs, banks' lending changes sharply: bank-originated borrowers become markedly safer on risk-related observables. Non-banks, who underwrite online across all loan sizes, display no such jump. This differential alters market structure along the loan-size margin: on small loans, where both lender types require online applications, banks and non-banks hold comparable market shares; in the large-loan segment, where banks switch to the relationship-manager channel and originate more selectively, the bank share drops sharply relative to non-banks.

Our descriptive analysis also reveals that lenders screen on soft information: even conditional on a rich set of firm observables, there is substantial residual dispersion in interest rates. Consistent with models of asymmetric information, we document the positive correlation property Chiappori and Salanié (2000): conditional on observables, higher interest rates predict higher ex-post default rates. The strength of this correlation varies across lender types and application channels, pointing to fundamental differences in risk-screening abilities. Finally, non-banks serve a pool of borrowers with higher average default rates and charge a substantial interest rate premium relative to banks. Taken together, these pricing strategies and allocation patterns reflect a complex interplay between application channels, screening abilities, and risk-based capital regulations, which our structural model is designed to disentangle.

To quantify the forces underlying these empirical observations, we develop a structural model of SME lending centered on asymmetric information regarding unobserved borrower risk. On the demand side, borrowers vary in their default probabilities. This heterogeneity is driven both by observable characteristics and a private unobserved risk type. The loan size reflects the borrower's specific need for external finance, which is endogenous to both their observable characteristics and their unobserved risk type. We motivate this structural link using the documented positive correlation between loan size and default, controlling for observables. Borrowers face a discrete choice among a menu of offers. Importantly, these menus are borrower-specific, derived from each lender's belief about the borrower's risk. Finally, the demand utility incorporates borrowers' preferences for different lender types, and can capture adverse selection.

On the supply side, the model features competition between banks and non-banks, allowing for heterogeneity in both screening precision and cost structures. Crucially, the bank's lending cost function incorporates balance sheet capacity cost as in Buchak et al. (2024), which is linked to the risk-weighted assets of each loan. Such formulation captures the fact that banks prefer to maintain capital buffers above minimum capital requirements, ensuring that regulatory capital is always valuable Plosser and Santos (2024). Lenders compete on the interest rates they offer, which depends on the lender's assessment of borrower risk. This assessment incorporates both observable characteristics and a posterior belief about the borrower's unobserved risk type. To form these beliefs, lenders use the requested loan size as a baseline public signal, exploiting its positive correlation with default. They then refine this risk assessment using a private screening signal, whose precision varies across banks and non-banks.

We estimate the model to match key empirical moments, including lenders' pricing behavior, borrower repayment outcomes, market shares, and the distribution of loan sizes. A central challenge in estimating credit demand with personalized pricing is that we observe only originated loans, while the other competing offers in the borrower's choice set remain unobserved. The standard approach in the literature approximates these missing offers using a pricing-prediction regression that captures price heterogeneity in a reduced-form way through borrower and bank-region-year fixed effects Crawford, Pavanini and Schivardi (2018), but this strategy is not well suited to our setting for two reasons. First, implementing the pricing-prediction regression requires multiple lending relationships per firm. For smaller SMEs, this is rarely the case due to the inherent challenges in accessing credit, where securing even a single loan is a significant hurdle, and our setting is no exception. Second, a reduced-form treatment of price variation cannot recover the object our question requires: because capital regulation ties banks' balance-sheet constraints directly to their internal risk estimates, which are themselves outcomes of screening, we need screening precision as a structural parameter rather than variation absorbed into fixed effects. We therefore estimate the demand and supply sides of the model jointly, incorporating supply-side heterogeneity through differences in screening precision and cost structure between banks and non-banks, allowing us to simulate the latent choice set of borrowers.

Our structural estimation quantifies the key parameters governing borrower demand, lender cost structures, and information processing. On the demand side, we estimate average own-price elasticities of 1.9 for banks and 2.7 for non-banks, implying that a 10% increase in the interest rate reduces the corresponding lender's market share by 19% and 27%, respectively. On the supply side, we identify a substantial cost asymmetry: non-banks face an average effective marginal cost of 7%, more than twice the bank's 2.86%. This gap reflects two reinforcing forces. Non-banks lack access to deposit funding, which raises their funding cost relative to banks; and they serve a pool with higher average default rates, which raises the expected-loss component of their effective marginal cost. For banks, the shadow cost of balance-sheet capacity, which embeds the risk-based capital requirement, is a quantitatively important component of the effective marginal cost, particularly on large loans and on borrowers assessed as riskier. Despite their higher costs, non-banks earn slightly higher average effective markups than banks (4.4% versus 3.5%), reflecting the stronger non-price valuation borrowers assign to non-bank lenders in our demand estimates. On the information side, we find a pronounced reversal in screening precision across loan-size segments: non-banks are about 1.32 times more precise than banks on small loans, while banks are about 4.55 times more precise than non-banks on large loans. This pattern is consistent with the institutional fact that non-banks underwrite all applications through online platforms regardless of loan size, while banks complement automated screening on small loans with relationship-based, in-person underwriting on large ones. Both lender types possess private signals that are substantially more precise than the public signal extracted from the requested loan size, indicating that private screening, rather than the loan-size signal, is the primary source of information about borrower type in this market.

We use the estimated model to quantify the effects of changes in bank capital regulation. A 2 percentage point tightening of the minimum capital requirement raises the bank's average originated rate by approximately 83 basis points and reduces the bank's share of originations by 7.6 percentage points. Decomposing the bank's pricing response, most of the rate increase is driven by repricing within observable borrower groups, while a smaller compositional channel reallocates riskier borrowers away from the bank, leaving its pool tilted toward safer borrowers; this channel is more pronounced for large loans.

The paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the institutional setting and data, followed by the motivating empirical facts in Section 4. Section 5 develops the structural model. Section 6 details the estimation strategy and presents the estimation results. Section 7 outlines our counterfactual analysis. Section 8 concludes.

2 Related Literature

This paper contributes to the literature on the transmission of bank capital requirements across credit markets Peek and Rosengren (1995); Repullo (2004); Gropp et al. (2019); Benetton et al. (2021); de Ramon, Francis and Harris (2022); Plosser and Santos (2024). Our work is most closely related to Benetton (2021), who uses a structural model to quantify the impact of capital regulation in the UK mortgage market. We complement this literature by extending the structural approach to unsecured SME credit, a natural setting for examining regulatory transmission. Here, both the product (uncollateralized term loans) and the borrowers (opaque SMEs) are intrinsically riskier than in residential mortgage markets, and because risk-based capital regulation ties capital charges directly to default risk, capital requirements potentially play an even larger role in shaping credit outcomes. Furthermore, while pricing in the UK mortgage market is highly standardized conditional on observable factors such as Loan-to-Value and Loan-to-Income ratios, exhibiting little individualized variation (Benetton, 2021; Robles-Garcia, 2019; Benetton, Gavazza and Surico, 2025), the UK SME market is characterized by severe information opacity and substantial personalized price dispersion. Quantifying the impact of capital regulation in this context therefore requires a framework that explicitly incorporates lender screening and its endogenous interaction with regulatory capital constraints.

That framework places our work within a broader empirical literature on information asymmetry in credit markets, building on the seminal work of Stiglitz and Weiss (1981).[1] The closest empirical antecedent is Crawford, Pavanini and Schivardi (2018), who study adverse selection and market power in Italian SME lending. While they recover each borrower's unobserved competing offers in reduced form using borrower and bank-region-year fixed effects, we model the structural screening mechanism that generates those offers. This distinction is essential in our setting because a bank's capital charge is tied directly to its internal risk assessment, which a reduced-form fixed effect cannot recover.

Two recent papers share our approach of treating screening as a structural primitive. Setting aside the capital regulation and the competition between banks and non-banks that are central to our question, the way we model screening relates closely to these two, and the contrasts sharpen what is distinctive in our approach. Taburet, Polo and Vo (2024) estimate a screening model in the UK mortgage market, but the mechanism differs fundamentally from ours, and the difference is rooted in how the two markets price. Mortgages are offered through posted, largely standardized contracts, so in their setting lenders design menus and do not

[1] See, for example, (Petersen and Rajan, 1994; Sufi, 2007; Ivashina, 2009; Einav, Jenkins and Levin, 2012; Iyer et al., 2015; Darmouni, 2020; Bosshardt, Kakhbod and Kermani, 2025).

condition prices on a private, borrower-specific signal; screening arises as borrowers self-select across a common set of posted contracts, and separation is a property of equilibrium menu design. SME lending, by contrast, is individually assessed: each lender forms a private judgment of a borrower's risk and extends a personalized price, so the primitive we recover is the precision of that private signal rather than the shape of a posted menu.

Matcham (2025) is closer to us on this dimension: his lenders form individualized assessments, and he too recovers a lender-specific signal precision in the UK credit-card market. The difference is again institutional. Because borrowers face a posted advertised rate before any individualized terms are set, demand there depends only on a predetermined price, and he estimates it separately from supply; screening precision is then backed out from the dispersion of credit limits, the quantity margin lenders individualize once regulation has closed off price. In our market, no such posted price exists: each offer is personalized, so the price entering demand is itself the equilibrium object supply produces, forcing us to estimate demand and supply jointly and recover precision from the dispersion of prices rather than quantities. What is a sequential problem under posted pricing becomes a simultaneous one under personalized pricing.

A closely related strand studies how a regulatory instrument interacts with lenders' screening. Stillerman (2024) is nearest: he models screening in US SME lending under the SBA guarantee program. Guarantees and capital requirements act on lending through opposite forces, however: guarantees insure lenders against default, lowering the marginal cost of lending while weakening screening incentives, whereas the capital requirements we study raise the cost of risky lending and tie it directly to each bank's own risk assessment. More broadly, our work joins a literature applying industrial-organization methods to financial markets.[2] We extend this agenda by quantifying the interaction between capital regulation and screening in the market for unsecured small-business credit.

[2]For example, Benetton and Buchak (2024) study the SME business card market, paralleling work on consumer credit cards by Nelson (2018) and Galenianos and Gavazza (2022). Others examine household finance, including mortgages Benetton, Gavazza and Surico (2025); Fisher et al. (2024) and pensions Hastings, Hortaçsu and Syverson (2017), and Koijen and Yogo (2016) apply these tools to insurance.

Finally, this paper contributes to the vast literature on lending by non-bank financial institutions (NBFIs).[3] This literature studies the interaction of non-banks with traditional banks, including how differential regulation influences competitive dynamics between banks and non-banks Buchak et al. (2018); Irani et al. (2021); Gopal and Schnabl (2022); Lee, Lee and Paluszynski (2024). A key contribution in this domain is Buchak et al. (2024), who develop a model with substitution towards shadow banks and balance sheet loan retention margins to explore the implications of capital regulation and monetary policy. We extend their approach by showing how banks' balance sheet capacity, which links capital requirements and loan default risk, interacts with asymmetric information and screening, further influencing the interplay between banks and non-banks. By doing so, we can further explore the implications of risk-based regulation in an environment where asymmetric information is prevalent.

3 Institutional Setting and Data

3.1 SME Lending and Risk-Based Capital Requirements

Small and medium-sized enterprises (SMEs)—defined as firms with fewer than 250 employees—play a central role in the UK economy, accounting for over 99% of all businesses, more than 60% of private-sector employment, and approximately half of total business turnover.[4] Importantly, external finance plays a vital role in supporting SMEs' working capital, investment, and expansion. Survey evidence from the British Business Bank indicates that the availability and cost of finance are among the most frequently cited obstacles to innovation, exceeded only by broad macroeconomic shocks such as the COVID-19 pandemic and energy price volatility. Moreover, SMEs are nearly twice as likely as large firms to report financing availability and cost as binding constraints, with these concerns declining monotonically as

[3] See, for example, Fuster et al. (2019); Tang (2019); Aldasoro, Doerr and Zhou (2025); Fleckenstein et al. (2025); Lyonnet and Chrétien (2025)

[4] Source: UK Small Business Statistics from the Federation of Small Businesses.

firm size increases *within* the SME sector British Business Bank (2023).

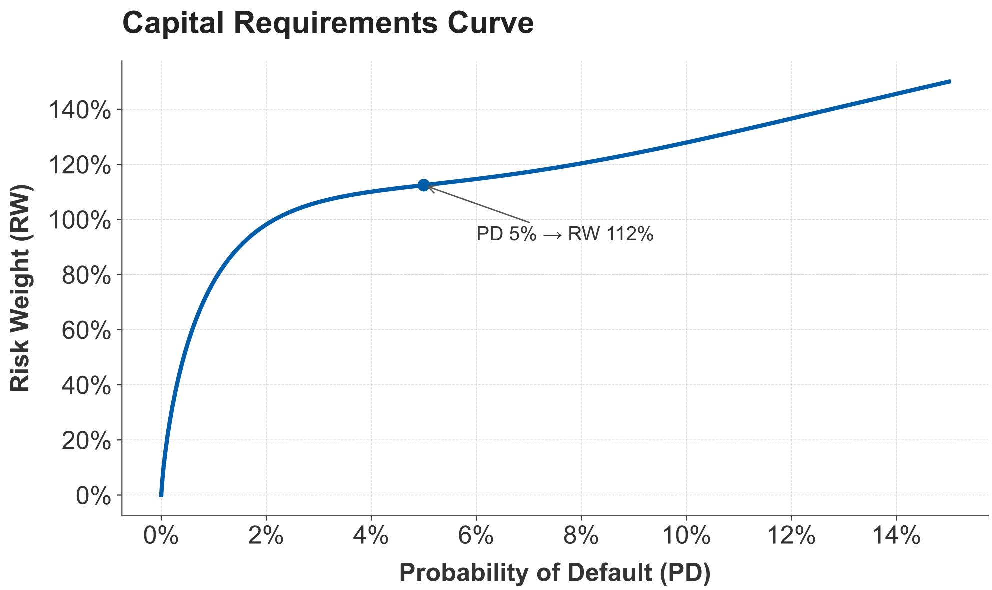
A key factor underlying these financing challenges is asymmetric information. Relative to large corporations, SMEs typically lack audited financial statements and standardized disclosure, making borrower quality more difficult for lenders to assess. This opacity increases the uncertainty surrounding loan default risk in SME lending. Default risk, in turn, plays a central role in the design of risk-based capital regulation. Under the Basel framework, banks are required to hold minimum capital proportional to their risk-weighted assets (RWA), with higher capital requirements applied to exposures deemed riskier. In the UK, banks are also subject to additional bank-specific capital requirements set by the prudential regulator de Ramon, Francis and Harris (2022).

To determine RWAs, regulators allow typically large banks to adopt the Internal Ratings-Based (IRB) approach.[5] Under this framework, banks use approved internal models to estimate asset-level risk parameters, including the probability of default (PD), loss given default (LGD), and exposure at default (EAD). These estimates are then mapped into regulatory risk weights through a formula prescribed by the regulator (see Appendix A). Figure 1 illustrates that over the relevant range of PDs, this relationship is strictly increasing: for a given LGD, regulatory risk weights are increasing in the estimated PD, implying higher capital requirements for riskier loans.

A loan's contribution to a bank's RWAs is given by the product of this risk weight and the loan's EAD, so that capital requirements rise with both borrower risk and loan size. Non-bank lenders are not subject to risk-based capital requirements and therefore do not face capital charges that vary with these dimensions. These institutional differences highlight the importance of understanding how regulatory capital requirements interact with lender behavior and competition, and how they shape access to external finance for SMEs.

[5] Banks have to satisfy a set of minimum requirements for entry and on-going use of IRB models, as described in BCBS CRE 36, available at `https://www.bis.org/basel_framework/standard/CRE`.

Figure 1: Default Risk and Regulatory Risk Weights



Note: This figure displays the regulatory risk weight of a hypothetical unsecured retail SME loan as a function of the estimated probability of default (PD) under the IRB approach, under the assumption of LGD=100%, as per RWA formula disclosed in CRE31, available at `https://www.bis.org/basel_framework/standard/CRE`.

3.2 Data

Loan-level Data: The dataset utilized in this project contains comprehensive monthly financial account information from SMEs within major banking groups in the UK, as well as some non-bank lenders such as Fintech lenders. This loan-level data is reported to the Bank of England by Experian, a private sector credit reference agency, in compliance with the Commercial Credit Data Sharing (CCDS), which operates under the Small Business Enterprise and Employment Act requirements. The CCDS regulation required nine UK banks to share current account and loan level data of their SME borrowers (with annual sales below £25 million) with other lenders, including both banks and non-banks Babina et al. (2025).

The dataset covers a broad range of loan account types. In this paper, we focus on unsecured SME loans, which are particularly relevant for the smallest SMEs in the UK. Our sample begins in 2019 and provides a panel at monthly frequency, allowing us to track the performance of unsecured loans over time. In particular, we are able to impute the interest rate charged on each loan by tracking the pattern of changes in the outstanding balance of the loans, along with the monthly payments realized by the borrowers. The information on each unsecured loan includes transaction details such as the loan's origination date and maturity, and other characteristics such as ex-post default, along with borrower unique identifier.

Firm-level Data: All incorporated firms in the UK are legally required to file annual accounts with Companies House, the official registrar of companies, under the Companies Acts of 1985 and 2006. We access these filings via Bureau van Dijk (BvD), which consolidates the raw submissions and provides standardized firm-level information, including asset size, location, age, and industry classification based on Standard Industrial Classification (SIC-2007) codes. Our loan-level data includes company registration numbers, which we use to link each firm to their corresponding firm characteristics from the Companies House database. We also collect firm credit scores from CRIF, a leading Account Information Service Provider, which we access via BvD. The credit scores range from 0 to 100 and measure the possibility of a firm becoming insolvent, with higher values indicating lower probability of insolvency. We map these scores to three risk categories: risky, normal and safe.

Bank-level Data: We also access the Bank of England's Historical Banking Regulatory Database (HBRD), which includes confidential regulatory information at the bank-level, such as total assets, deposits, and bank equity.[6] We classify lenders in our loan-level data as *banks* if they are included in the HBRD, and *non-banks* otherwise. Bank lenders in the UK must not only adhere to the standard 8% minimum capital requirement threshold imposed by Pillar I of international Basel Standards, but they are also subject to lender-specific supervisory add-ons de Ramon, Francis and Harris (2022). The data includes both the bank-specific minimum requirement imposed on each bank and the actual capital ratio they hold, allowing us to measure each bank's capital buffer relative to its own regulatory

[6] For more information on the HBRD, see de Ramon, Francis and Milonas (2017).

minimum.

Summary Statistics: Table 1 presents descriptive statistics for the final estimation sample. The data exhibits significant heterogeneity across borrowers and loan terms, motivating a structural approach that accounts for diverse risk profiles and preferences.

TABLE 1: **Summary Statistics**

Variable	**Mean**	**Median**	**P25**	**P75**
Loan Characteristics				
Loan Amount (£'000s)	76.5	47	20	105.7
Interest Rate (%)	13.15	11.07	9.28	16.09
Maturity (Months)	53.1	60.0	36.0	60.0
Firm Characteristics				
Total Assets (£'000s)	494	165	55	499
Firm Age (Years)	10.7	8.0	5.0	14.0

Note: This table reports summary statistics of key variables for the full estimation sample. P25 and P75 denote the 25th and 75th percentiles, respectively. Source: Experian, BvD, and authors' calculations.

The distribution of loan sizes is right-skewed, with a mean of £76,487 compared to a median of £47,001, indicating the presence of a "long tail" of large exposures. Similarly, borrower size (measured by total assets) varies substantially, ranging from £55,000 at the 25th percentile to nearly £500,000 at the 75th percentile. We also observe meaningful dispersion in pricing: while the median interest rate is roughly 11%, the interquartile range spans from 9.28% to 16.09%, reflecting the variation in credit risk and lender pricing strategies within the market.

4 Empirical Patterns in SME Lending

This section presents descriptive evidence on the allocation, pricing, and performance of unsecured loans in the UK SME market. These facts highlight the distinct roles played by banks and non-banks: banks offer cheaper credit but cater to safer borrowers, whereas non-banks provide broader access, including to riskier firms, at a significant interest-rate premium. A central feature of the market is that banks and non-banks accept applications through different channels, and bank lending behavior shifts sharply across these channels. These patterns motivate the demand and supply features we incorporate into the structural model in Section 5.

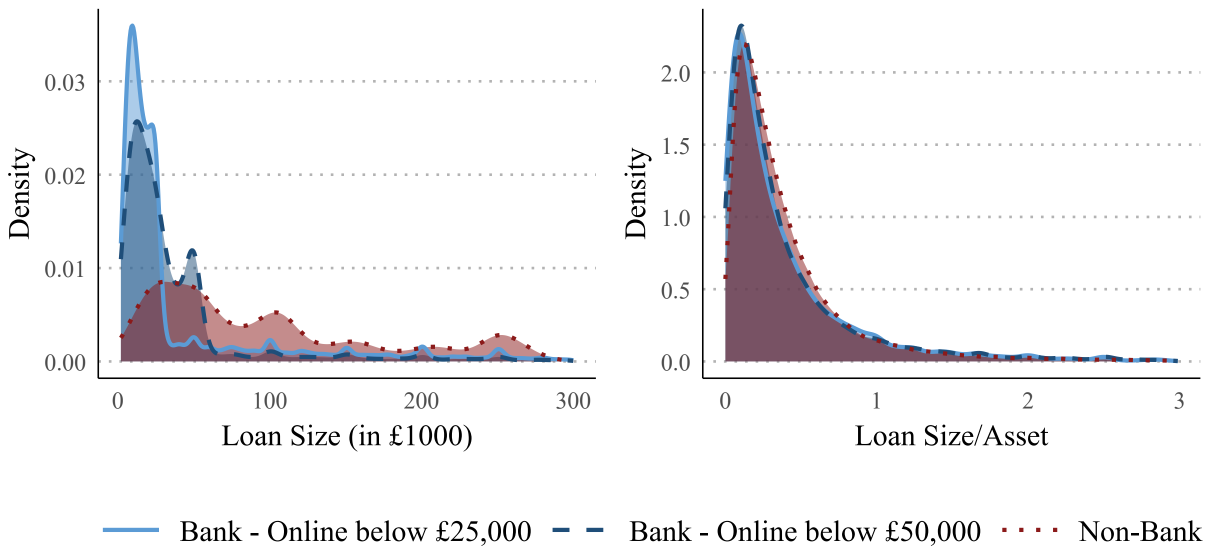
We document four empirical patterns: (1) bank lending is organized around the application channel: banks process online applications for smaller loans but require a relationship-manager application for larger ones, becoming markedly more conservative once this shift occurs, with safer borrowers and lower realized default rates. Non-banks, which operate online across all loan sizes, exhibit no comparable shift. Second, after controlling for observable characteristics, we find that: (2) loan prices are positively correlated with ex-post default, consistent with screening on private information; (3) non-banks serve a pool with higher residual risk; and (4) loan size is positively correlated with ex-post default, which our model exploits as a public signal of borrower risk.

4.1 Application Channels and Market Segmentation

We begin by documenting how bank lending is organized around the application channel and how this shapes the allocation of credit across lender types. Banks accept unsecured SME loan applications through two channels: an online application process, available up to a bank-quarter-specific loan-size cap, and an application through a relationship manager for loans above that cap. We recover these caps from banks' public websites using archived snapshots from the Internet Archive's Wayback Machine. The caps cluster at two values: most banks set the online cap at either £25,000 or £50,000. Very few loans in our sample come from lenders in the remaining categories, namely, those accepting no online applications or those setting a cap below £25,000."

These caps shape lending activity itself. Figure 2 plots the densities of loan characteristics, grouping banks by their online application cap: the first group comprises banks whose

Figure 2: Loan Size Activity by Online Application Cap



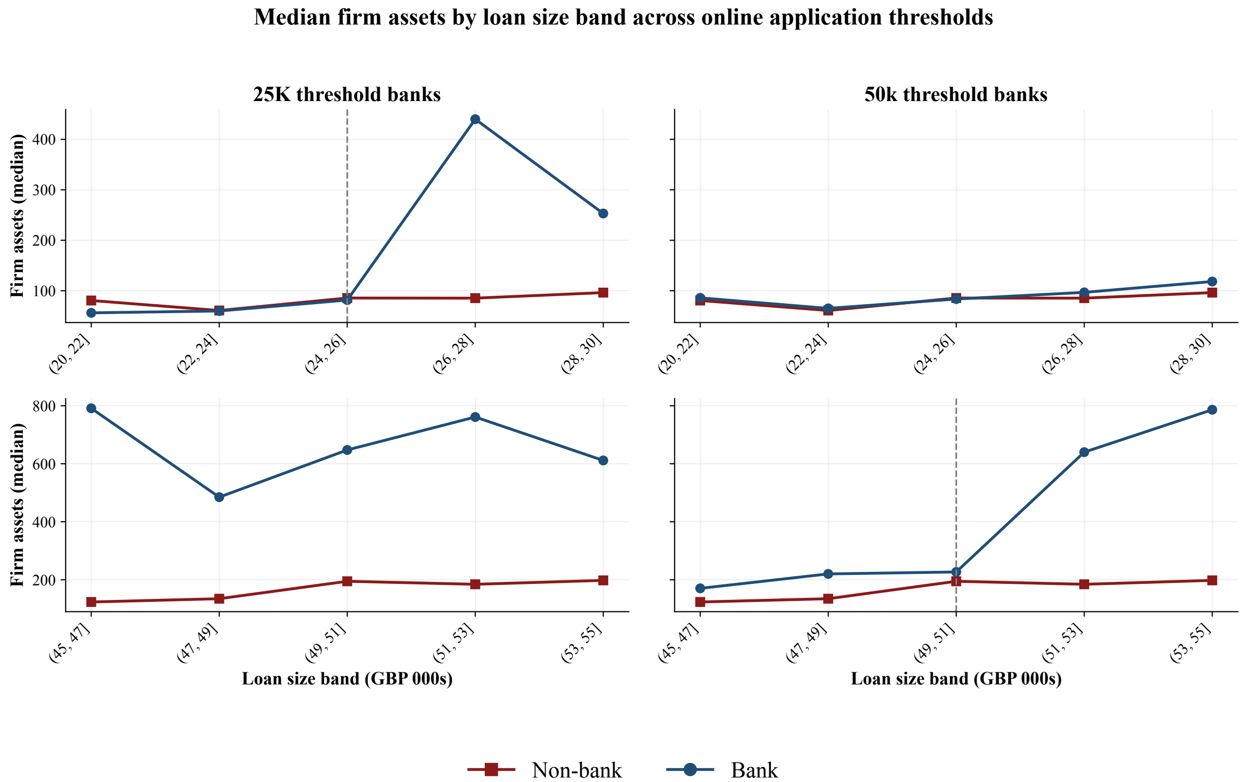
Note: Density of loan amounts (Panel A) and loan-to-asset ratio (Panel B) for banks whose online application cap is at most £25,000, banks whose cap is at least £50,000, and non-banks. Bank origination density contracts just beyond each group's cap in Panel A, while the loan-to-asset distributions of the two bank groups are nearly identical in Panel B. Non-banks show no contraction.

cap is at most £25,000 and the second those whose cap is at least £50,000, shown alongside non-banks. Panel A displays the distribution of loan amounts. Each group of banks originates heavily below its own cap and contracts sharply beyond it, the contraction appearing near £25,000 for the first group and near £50,000 for the second, while non-bank portfolios show no such sudden contraction.

To understand whether this segmentation is driven by leverage risk, Panel B plots the distribution of the loan-to-asset ratio (loan size normalized by firm total assets). Strikingly, these normalized distributions are nearly identical. This suggests that banks are not averse to leverage per se. The fact that segmentation appears in nominal terms (Panel A) but vanishes in relative terms (Panel B) indicates that the friction is linked to the absolute magnitude of the exposure. These findings are consistent with a supply-side constraint where large risky exposures are particularly unattractive for regulated lenders.

The role of the cap is sharpest immediately around each threshold. Figure 3 plots median borrower firm assets in narrow loan-size bands on either side of £25,000 (top row) and

Figure 3: Borrower Composition Shifts at Each Bank's Own Application Cap



Note: Median borrower firm assets by loan-size band, in narrow windows around £25,000 (top row) and £50,000 (bottom row), for banks whose online application cap is £25,000 (left column) and £50,000 (right column), with non-banks for comparison. Dashed lines mark the threshold. Bank median assets jump at each group's own cap and not at the other group's threshold; non-banks show no discontinuity. The same pattern holds using firm credit score in place of firm assets.

£50,000 (bottom row), separately for £25,000-cap and £50,000-cap banks, with non-banks for comparison. Each group's median assets jump at its own cap and nowhere else: £25,000-cap banks jump just above £25,000 (top-left) but not around £50,000 (bottom-left), where their borrowers already lie above the cap, while £50,000-cap banks jump at £50,000 (bottom-right) but not at £25,000 (top-right), where they still accept online applications and track non-banks. Non-banks show no discontinuity in any panel.

Because the shift occurs exactly at each group's own cap and is absent both for the other group and for non-banks, it cannot reflect loan size or borrower risk at a fixed loan amount; it coincides with the channel switch. The same discontinuity appears, at the same threshold, using firm credit score in place of assets: at the cap, banks move sharply toward safer borrowers, precisely where the application shifts from an automated online process to one mediated by a relationship manager. The online cap, rather than loan size as such, is the margin that organizes bank lending.

Motivated by the evidence so far, we classify borrowers by the application channel. We do so using each firm's main current-account provider. A firm may hold accounts at several banks, but its bank borrowing comes overwhelmingly from its main current-account provider: in 92% of bank-originated loans, the lender is the firm's main current-account provider. The application channel that governs a firm's mode of access to bank credit is therefore determined by its primary bank. Accordingly, for each firm we read the online cap of its main current-account provider and assign the firm to the *online segment* if its loan falls below that cap and to the *relationship-manager (RM) segment* if it falls above. We apply this borrower-level classification to every loan the firm takes, whether from a bank or a non-bank, which lets us compare bank and non-bank lending within a segment while holding fixed the channel the borrower would face at its own bank.

For non-bank loans the segment does not describe how the loan was processed, since non-banks accept applications online regardless of size; an RM-segment non-bank loan instead identifies a borrower who would face the relationship-manager channel for a loan of this size at its main bank. The segment is thus a characteristic of the borrower's bank-credit environment, not of the originating lender's process.

Table 2 reports market shares and realized one-year default rates for banks and non-banks in each segment. Two patterns stand out. First, the allocation of credit shifts sharply across segments: banks originate the majority of loans in the online segment but a much smaller share in the RM segment, where non-banks account for most originations. Second, and most strikingly, bank lending in the RM segment carries an exceptionally low default rate of just 0.30%. This echoes the composition shift in Figure 3: once loans require a relationship manager, banks lend to a markedly safer pool.

Table 2: Market Shares and Performance by Application Segment

	Online Segment		RM Segment	
Lender	Bank	Non-bank	Bank	Non-bank
Market Share (%)	70	30	19	81
Default Rate (%)	1.76	3.76	0.30	2.55

Notes: Market shares and realized one-year default rates by lender type and segment, computed by loan count. Firms are assigned to the online or relationship-manager (RM) segment according to whether their loan falls below or above the online application cap of their main current-account provider; the same borrower-level rule classifies bank and non-bank loans. Shares are computed within segment.

4.2 Pricing and Private Information

We next turn to the pricing of credit risk, investigating whether lenders actively screen borrowers to uncover risk factors unobservable to the econometrician. In a market with asymmetric information, interest rates serve a dual role: they compensate lenders for observable risk and reflect private information gathered during the screening process. We investigate whether banks and non-banks successfully price this unobserved component of risk by estimating the correlation between interest rates and ex-post default, conditional on a rich set of observable firm and loan characteristics. We also examine how this correlation varies across lender types and loan sizes.

To study this pricing behavior, we estimate variants of the following regression:

$$r_{ijt} = \delta_1 \mathbb{1}_j^{\text{Bank}} + \delta_2 \mathbb{1}_{it}^{\text{RM}} + \lambda_{j,s} \mathbb{1}_{ijt}^{\text{Default}} + \Gamma X_{it} + \Phi_{F.E.} + \epsilon_{ijt} \,, \tag{1}$$

where r_{ijt} represents the interest rate charged to firm i by lender j at time t. The model relies on three key indicator variables: $\mathbb{1}_j^{\text{Bank}}$ takes the value of one if lender j is a bank; $\mathbb{1}_{it}^{\text{RM}}$ equals one if firm i is in the relationship-manager segment, i.e., its loan exceeds the online application cap of its main current-account provider; and $\mathbb{1}_{ijt}^{\text{Default}}$ indicates whether that specific loan defaulted within one year of origination. The coefficient $\lambda_{j,s}$ captures the sensitivity of prices to ex-post default, which we allow to vary additively across lender types (j) and application segments (s). The vector X_{it} controls for firm attributes (dummies for below-median age and asset size, and a categorical variable for credit score). We also include region, sector, and quarter fixed effects ($\Phi_{F.E.}$) to absorb granular spatial, industrial, and temporal variation, alongside loan maturity fixed effects to control for contract horizon.

Table 3 Column (1) establishes the baseline pricing differences using only the observable categorical controls. We find a persistent level difference: banks charge interest rates approximately 6 percentage points lower than non-banks for observably similar firms. The coefficients on the firm controls behave as expected: young firms, those with lower asset holdings, and those in lower credit score bands pay significantly higher rates, confirming that the baseline model captures standard risk-based pricing.

Column (2) introduces the ex-post default indicator and its interaction with lender type to test for private information screening. We find that, conditional on observable firm categories, firms that default ex-post pay significantly higher interest rates upon origination. In principle, a positive correlation between interest rates and ex-post default could reflect either lender screening on unobserved risk or moral hazard, where higher debt-service burdens directly induce firm default. In Appendix E, we exploit quasi-experimental variation from the post-pandemic interest rate hike on floating rate loans to demonstrate that higher rate burdens do not cause default probabilities to rise, allowing us to rule out moral hazard as a driving mechanism. Consequently, this positive "information premium" confirms that both banks and non-banks possess screening-derived information that allows them to identify and price latent risk factors orthogonal to firm observables. To visualize this, Figure 4 implements a positive correlation test Chiappori and Salanié (2000), plotting predicted default probabilities against interest rates while controlling for observables, illustrating a monotonic positive relationship for both lender types.

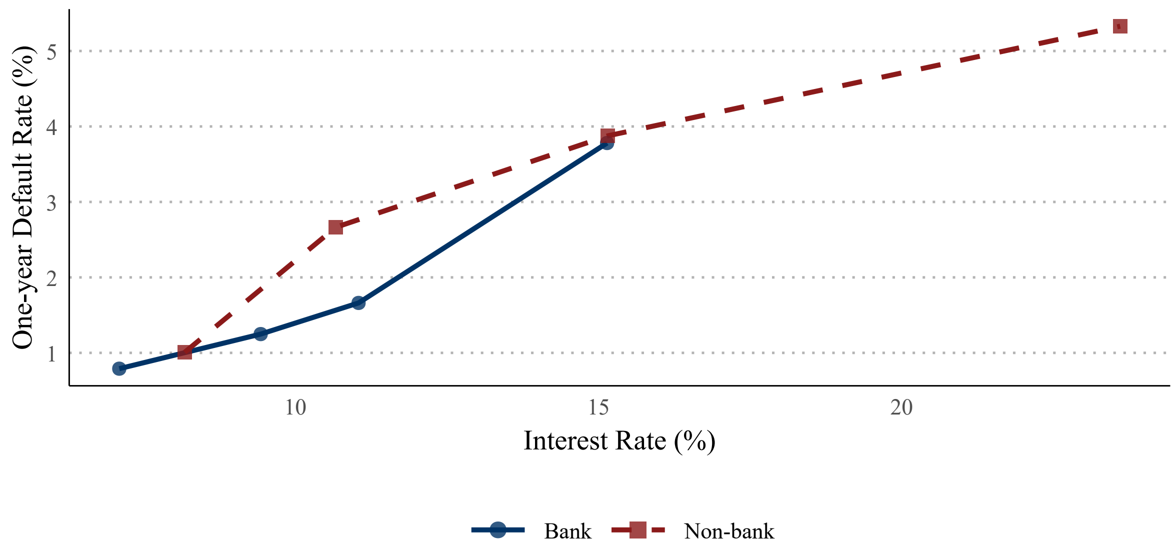
Column (3) adds the application segment, interacting the ex-post default indicator with both the bank dummy and the RM-segment indicator. This triple-interaction specification

Table 3: Loan Pricing and Private Information

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
Firm Controls				
Young Firm	0.961***	0.945***	0.958***	0.921***
	(0.041)	(0.041)	(0.041)	(0.037)
Small Asset (Below Med.)	1.072***	1.062***	0.533***	0.608***
	(0.044)	(0.043)	(0.039)	(0.035)
Credit Score (Normal)	0.676***	0.666***	0.620***	0.553***
	(0.046)	(0.047)	(0.048)	(0.041)
Credit Score (Risky)	1.553***	1.520***	1.415***	1.381***
	(0.054)	(0.054)	(0.055)	(0.048)
Lender & Outcome				
$\mathbb{1}_j^{\text{Bank}}$	−6.332***	−6.266***	−7.811***	
	(0.077)	(0.076)	(0.116)	
$\mathbb{1}_{ijt}^{\text{Default}}$		2.676***	5.152***	4.912***
		(0.171)	(0.483)	(0.487)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Default}}$		−1.488***	−4.009***	−3.775***
		(0.303)	(0.547)	(0.548)
Application Segment Effects				
$\mathbb{1}_{it}^{\text{RM}}$			−2.448***	−2.885***
			(0.102)	(0.090)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{it}^{\text{RM}}$			1.694***	2.207***
			(0.151)	(0.114)
$\mathbb{1}_{ijt}^{\text{Default}} \times \mathbb{1}_{it}^{\text{RM}}$			−3.289***	−3.042***
			(0.509)	(0.511)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Default}} \times \mathbb{1}_{it}^{\text{RM}}$			**3.996*** **	**3.981*** **
			(1.247)	(1.175)
Observations	82,768	82,768	82,768	82,766
R^2	0.487	0.490	0.502	0.579

Notes: This table reports OLS estimates of the relationship between loan interest rates and ex-post default. The dependent variable is the annualized interest rate in percentage points. $\mathbb{1}_j^{\text{Bank}}$, $\mathbb{1}_{it}^{\text{RM}}$, and $\mathbb{1}_{ijt}^{\text{Default}}$ are indicator variables for banks, RM-segment loans, and default within one year of origination, respectively. Firm controls include categorical dummies for age, asset size, and credit score. All columns include region, sector, and quarterly time fixed effects. Column (4) additionally includes individual lender fixed effects, replacing the aggregate bank indicator. The omitted category baseline defines an old firm with above median assets and a risky credit score, borrowing from a non-bank in the online segment. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 4: Positive Correlation Test (Interest Rates vs. Default).



Notes: This figure plots the relationship between the annualized interest rate and the predicted probability of default within one year of origination, conditional on observable firm characteristics (age, asset size, credit score) and fixed effects. The monotonic positive slope for both Banks (solid line) and Non-Banks (dashed line) provides evidence of screening based on private information, consistent with the positive correlation test of Chiappori and Salanié (2000).

allows us to compare how the relative screening sensitivity of banks versus non-banks varies across application channels. We find a positive and statistically significant coefficient on the triple interaction term. This indicates that the channel switch materially alters relative pricing dynamics: while non-banks exhibit higher price sensitivity to unobserved risk in the online segment, banks become relatively more price-sensitive to unobserved risk once lending moves to the RM segment. This finding complements Fact 1, demonstrating that the contraction in bank lending capacity for larger loans in the RM channel is accompanied by heightened screening precision, ensuring that higher ex-post risk is priced significantly more aggressively by banks in this segment. Column (4) replaces the aggregate bank dummy with individual lender fixed effects, absorbing all time-invariant heterogeneity across individual banks and non-bank lenders. The comparison between column (3) and (4) shows that the addition of lender fixed effects does not alter the main coefficients of interest meaningfully, suggesting a limited role for within lender type heterogeneity. Finally, across all specifications, the model explains approximately half of the variation in interest rates. The remaining unexplained variation in interest rates is consistent with a market characterized by highly individualized pricing, where borrower-lender interactions play an important role.

4.3 Residual Risk and Ex-Post Performance

Next, we consider the ex-post performance of these loans by analyzing default outcomes. We do so by estimating the following linear probability model:

$$\mathbb{1}^{\text{Default}}_{ijt} = \alpha + \beta_1 \mathbb{1}^{\text{Bank}}_{j} + \beta_2 \mathbb{1}^{\text{RM}}_{it} + \beta_3 (\mathbb{1}^{\text{Bank}}_{j} \times \mathbb{1}^{\text{RM}}_{it}) + \Gamma X_{it} + \Phi_{F.E.} + \epsilon_{ijt} \,, \tag{2}$$

where $\mathbb{1}^{\text{Default}}_{ijt}$ is a dummy variable equal to 1 if firm i defaulted on a loan from lender j originated in quarter t, and the remaining variables are defined as in Equation 1. The results, reported in Table 4, indicate that firm characteristics affect default risk in the expected directions.[7] Specifically, larger firms (those with assets above the median) are significantly less likely to default compared to firms in the bottom half of the size distribution, while younger firms exhibit a higher probability of distress compared to older firms.

More interestingly, the results reveal significant heterogeneity in the realized performance of loans held by different lender types. Conditional on firm characteristics and the full set of fixed effects, Fact 3 documents that loans held by banks exhibit significantly lower default rates than those held by non-banks. Column (1) shows that the bank coefficient is negative and economically significant, indicating that for observably equivalent firms, the realized probability of default is approximately 2 percentage points lower at a bank on average. This finding confirms that the non-bank portfolio carries significantly higher residual risk. This result likely reflects a compound effect: a compositional shift of unobserved risk toward non-banks, reinforced by structural incentives that render borrowers more likely to default on

[7] We report point estimates for our dummy dependent variable multiplied by 100.

Table 4: Residual Risk: Ex-Post Default Analysis

	Default Dummy ($\times$100)		
	(1)	(2)	(3)
Firm Controls			
Young Firm	0.700***	0.698***	0.702***
	(0.116)	(0.116)	(0.116)
Small Asset (Below Med.)	0.496***	0.415***	0.436***
	(0.145)	(0.156)	(0.156)
Credit Score (Normal)	−0.994***	−0.985***	−0.999***
	(0.146)	(0.146)	(0.147)
Credit Score (Safe)	−1.385***	−1.363***	−1.371***
	(0.173)	(0.174)	(0.175)
Lender Type Effect			
$\mathbb{1}_j^{\text{Bank}}$	−1.793***	−1.889***	
	(0.111)	(0.211)	
Application Segment			
$\mathbb{1}_{it}^{\text{RM}}$		−0.248	−0.341
		(0.219)	(0.223)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{it}^{\text{RM}}$		−0.018	0.291
		(0.245)	(0.302)
Observations	82,768	82,768	82,766
R^2	0.013	0.013	0.014

Notes: This table reports OLS estimates of the Linear Probability Model in Equation 2. The dependent variable is the ex-post one-year default indicator scaled by 100. $\mathbb{1}_j^{\text{Bank}}$ and $\mathbb{1}_{it}^{\text{RM}}$ are indicator variables for banks and RM-segment loans, respectively. Firm controls include categorical dummies for age, asset size, and credit score. All columns include region, sector, and quarterly time fixed effects. Column (3) additionally includes individual lender fixed effects, replacing the aggregate bank indicator. The omitted baseline category defines an old firm with above median assets and a risky credit score, borrowing from a non-bank in the online segment. Standard errors are clustered at the Region $\times$ Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

non-bank lenders than on banks.[8]

Column (2) examines whether this performance gap varies by loan size. While the interaction term is statistically insignificant—likely due to the high correlation between the firm asset size control and the loan size and consequently the application segment, the point

[8]We further validate this structural mechanism by estimating the same regression on the subsample of firms that simultaneously borrow from both lender types. Table B.1 in the Appendix shows the results. We find that, even within the same firm, the probability of default is more than one percentage point larger for non-bank loans compared with bank loans. This suggests that the result is not driven solely by firm-level unobservables (selection) but also by a lender-specific default shifter.

estimate is negative (−0.018). This directional result suggests that the lower default rate of banks is not merely an artifact of the online application segment. If anything, the bank performance advantage appears to widen slightly for large exposures in the RM segment, indicating that the factors driving higher non-bank default rates persist across the entire size distribution. Finally, Column (3) shows little impact when adding lender fixed effects, further suggesting a limited role for within lender type heterogeneity.

4.4 Determinants of Loan Size

Finally, we investigate the determinants of loan size to characterize the equilibrium allocation of credit exposures. We estimate:

$$\log(\ell_{ijt}) = \alpha + \beta_1 \mathbb{1}^{\text{Default}}_{ijt} + \Gamma X_{it} + \Phi_{F.E.} + \epsilon_{ijt}\ , \tag{3}$$

where ℓ_{ijt} is is the log of the loan amount originated to firm i by lender j. The specification includes our standard set of firm controls and fixed effects. The results are reported in Table 5.

First, looking at observable firm characteristics, we find that age, asset size, and credit score are strong predictors of loan size. Specifically, older firms, those with total assets above the median, and borrowers with safer credit scores are significantly more likely to carry large loans. This pattern reflects a standard equilibrium outcome where credit capacity scales with firm size, reputation, and observable credit quality.

Finally, loan size is positively correlated with ex-post default. Conditional on observable firm characteristics (age, assets, and credit score), the coefficient on $\mathbb{1}^{\text{Default}}_{ijt}$ is positive and statistically significant, showing that defaulting borrowers systematically obtain larger loans. This pattern reveals that unobserved risk maps into larger exposures in equilibrium, motivating our use of loan size as an informative signal in the structural model in Section 5.

TABLE 5: Determinants of Loan Size

	Large Loan Dummy (×100)		Log(Loan Amount)$_{ijt}$
	(1)	(2)	(3)
Firm Controls			
Young Firm	−1.254***	−1.279***	−0.0515***
	(0.375)	(0.376)	(0.0078)
Small Asset (Below Med.)	−48.32***	−48.33***	−1.106***
	(0.606)	(0.604)	(0.0142)
Credit Score (Normal)	5.397***	5.444***	0.1362***
	(0.406)	(0.406)	(0.0084)
Credit Score (Safe)	9.392***	9.475***	0.3161***
	(0.559)	(0.559)	(0.0121)
Outcome			
$\mathbb{1}_{ijt}^{\text{Default}}$		4.989***	0.0664***
		(1.005)	(0.0177)
Observations	64,711	64,711	82,768
R^2	0.444	0.444	0.563

Notes: This table reports OLS estimates of the loan-size determinants. Columns (1) and (2) estimate a Linear Probability Model where the dependent variable is an indicator variable for a large loan scaled by 100. Column (3) reports OLS estimates of Equation 3, where the dependent variable is the log of the loan amount originated to firm i by lender j in quarter t. $\mathbb{1}_{ijt}^{\text{Default}}$ is an indicator variable for ex-post default within one year of origination. Firm controls include categorical dummies for age, asset size, and credit score. All columns include Region, Sector, and Quarterly Time fixed effects. The omitted baseline category defines an old firm with above-median assets and a risky credit score. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Model

Motivated by the empirical patterns in Section 4, we develop a structural model of the unsecured SME credit market to quantify the equilibrium effects of risk-based capital regulation. The framework explicitly captures the interaction between information asymmetry, lender screening, and regulatory constraints, highlighting how these forces shape competition between banks and non-banks. On the supply side, we abstract to one representative bank and one representative non-bank. Two empirical features render this abstraction natural. First, within-lender-type heterogeneity plays a minimal role in our pricing and default regressions (Tables 3 and 4), indicating that a single representative lender per type captures the primary market variation. Second, bank choice is largely predetermined: in 92% of bank-originated loans, the lender is the firm's main current-account provider. Modeling a single bank option with an exogenous application channel cap is therefore consistent with the institutional environment, as a firm's relevant bank choice is established when its current account is opened, prior to its decision to seek credit.

We begin by specifying borrowers' indirect utilities from loan uptake and default, which determine their lender choice and default outcomes, as well as the equilibrium loan size. We then formalize the information structure in the market and characterize the lenders' optimization problems, leading to the pricing equations.

5.1 Borrower Setup

Borrowers, indexed by i, are heterogeneous in observable attributes X_i and unobservable risk θ_i. Each firm seeks an unsecured term loan from a choice set $j \in \mathcal{J} = \{B, N\}$, where B denotes the representative bank associated with the firm's primary current account, N denotes the representative non-bank, and $j = 0$ represents the outside option of no borrowing.

A key feature of a firm's environment is its application channel segment, $m(i) \in \{\text{Online}, \text{RM}\}$. From the borrower's perspective, this segment is exogenously determined by whether their required loan scale ℓ_i falls below or exceeds the online application cap $\bar{\ell}_i$ established by their primary bank:

$$m(i) = \begin{cases} \text{Online} & \text{if } \ell_i \leq \bar{\ell}_i \\ \text{RM} & \text{if } \ell_i > \bar{\ell}_i \end{cases} \tag{4}$$

For non-bank applicants, $s(i)$ defines the counterfactual bank channel the firm would face for a loan of scale ℓ_i. Taking this exogenous segment as given, the firm's primary decision is whether to borrow from its current account bank or pivot to a non-bank, where processing friction, capital requirements, and screening technologies differ across lender types within segment $s(i)$.

Loan Size Each borrower enters the market seeking to finance an investment opportunity or working capital need of scale ℓ_i. We model this funding requirement as a function of the borrower's fundamental characteristics:

$$\ell_i = \beta^{\ell} X_i + \beta^{\ell}_{\theta}\theta_i + \epsilon^{\ell}_i \,, \tag{5}$$

where ϵ^{ℓ}_i is an idiosyncratic credit demand shock. In this specification, $\beta^{\ell} X_i$ captures the baseline relationship between observable firm attributes (such as total assets) and credit demand. Crucially, the term $\beta^{\ell}_{\theta}\theta_i$ incorporates a structural link between unobserved risk and loan scale, capturing the intuition that riskier or distressed firms require larger liquidity injections. This specification is directly motivated by Fact 4, which shows that latent risk is positively correlated with exposure size conditional on observables. For tractability, we assume that this requested loan size reflects the borrower's true financial scale need determined by (X_i, θ_i) and takes place prior to lender interaction, rather than being strategically manipulated by the firm or enforced along a quantity-rationing margin by the lender.

Default Outcome (Ex-Post) Conditional on obtaining a loan of size ℓ_i from lender j, the borrower decides whether to repay or default. The borrower's indirect utility from defaulting is given by:

$$U^F_{ij} = \beta^F X_i + \beta^F_{\theta}\theta_i + \delta^F_j + \epsilon^F_{ij} \,:, \tag{6}$$

where ϵ^F_{ij} is an ex-post idiosyncratic shock. Importantly, U^F_{ij} does not depend on the offered interest rate r_{ij}. This specification reflects our empirical evidence in Section E, where we exploit quasi-experimental variation from rate hikes on floating rate loans to demonstrate that higher interest rate burdens do not increase firm default probabilities, ruling out rate-driven moral hazard. The parameter δ^F_j represents a lender-specific default shifter, capturing structural variation in repayment incentives, such as the severity of contract enforcement or the value of the banking relationship, across lender types. Including a lender-specific default shifter aligns with the evidence in Table B.1 in the Appendix, which indicates that firms that borrow from both lender types are more likely to default on non-bank loans. Anticipating this ex-post contingency, the borrower calculates their expected probability of default at the time of origination as:

$$PD_{ij}(X_i, \theta_i) = \Phi\left(\beta^F X_i + \beta^F \theta \theta_i + \delta_j^F - U_0^F\right) :, \tag{7}$$

where $\Phi(\cdot)$ is the cumulative distribution function governing the idiosyncratic shock ϵ_{ij}^F.

Lender Choice (Ex-Ante) Given the offered interest rate r_{ij} and anticipated repayment burden, the borrower chooses the lender that maximizes ex-ante utility. The indirect utility from accepting a loan from lender $j \in \mathcal{J}$ is defined as:

$$U_{ij}^D = -\alpha_i r_{ij} + \beta^D X_i + \delta_{j,m(i)}^D + \epsilon_{ij}^D = V_{ij}^D + \epsilon_{ij}^D \,, \tag{8}$$

where $\delta_{j,m(i)}^D$ represents the segment-specific vertical quality of lender j. This term captures processing convenience and speed, as well as the disutility or operational burden a borrower incurs when bank credit requires moving from a seamless online process to a relationship-manager evaluation in segment $m(i) = \text{RM}$. The idiosyncratic demand shock is given by ϵ_{ij}^D. Crucially, borrower price sensitivity α_i is heterogeneous and specified as:

$$\alpha_i = \alpha + \gamma_\ell \ell_i - \gamma_\theta \theta_i \,.$$

This functional form allows price elasticity to vary along two key dimensions. First, γ_ℓ governs the scale effect, where a positive coefficient implies that borrowers requiring larger exposures are more interest-rate sensitive due to higher debt-service costs. Second, γ_θ determines the correlation between unobserved risk and price sensitivity. If $\gamma_\theta > 0$, riskier borrowers are less sensitive to interest rate increases, generating an adverse selection mechanism where higher rates worsen applicant pool quality.

The borrower's effective choice set $\mathcal{J}_i(m(i)) \subseteq \{B, N\}$ is endogenous to lender participation within segment $m(i)$. Each lender extends an offer only if its expected origination profit is positive given its segment-specific screening technology and capital constraints. Normalizing the outside option utility to $U^D_{i0} = \epsilon^D_{i0}$ and assuming demand shocks ϵ^D_{ij} follow a Type I extreme value distribution, the probability that borrower i chooses lender $j \in \mathcal{J}_i(m(i))$ takes the standard multinomial logit form:

$$Q_{ij} = \frac{e^{V^D_{ij}}}{1 + \sum_{k \in \mathcal{J}_i(s(i))} e^{V^D_{ik}}} \ . \tag{9}$$

When no lender finds it profitable to serve borrower i in segment $m(i)$, such that $\mathcal{J}_i(m(i)) = \emptyset$, the firm is credit-rationed and selects the outside option with probability one.

5.2 Information Structure

Lenders infer the borrower's unobserved type θ_i by aggregating public and private information. The information aggregation process is summarized in Figure 5:

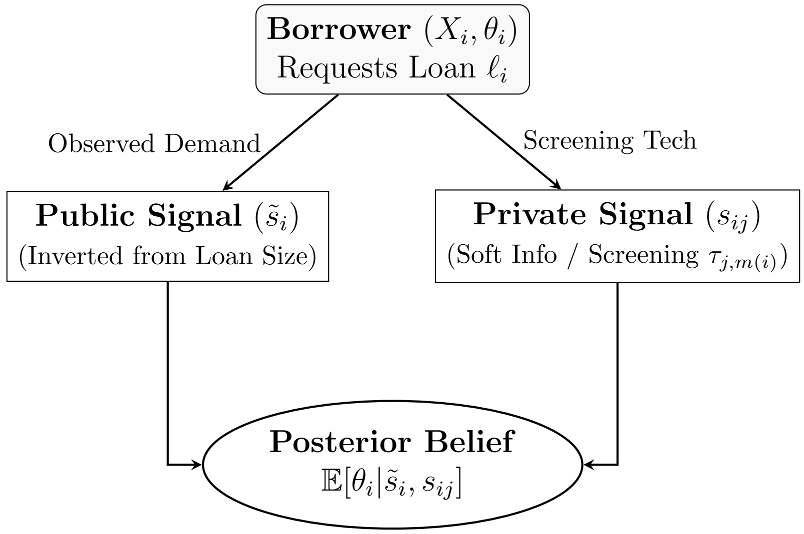
First, the requested loan scale ℓ_i provides a public signal of risk. Since credit demand is structurally linked to borrower attributes, lenders extract a noisy estimate of type, $\tilde{s}_i$, by inverting the loan demand equation:

$$\tilde{s}_i \equiv \frac{\log(\ell_i) - \beta^\ell X_i}{\beta^\ell_\theta} = \theta_i + \tilde{\epsilon}_i \ . \tag{10}$$

Second, lender j acquires a private screening signal s_{ij}. This signal captures soft information generated through due diligence, such as relationship history, qualitative assessment, or proprietary algorithms. We model this as:

$$s_{ij} = \theta_i + \epsilon^s_{ij} \ , \quad \epsilon^s_{ij} \sim \mathcal{N}(0, \tau^{-1}_{j,m(i)}) \ , \tag{11}$$

FIGURE 5: Information Structure and Bayesian Updating



Notes: This figure displays the information structure of the model, characterized by Bayesian updating on public signals and segment-specific private signals.

where $\tau_{j,s(i)}$ denotes the precision of lender j's screening technology in application segment $m(i) \in \{\text{Online}, \text{RM}\}$.

We allow the bank's screening precision to vary across application channels, $\tau_{B,s(i)} \in \{\tau_{B,\text{Online}}, \tau_{B,\text{RM}}\}$. When the requested loan scale falls below the primary bank cap ($\ell_i \leq \bar{\ell}_i$), processing occurs via the automated online channel with precision $\tau_{B,\text{Online}}$. When the loan exceeds the cap ($\ell_i > \bar{\ell}_i$), the application shifts to a relationship manager, unlocking additional soft information and human due diligence that operates at precision $\tau_{B,\text{RM}}$. Non-bank lenders, by contrast, operate automated digital platforms across all loan sizes, motivating a single invariant precision τ_N on the non-bank side.

Conditional on the total information set $\mathcal{I}_{ij} = \{\tilde{s}_i, s_{ij}\}$, the lender forms a posterior belief about θ_i. Under standard normality assumptions, the posterior mean is a linear combination of the public signal $\tilde{s}_i$ and the private signal s_{ij}, weighted by their respective precisions.

5.3 Lender Optimization and Pricing

We now turn to the competition phase. While lenders face uncertainty regarding the borrower's unobserved type θ_i, they leverage both observable characteristics and extracted signals to infer the underlying risk. Based on these inferences, lenders compete simultaneously by offering interest rates r_{ij}. Borrowers then observe these offers and select the lender that yields the highest indirect utility, U_{ij}^D.

Before characterizing the equilibrium, it is useful to highlight the theoretical complexity inherent in this setting. To simplify the exposition, consider only the supply side by setting aside the demand model with a taste shock and assume that the borrower chooses the lowest interest rate. In this context, the game mirrors a common-value auction subject to the "winner's curse." Lenders receive noisy signals correlated with the borrower's unobserved type; consequently, the lender who wins the borrower is statistically likely to have received the most optimistic signal, implying the true risk is higher than their internal estimate.

In standard common-value auctions with symmetric bidders, Milgrom (1981) derives a closed-form solution for the equilibrium bidding strategy. However, our model introduces additional complexities beyond the standard common-value auction, primarily due to differential capital requirement regulations. In a standard common-value auction, a symmetry assumption requires that all bidders' payoffs respond identically to the underlying signal. In our setting, however, banks incur capital charges that are tied to the perceived risk, and thus to the signal, while non-banks do not. As a result, lenders' profit functions depend asymmetrically on their signals.

A key feature of our framework is that the idiosyncratic taste shock ϵ_{ij}^D resolves this intractability by restoring smoothness to the competitive game. Without it, an arbitrarily small undercut shifts the entire mass of borrowers from one lender to the other, so demand at the lender level is a step function and best responses are discontinuous in the rival's offer. Combined with the asymmetric capital charges described above, this discontinuity generically rules out pure-strategy equilibria and renders the winner's-curse correction analytically intractable. The taste shock replaces the step function with a smooth Logit demand system: winning probabilities and posteriors over θ_i become continuous, interior functions of prices, the lenders' first-order conditions are well-defined, and a pure-strategy equilibrium exists despite the regulatory asymmetry. This modeling device is standard in the structural IO literature on firms' credit choices Crawford, Pavanini and Schivardi (2018); Benetton and Buchak (2024); Stillerman (2024), where it additionally captures borrower-lender idiosyncratic match heterogeneity such as prior relationship with a specific institution, geographic proximity, familiarity with the application process, or recommendation from the firm's accountant.

5.3.1 Non-Bank Lender

We start by characterizing the optimization problem for the non-bank lender ($j = N$). Unlike banks, non-banks are not subject to risk-weighted capital requirements; consequently, borrower risk affects their objective function solely through expected credit losses. The non-bank selects the interest rate r_{iN} to maximize expected profit, conditional on its information set $\mathcal{I}_{iN}$. In this decision process, the non-bank faces two primary sources of uncertainty: the borrower's unobserved true risk type, θ_i, and the realized private signal of the competitor, s_{iB}. Because the probability of winning the loan, Q_{iN}, depends on the competitor's offer, which is a function of s_{iB}, the non-bank must integrate over the distributions of both variables. Taking application mode $m(i)$ as given, the maximization problem considers both repayment and default scenarios and is given by:

$$\max_{r_{iN}} \iint Q_{iN}(\cdot)\ell_i \Big[(1 - PD_{iN}(\cdot))\, r_{iN} - LGD_N \cdot PD_{iN}(\cdot) - c_N \Big]\, dF_{\theta_i|\mathcal{I}_{iN}}\, dF_{s_{iB}|\mathcal{I}_{iN}},$$

where PD_{iN} represents the borrower's true probability of default given type θ_i, and LGD_N denotes the non-bank loss given default. The parameter c_N denotes the marginal cost of loan origination. The outer integral over s_{iB} captures the strategic interaction: the non-bank forms an expectation over the competitor's private signal to anticipate the rival's offer. This formulation explicitly accounts for the winner's curse. The non-bank anticipates that winning the loan (a high realization of Q_{iN}) is statistically more likely when the competitor has observed a negative signal s_{iB} and priced high. By integrating over s_{iB}, the lender adjusts its bid to account for this winner's curse in the competitive process.

5.3.2 Bank Lender

We now turn to the bank's optimization problem ($j = B$). Banks differ from non-banks as they are subject to minimum risk-based capital requirements. The literature suggests these regulations have loan pricing implications due to the associated shadow cost of capital Benetton (2021); Plosser and Santos (2024). As noted earlier, regulation requires banks to maintain a capital ratio, defined as the ratio of equity capital to risk-weighted assets, above a minimum threshold. Moreover, banks maintain buffers above minimum capital requirements, to minimize the risks of breaches that would trigger regulatory and market reactions. Importantly, the size of banks' capital buffer also matters, as the impact of regulation on interest rates and loan amounts is larger for less capitalized banks Benetton et al. (2021); Plosser and Santos (2024).[9]

In this environment, each new loan a bank originates adds to its risk-weighted assets and, holding equity fixed in the short run, mechanically shrinks the capital buffer the bank holds above the regulatory minimum. We refer to the bank's ability to absorb additional risk-weighted exposures without pushing this buffer toward the binding threshold as its *balance sheet capacity*. Lending therefore consumes balance sheet capacity, and the marginal value of preserving that capacity acts as a shadow cost on every new loan.

Following Buchak et al. (2024), we model this shadow cost as a convex function of the

[9]This also aligns with patterns in our data: in Appendix C, using confidential bank-level supervisory data, we provide suggestive evidence of a negative correlation between capital buffers and loan interest rates.

distance between the bank's actual capital ratio and the regulatory minimum:

$$C(\rho_B) = \kappa(\rho_B - \bar{\rho})^{-\phi}, \tag{12}$$

where $\rho_B = E_B/RWA_B$ is the bank's aggregate risk-adjusted capital ratio, E_B is total equity, RWA_B is total risk-weighted assets, and $\bar{\rho}$ is the target minimum capital ratio imposed by the regulator. The use of a convex function for the shadow cost of balance sheet capacity, rather than a hard constraint, explains why banks consistently hold a capital buffer above the minimum ratio, as approaching the threshold increases the risk of severe penalties.

We now bridge the bank's aggregate regulatory constraints to individual loan pricing. A direct application of the cost function $C(\rho_B)$ at the bank-wide level would imply that any single SME loan has a negligible effect on the bank's overall capital ratio: relative to the hundreds of billions of pounds of risk-weighted assets on a major UK bank's balance sheet, even a £100,000 unsecured SME loan is microscopic, and the shadow cost it generates would be too small to influence pricing or generate the sharp market-share contraction we observe across application modes (Table 2). To match these empirical patterns, the relevant balance sheet against which a marginal SME loan is priced must be substantially smaller than the bank's aggregate book.

We capture this by modeling lending decisions at the level of a local business unit, motivated by the trade-off between decentralized information production and hierarchical capital allocation in Stein (2002). Local units possess superior information about borrowers, while headquarters manages the aggregate balance sheet. We assume the bank operates an internal capital market that transmits the shadow cost of balance sheet capacity to the unit level: each unit is allocated equity in proportion to the bank-wide capital ratio ρ_B and prices new loans against its own portfolio's capacity, internalizing the wider capital implications of its lending decisions.

We define η_B as the existing risk-weighted exposure of the specific business unit's portfolio. The bank allocates equity to each unit proportionally to the bank-wide ratio ρ_B, such that the unit's implicit equity is $\rho_B \eta_B$. When a unit considers originating a new loan i under application mode $m(i)$, it evaluates how the additional risk-weighted assets associated with this loan dilute its specific portfolio's capital ratio. The new loan increases the portfolio's RWA by $RW_{iB}\ell_i$, where ℓ_i is the loan amount and RW_{iB} is the risk weight assigned to the loan. Importantly, RW_{iB} is calculated using the regulatory mapping applied to the bank's estimated probability of default, PD_{iB}, and LGD_B. This link connects capital regulation and balance sheet capacity directly to the information asymmetry and screening mechanics of our model.

The incremental shadow cost of balance sheet capacity, $\mathcal{C}_{iB}^{cap}$, is therefore calculated as the increase in the shadow cost of capital caused by adding this specific loan to the unit's existing book:

$$\mathcal{C}_{iB}^{cap} = C(\rho^{\text{post}}) - C(\rho^{\text{pre}}) = \kappa \left[\left(\frac{\rho_B \eta_B}{\underbrace{\eta_B + RW_{iB}\ell_i}_{\text{Increased RWA}}} - \bar{\rho} \right)^{-\phi} - (\rho_B - \bar{\rho})^{-\phi} \right], \tag{13}$$

This formulation has two key implications. Because $\mathcal{C}_{iB}^{cap}$ is convex in the bank's distance from the regulatory threshold and increasing in both the loan size ℓ_i and the risk weight RW_{iB}, banks with larger capital buffers should offer lower interest rates and be more likely to originate large loans. Both patterns are confirmed in our data: Appendix C uses confidential bank-level supervisory data to show that increases in banks' capital buffers are associated with lower SME loan interest rates and a higher likelihood of originating large loans.

Under these assumptions, taking application mode $m(i)$ as given, the full maximization problem for the Bank ($j = B$) is:

$$\max_{r_{iB}} \iint Q_{iB}(\cdot) \left[\ell_i \Big((1 - PD_{iB}(\cdot)) r_{iB} - LGD_B \cdot PD_{iB}(\cdot) - c_B \Big) - \mathcal{C}_{iB}^{\text{cap}}(\cdot) \right] dF_{\theta_i | \mathcal{I}_{iB}} dF_{s_{iN} | \mathcal{I}_{iB}}, \tag{14}$$

The true default probability $PD_{iB}(\cdot)$ governs expected credit losses, while the bank's assessed default probability, defined as the expectation over its posterior beliefs given screening under mode $m(i)$,

$$\overline{PD}_{iB} \equiv \mathbb{E}\big[PD_{iB}(\cdot) \,\big|\, \mathcal{I}_{iB}\big] \,, \tag{15}$$

governs the regulatory risk weight $RW_{iB} = RW(\overline{PD}_{iB}, LGD_B)$ and therefore enters $\mathcal{C}^{cap}_{iB}$. This distinction reflects the institutional fact that capital requirements depend on the bank's internal risk assessment, rather than the borrower's unobserved true type.

5.3.3 Optimal Pricing Strategy

Solving the maximization problem for both lenders yields a general first-order condition that characterizes the optimal interest rate r_{ij}. Taking application mode $m(i)$ as given, the resulting pricing equation decomposes the optimal rate into two distinct components: an effective marginal cost, which incorporates credit risk, funding costs, and regulation, and an effective markup, which is determined by competitive pressure:

$$\begin{aligned} r_{ij}(s_{ij}, X_i, \ell_i, m(i)) = & \frac{\mathbb{E}_{\mathcal{I}_{ij}}\left[Q'_{ij}(\cdot)\left(c_j + LGD_j \cdot PD_{ij}(\cdot) + \mathbb{1}_{j=B}\dfrac{\mathcal{C}^{\text{cap}}_{ij}(\cdot)}{\ell_i}\right)\right]}{\mathbb{E}_{\mathcal{I}_{ij}}\left[Q'_{ij}(\cdot)\left(1 - PD_{ij}(\cdot)\right)\right]} \qquad \text{Effective MC} \\ & - \frac{\mathbb{E}_{\mathcal{I}_{ij}}\left[Q_{ij}(\cdot)\left(1 - PD_{ij}(\cdot)\right)\right]}{\mathbb{E}_{\mathcal{I}_{ij}}\left[Q'_{ij}(\cdot)\left(1 - PD_{ij}(\cdot)\right)\right]} \qquad \text{Effective Markup} \end{aligned} \,, \tag{16}$$

where $\mathbb{E}_{\mathcal{I}_{ij}}[\cdot] \equiv \mathbb{E}_{\theta_i, s_{-j}|\mathcal{I}_{ij}}[\cdot]$ denotes the expectation taken over the borrower's unobserved risk type θ_i and the competitor's private signal s_{-j}, conditional on lender j's information set $\mathcal{I}_{ij}$. We note that Equation (16) does not yield a closed-form analytical solution for r_{ij}, as the demand terms $Q_{ij}(\cdot)$ and $Q'_{ij}(\cdot)$ are endogenous functions of the rate r_{ij} and depend on the rival's simultaneous optimization under application mode $m(i)$. Consequently, the equilibrium pricing schedule characterizes a fixed-point problem which we solve using numerical methods.

Credit rationing arises endogenously through the lender's participation decision. Let r^*_{ij} denote the equilibrium rate implied by the first-order condition in Equation (16), and let Π^*_{ij} denote the corresponding expected profit evaluated at r^*_{ij}, integrating over the lender's beliefs about θ_i and the rival's signal s_{-j}. Lender j extends an offer to borrower i only if

$$\Pi^*_{ij} \;\geq\; 0\,. \tag{17}$$

When this condition fails for both lenders, the borrower's effective choice set is empty and the borrower is rationed. When it fails for one lender, the borrower's choice set collapses to the remaining lender plus the outside option. Rejections therefore occur whenever the optimal risk-adjusted margin at r^*_{ij} is insufficient to make origination profitable.

6 Estimation and Results

In this section, we outline the econometric strategy used to recover the structural parameters governing borrower preferences and the supply-side cost and information structures.

The primary econometric challenge is that we observe only the rate on the loan actually originated, not the full menu of offers each borrower faced. As discussed in Section 2, the standard solution of recovering the choice set through a pricing-prediction regression with borrower and bank-region-year fixed effects Crawford, Pavanini and Schivardi (2018) is not well-suited to our setting for two reasons. First, the channel of interest in our paper, which is how capital regulation interacts with banks' internal risk assessment, operates through banks' screening precision, which must be recovered as a structural primitive rather than absorbed into the reduced-form object formed by the sum of firm and lender-region-time fixed effects. Second, multiple lending relationships per firm, required to identify the borrower fixed effect, are very rarely observed in our data. Our approach instead leverages the structural model itself. By jointly solving the demand and supply systems and explicitly modeling the regulatory and informational asymmetries between banks and non-banks across application modes $m(i)$, we simulate the equilibrium menu of contracts each borrower would face given their characteristics and unobserved risk type. This recovers the latent offer distribution without requiring multiple banking relationships.[10] In what follows, we detail the simulation-based estimation framework and present our results.

6.1 Estimation Strategy

We estimate the structural parameters Θ using Indirect Inference Gourieroux, Monfort and Renault (1993), minimizing the weighted distance between empirical moments and their model-simulated counterparts:

$$\hat{\Theta} = \arg\min_{\Theta} \left[\mu^{\text{sim}}(\Theta) - \mu^{\text{data}}\right]' W \left[\mu^{\text{sim}}(\Theta) - \mu^{\text{data}}\right]$$

where μ^{data} is the vector of empirical target moments, $\mu^{\text{sim}}(\Theta)$ is the corresponding vector obtained by simulating the model at parameter values Θ, and W is a positive semi-definite diagonal weighting matrix. Under standard regularity conditions, the estimator is consistent and asymptotically normal Gourieroux, Monfort and Renault (1993).

Target Moments. We match 43 moments organized into three groups that together discipline the key margins of the model: pricing, screening, and market structure.

The first group consists of coefficients from auxiliary regressions that summarize the conditional correlations in the data. We target the pricing regression (Table 3, Column 3), which captures how interest rates vary with borrower risk, lender type, and loan size; an extended pricing specification that interacts firm-level controls (age, asset size, and credit score) with the bank indicator, reported in Appendix D, which captures how the pricing of

[10] In this version of the draft, the structural parameters and model-fit moments are reported using the preliminary estimation baseline where segments were defined by loan size thresholds ($\ell_i \gtrless £50,000$). Structural estimation under the updated application channel mapping $m(i) \in \{\text{Online}, \text{RM}\}$ is currently being executed for the final revision.

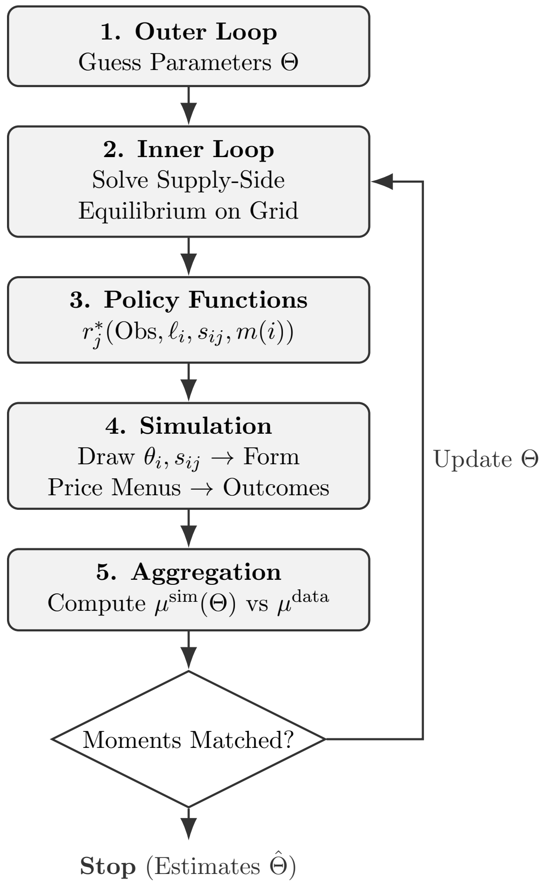
observable risk characteristics differs between banks and non-banks; the default regression (Table 4, Column 1), which disciplines the relationship between observables and loan performance; and the loan size regression (Table 5, Column 2), which reflects the determinants of lending volume. These moments are particularly informative for the demand parameters, screening precision, and cost structure, as they encode the equilibrium pass-through of risk characteristics to contract terms.

The second group comprises default rates and market shares by lender type and application channel segment $m(i)$. These moments are essential for separately identifying bank and non-bank cost functions: default rates reveal how screening quality varies across lenders and channel segments, while segment-specific market shares discipline the relative competitiveness of each lender type along the intensive margin. Because this group contains only six moments compared to 23 in the regression group, equal weighting would allow regression fit to crowd out these economically central margins, a point we return to below.

The third group consists of market shares by borrower demographics (age, asset holdings, and credit score), separately for bank and non-bank lenders. These moments pin down the demand-side heterogeneity parameters that govern substitution patterns across lender types. We define the outside option as SMEs that maintain an active current account, defined as a current account with at least one transaction in the preceding 12 months, but hold no formal credit product such as a term loan, mortgage, overdraft facility, lease, or credit card.

Computational Method. The objective function is non-convex and computationally expensive: each evaluation requires solving for equilibrium interest rates via fixed-point iteration and simulating four million loan-level outcomes. We employ the TikTak algorithm of Arnoud, Guvenen and Kleineberg (2024), a two-phase global optimizer designed for high-dimensional simulation-based estimation. The first phase evaluates the objective at a large number of Sobol quasi-random points spanning the parameter space Sobol' (1967). The second phase warm-starts multiple independent local searches from the most promising exploration points using Powell's conjugate direction method Powell (1964), which adaptively learns the ridge structure of the objective without requiring gradient information.

FIGURE 6: Overview of the Numerical Estimation Algorithm



Notes: This figure displays the numerical algorithm used to solve and estimate the structural model across application modes $m(i)$.

Numerical Implementation The estimation relies on a nested fixed-point algorithm, illustrated in Figure 6. Because the equilibrium pricing function lacks a closed-form solution, we first solve the supply-side equilibrium on a discretized state space of borrower characteristics and application modes. We do this by iterating on the lenders' first-order conditions (Equation 16) until convergence. This yields the equilibrium policy functions that map borrower observables, loan scales ℓ_i, lender signals s_{ij}, and application modes $m(i)$ to optimal interest rates.

We then simulate a synthetic population of firms, adding unobserved heterogeneity via latent risk draws $\theta_i \sim \mathcal{N}(0,1)$ and corresponding signal realizations under channel mode $m(i)$. By evaluating the estimated policy functions at these draws, we construct the realized menu of prices available to each individual borrower. Finally, we determine the resulting market outcomes, including the winning lender and ex-post loan performance. These micro-level outcomes are then aggregated to compute the vector of simulated moments $\mu^{\text{sim}}(\Theta)$. The estimator minimizes the distance between these simulated moments and the empirical targets described above.

6.2 Identification

The structural parameters governing borrower demand, lender costs, screening technologies, regulatory capital costs, and borrower risk are identified from equilibrium relationships between interest rates, lender market shares, loan sizes, and realized default outcomes across borrower segments. Because demand and supply sides are estimated jointly, rather than following the standard approach of first recovering demand from observed price variation and then backing out costs from estimated markups, identification does not rely on single-equation exclusion restrictions or a one-to-one mapping between moments and parameters. Instead, each parameter is disciplined by the way it shapes the joint distribution of equilibrium outcomes, and identification exploits the fact that different parameters distort this distribution in distinguishable ways. We organize the discussion around three groups of parameters: demand and cost, screening and regulation, and borrower risk.

Demand, Cost, and Price Sensitivity. Borrower price sensitivity, lender demand shifters, and lender marginal costs are identified jointly from the co-movement of interest rates and lender market shares across borrower segments. These three sets of parameters generate distinguishable predictions for equilibrium prices and market shares. A lender facing higher marginal costs must charge higher rates, which causes borrowers to substitute toward the competitor, reducing the high-cost lender's market share. A lender benefiting from a stronger non-price preference can sustain higher prices without losing borrowers, so both its price and market share increase. This opposing covariation is the source of demand-versus-cost separation: lenders with high prices and low market shares are revealed as having higher costs, while lenders with high prices and high market shares are revealed as benefiting from stronger borrower preferences.

Price sensitivity governs the magnitude of borrower substitution in response to price differentials across lenders, and is therefore identified from the responsiveness of market shares to cross-sectional price variation. When equilibrium prices differ across borrower segments, because costs or risk vary, the resulting reallocation of borrowers across lenders reveals the demand elasticity. This variation is distinct from what identifies costs and demand shifters: price sensitivity determines how strongly shares respond to a given price differential, whereas costs and demand shifters determine the price differential itself.

The model allows price sensitivity to vary with loan size and borrower risk. The loan size component is identified from the differential sorting of borrowers with large versus small exposures across lenders. If price sensitivity depends on loan size, borrowers seeking larger loans respond differently to cross-lender price differentials, generating a pattern in how market shares co-vary with loan size that would not arise under uniform price sensitivity. The risk component is identified from the interaction between pricing and realized default outcomes. If riskier borrowers are less price-sensitive, they are less likely to switch lenders when rates rise, causing the borrower pool at each lender to deteriorate with higher prices. This adverse selection mechanism produces a distinctive covariation between equilibrium prices, default rates, and market shares that pins down the risk component of price sensitivity separately from the baseline level.

Screening Precision, Risk Dispersion, and Default Shifters. The model allows borrower default risk to depend on both observable firm characteristics and a latent risk factor not observed by the econometrician. Three sets of parameters govern the relationship between this unobserved heterogeneity and equilibrium outcomes: the dispersion of latent risk across borrowers, the precision with which lenders screen for that risk, and lender-specific shifters that capture systematic differences in default rates across lender types.

Risk dispersion and screening precision are conceptually distinct but interact in equilibrium. Risk dispersion governs how much hidden variation in default probabilities exists within groups of observationally equivalent borrowers. Screening precision governs how well lenders detect this hidden variation when setting prices. The two are separated because they leave different traces in equilibrium outcomes. Higher risk dispersion increases the residual variation in default rates within observable borrower groups and amplifies the sorting of latently risky borrowers toward lenders with less precise screening. These effects are disciplined by the default regression coefficients on borrower characteristics, which capture how default risk varies with observables, and by unconditional default rates across lender types, which capture the overall level of risk in each lender's portfolio. Screening precision, by contrast, governs how strongly prices respond to borrower risk that is not captured by observables. Higher precision generates a steeper relationship between interest rates and realized default outcomes, because lenders with better signals can more accurately rank borrowers and price accordingly. However, because borrowers endogenously sort across lenders, the observed relationship between prices and default reflects both risk-based pricing and selection. For this reason, screening precision must be consistent with both the slope of prices with respect to realized default in the pricing regression and the composition of defaults within each lender's portfolio.

The model also incorporates lender-specific default shifters that allow the average default probability to differ between bank and non-bank portfolios for reasons beyond borrower selection and screening. These parameters capture post-origination differences in how each lender type affects repayment outcomes, such as variation in monitoring intensity, enforcement mechanisms, or contractual features. These shifters are identified from the difference in realized default rates between bank and non-bank portfolios that remains after the model accounts for endogenous borrower sorting. The demand, cost, and screening parameters jointly determine which borrowers select into each lender type, generating a predicted default rate for each portfolio based on its equilibrium composition. The default shifters are then disciplined by the gap between these predicted rates and the observed rates: any systematic residual in default outcomes at a given lender type that cannot be attributed to the composition of its borrower pool is absorbed by the lender-specific shifter.

Regulatory Parameters. For banks, the pricing schedule is shaped by an additional force beyond screening: balance sheet capacity constraints. Both screening precision and regulatory capital charge steepen the relationship between interest rates and borrower risk, but they do so with distinguishable consequences for the level and slope of the pricing schedule. Higher screening precision steepens the schedule by lowering rates for borrowers identified as safe and raising rates for those identified as risky, without necessarily shifting the overall level of bank prices. Tighter regulatory capital charges also steepen the schedule, because capital charges are convex in assessed risk, but simultaneously raise the level of prices even for the safest borrowers. The identification therefore rests on the opposing effects at the safe end of the pricing schedule, that is, borrowers with the lowest assessed probability of default: higher screening precision lowers rates for these borrowers, while tighter regulatory charges raise them.

Within the bank balance sheet capacity structure itself, three parameters play distinct roles in shaping how capital charges vary across borrowers and loan sizes: a scale parameter κ, a curvature parameter ϕ, and the size of the local business unit's risk-weighted portfolio η. The scale primarily governs the average level of regulatory capital charges across all bank loans. The curvature determines how convex the shadow cost is in the bank's capital buffer, and therefore primarily shapes how aggressively banks differentiate prices across borrowers within observable risk groups based on their internal risk assessment. The portfolio size predominantly affects how differently banks treat small and large loan exposures: a smaller local portfolio implies that each additional loan has a larger proportional impact on the unit's capital ratio, amplifying the bank's risk resistance for large exposures relative to small ones. The estimation recovers these parameters by matching the joint variation in bank pricing, default rates, and market shares across loan size and borrower risk segments.

Observable Borrower Characteristics. The coefficients governing how observable firm characteristics enter the default, demand, and loan size equations are identified from the cross-sectional variation in outcomes across borrower groups. The default coefficients, which allow default probabilities to vary with firm age, asset size, and credit score, are identified from the default regression. The characteristic-specific outside option values, which allow the attractiveness of the no-borrowing alternative to vary with firm type, are identified from the cross-sectional pattern of overall take-up rates: if borrowers with a given characteristic are less likely to accept any lender's offer despite facing competitive prices, the model attributes this to a higher outside option for that group. Finally, the loan size coefficients, which govern how the requested exposure varies with observable characteristics and latent risk, are identified from the loan size regression. The coefficients on observables capture the standard relationship between firm characteristics and borrowing scale. The coefficient on latent risk is identified from the conditional correlation between loan size and realized default: a positive coefficient implies that, within groups of observationally equivalent borrowers, those who eventually default tend to have requested larger loans. This parameter disciplines how lenders use the requested loan amount as a public signal when updating their beliefs about borrower type.

In summary, the identification of the model's parameters rests on the joint variation in equilibrium prices, market shares, default rates, and loan sizes across borrower groups and lender types. Each parameter group leaves a distinct imprint on the joint distribution of these outcomes, and the estimation exploits these differences to recover the structural primitives simultaneously.

6.3 Estimation Results

Table 6 presents the structural parameter estimates. Figures 7 and 8 illustrate the goodness of fit. Figure 7 shows that the model closely tracks market shares and realized default rates across borrower types and loan-size segments, while Figure 8 reports the fit to the targeted regression coefficients. In what follows, we discuss the quantitative implications for borrower demand, lender cost structures, and information frictions.

Demand Estimates The demand parameters (Panel A) imply an average own-price elasticity of 2.7 for non-banks and 1.9 for banks. In economic terms, these values indicate that a 10% increase in the interest rate results in a 27% and 19% decline in market share, respectively. Our estimated elasticities are larger than those reported by Benetton and Buchak (2024) for US SME revolving credit, reflecting two differences between the two settings. First, the demand systems differ in how the outside option is defined. Our specification treats no external borrowing as the outside option, which is the relevant comparison for analyzing the extensive margin of credit access in our counterfactuals. Their specification, in contrast, conditions on firms that have already chosen to borrow an unsecured product and analyzes substitution between credit cards and term loans, with term loans serving as the outside option; the choice not to borrow at all is therefore not part of their decision problem. Because the no-borrowing alternative carries a substantially larger market share than any single substitute credit product, our outside option absorbs a higher baseline share of borrowers, which mechanically increases the elasticity of inside products with respect to their own prices. Second, the products themselves are different. As Benetton and Buchak (2024) note, firms often acquire credit cards for transactional rather than financing purposes, dampening price sensitivity for rates they do not anticipate paying. In contrast, the unsecured term loans in our setting represent a deliberate, upfront borrowing decision, for which

Table 6: Structural Parameter Estimates

Panel A: Demand Parameters

Parameter	Sym.	Est.
Price Sensitivity	α	34.597
Interaction: Size	γ_ℓ	0.008
Interaction: Risk	γ_θ	5.938
Intercept: Bank	δ_B^D	−0.353
Intercept: Non-Bank	δ_N^D	2.878
Observable Controls (β^D):		
Young Firm	β_y^D	0.655
Low Asset	β_{la}^D	0.026
Normal Credit	β_{nc}^D	−0.302
Safe Credit	β_{sc}^D	−0.223

Panel B: Supply & Regulation

Parameter	Sym.	Est.
Reg. Scale	κ	0.037
Reg. Ref. RWA Size	η	4544.5
Parameter for cap. adequacy	ϕ	1.106
Funding Cost: Bank	c_B	0.006
Funding Cost: NB	c_N	0.036

Panel C: Default Technology

Parameter	Sym.	Est.
Intercept: Bank	δ_B^F	−5.471
Intercept: Non-Bank	δ_N^F	−4.206
Risk Sensitivity	β_θ^F	1.014
Observable Controls (β^F):		
Young Firm	β_y^F	0.452
Low Asset	β_{la}^F	0.591
Normal Credit	β_{nc}^F	−0.474
Safe Credit	β_{sc}^F	−1.074

Panel D: Information & Loan Size

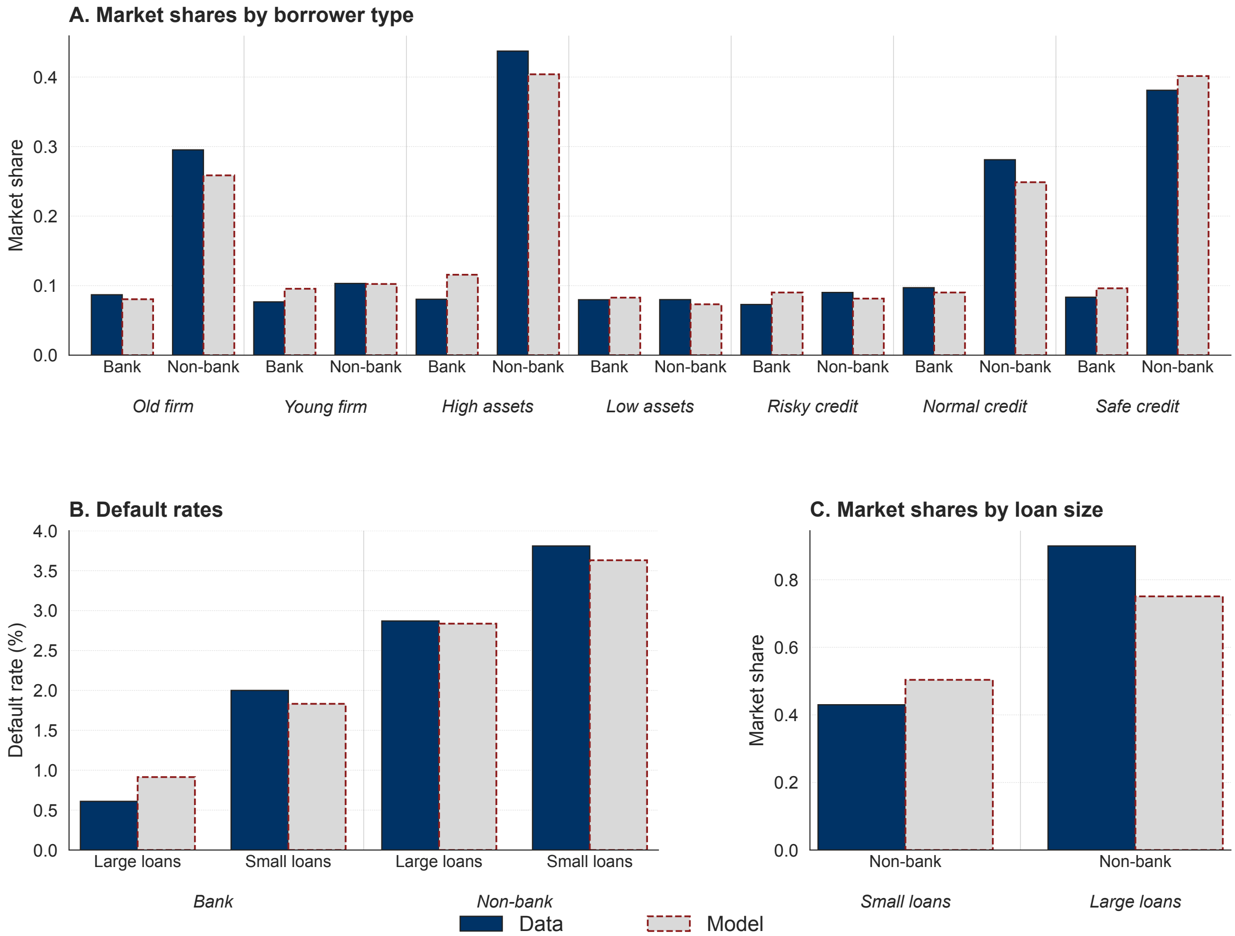
Parameter	Sym.	Est.
Signal Noise: Bank (Sm.)	$\sigma_{s,B}^s$	1.709
Signal Noise: Bank (Lg.)	$\sigma_{s,B}^\ell$	0.699
Signal Noise: NB	$\sigma_{s,N}$	1.490
Size Shock SD	σ_ϵ	3.783
Loan Size Controls (β^ℓ):		
Young Firm	β_y^ℓ	0.221
Low Asset	β_{la}^ℓ	8.922
Normal Credit	β_{nc}^ℓ	−0.680
Safe Credit	β_{sc}^ℓ	−1.799
Unobserved Risk	β_{lg}^θ	0.161

Note: This table reports the structural parameter estimates obtained via Indirect Inference. Panel A reports borrower demand parameters. Panel B reports lender funding costs (c_j) and regulatory cost parameters. Note that the bank capital parameters are calibrated using weighted averages from the bank-level data: ρ_B (actual capital ratio) and $\bar{\rho}_B$ (minimum requirement) are set to 16.30% and 12.97%, respectively. Panel C reports the parameters governing the default probability logistic function. Panel D reports the standard deviation of private signals ($\sigma_{s,j}$) and loan size shocks.

the borrower is fully exposed to the contracted rate.

A complementary view of demand is provided by the semi-elasticity, which measures the percentage change in market share per one-percentage-point change in the rate. The estimated semi-elasticities equal 0.31 for banks and 0.24 for non-banks. The reversal relative to the proportional elasticity reflects the higher equilibrium rates at non-banks, and is consistent with the estimated demand shifters, which assign higher non-price valuation to non-banks ($\delta_N^D - \delta_B^D = 3.2$).

Figure 7: Model Fit: Market Shares and Default Rates

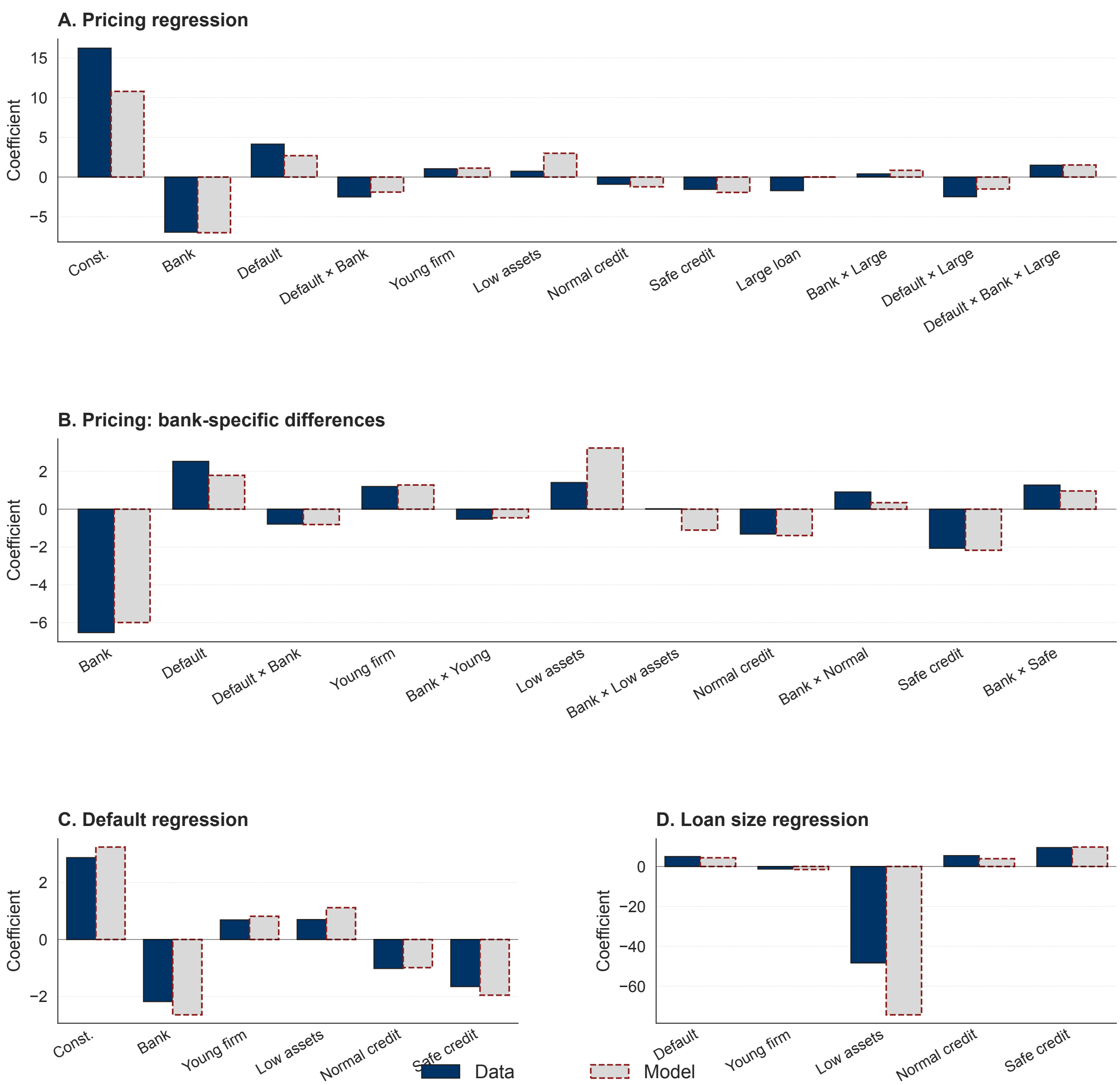


Note: This figure compares the empirical and simulated values of the cross-sectional moments targeted in the structural estimation. Panel A reports market shares by borrower type and lender (Bank vs. Non-bank). Panel B reports realized default rates by lender and loan-size segment. Panel C reports market shares by loan-size segment. Simulated moments are generated using the estimated parameters in Table 6.

Supply Estimates. Table 7 details the distribution of equilibrium effective marginal costs across lender types and loan sizes. Following the first-order condition in Equation 16, the effective marginal cost represents an expected measure of the per-loan cost of lending, reflecting the funding cost c_j, the probability of default PD_{ij}, and, for banks, the shadow cost of balance sheet capacity, which is intrinsically linked to borrower risk, as capital requirements and the resulting shadow cost scale with the loan's risk weight.

The estimated average effective marginal cost is 7% for non-banks and 2.86% for banks.

Figure 8: Model Fit: Regression Coefficients



Note: This figure compares the empirical and simulated values of the auxiliary regression coefficients targeted in the structural estimation. Panel A reports coefficients from the pricing regression (Equation 1). Panel B reports coefficients from the extended pricing specification with bank interactions (Equation 23). Panel C reports coefficients from the default regression (Equation 2). Panel D reports coefficients from the loan size regression (Equation 3).

TABLE 7: Distribution of Equilibrium Effective Marginal Costs (%)

Lender/Size	**Mean**	**SD**	**Median**	**p10**	**p90**
Non-Bank (All)	7.00	3.34	6.01	4.26	11.08
Small Loans	8.78	3.98	7.67	4.96	12.91
Large Loans	5.81	2.11	5.21	4.15	8.20
Bank (All)	2.86	1.68	2.54	0.92	5.36
Small Loans	3.44	1.51	3.30	1.55	5.63
Large Loans	1.72	1.42	1.21	0.75	3.13

Note: This table summarizes the distribution of total marginal costs (funding + regulatory capital) for accepted loans in the simulated equilibrium. 'Small' and 'Large' refer to loans below and above the median loan size, respectively.

The gap is accounted for by two channels. Non-banks lack access to deposit funding, so the estimated funding cost parameter c_N exceeds the bank analogue c_B by a margin that more than offsets the regulatory capital charge borne by banks. In addition, the default technology estimates imply that non-bank borrowers carry a higher average probability of default conditional on acceptance, raising the expected loss component of non-bank effective marginal costs.

Turning to the effective markup, our estimates indicate that non-banks earn a slightly higher average effective markup than banks (4.4% versus 3.5%). Table 8 disaggregates the markup distribution by lender type and loan size. For non-banks, the effective markup is slightly higher on large loans than on small loans, by roughly 0.17 percentage points. For banks, the pattern reverses: the markup is roughly 0.42 percentage points lower on large loans than on small loans. This pattern points to the regulatory channel. The marginal cost of lending falls for both lenders when moving from small to large loans, but only banks face an additional cost on large loans through the balance sheet capacity charge. This additional cost prevents banks from translating the lower marginal cost into higher markups; non-banks, which face no such charge, do translate it into higher markups. For context, the magnitude of our markup estimates is slightly below, but broadly consistent with, those reported in Benetton and Buchak (2024) for US SME credit cards.

TABLE 8: Distribution of Equilibrium Effective Markups (%)

Lender/Size	**Mean**	**SD**	**Median**	**p10**	**p90**
Non-Bank (All)	4.44	0.32	4.43	4.05	4.87
Small Loans	4.35	0.34	4.32	3.96	4.83
Large Loans	4.52	0.31	4.53	4.14	4.91
Bank (All)	3.50	0.34	3.49	3.08	3.94
Small Loans	3.71	0.27	3.70	3.36	4.04
Large Loans	3.29	0.40	3.27	2.79	3.83

Note: This table summarizes the distribution of effective markups for accepted loans in the simulated equilibrium. 'Small' and 'Large' refer to loans below and above the median loan size, respectively.

We now turn to the parameters governing the bank's balance sheet capacity cost. For the bank's overall capital position, we set ρ_B and $\bar{\rho}_B$ to averages of bank-specific capital ratios and regulatory minima computed across all banks appearing in our loan-level sample over the sample period, fixing them at $\rho_B = 16.30\%$ and $\bar{\rho}_B = 12.97\%$. The remaining parameters of the shadow cost function are estimated structurally: the local portfolio size in terms of RWA (η_B), the scale parameter (κ), and the curvature parameter (ϕ). Our estimate of η_B (4545, in £'000s) defines the effective scale at which the regulatory constraint operates at the loan level. When adjusted for the average risk weight observed in our simulations (around 86%), this translates to a raw portfolio exposure of approximately £5.3 million per regulatory unit, implying a "span of control" of about 200 loans for an average loan size of £25,000. To put this magnitude in context, the average UK bank in our data holds roughly £2 billion of total SME retail exposure on its balance sheet, so our estimated regulatory unit represents about 0.0026 of the bank's overall SME book. This is consistent with the interpretation of η_B as a localized business unit rather than the bank's aggregate balance sheet, and implies roughly 400 such units per bank, in line with the number of unique two-digit postcode areas in which a bank appears in our loan data. Finally, our estimate of the curvature parameter ϕ implies a slightly more convex cost structure than Buchak et al. (2024).

Table 9: Comparison of Information Precision

Information Source	**Noise** (σ)	**Precision** ($1/\sigma^2$)
Non-Bank Private Signal	1.49	0.45
Bank Private Signal (Small Loans)	1.71	0.34
Bank Private Signal (Large Loans)	0.70	2.05
Public Signal (Loan Size Residual)	3.78	0.07

Note: Precision is calculated as the inverse of the variance of the signal noise. Higher precision indicates a superior ability to distinguish latent borrower risk types θ_i.

Information Structure. Panel D presents the parameters governing the information environment. A key finding is the asymmetry in screening technology between lender types and across loan-size segments. The estimated noise of the private signal for non-banks ($\sigma_{s,N} \approx 1.49$) is intermediate between the bank's noise on small loans ($\sigma^s_{s,B} \approx 1.71$) and on large loans ($\sigma^\ell_{s,B} \approx 0.70$). Table 9 translates these estimates into precision ($1/\sigma^2$). The results imply a reversal in the precision ranking across loan-size segments. On small loans, non-banks possess a screening technology that is about 1.32 times more precise than the bank's screening (0.45 vs. 0.34). This suggests that within the segment where both lender types rely primarily on automated online application processing, the implementation of that process is more informative at non-banks than at banks. On large loans, however, the pattern reverses: banks are about 4.55 times more precise than non-banks (2.05 vs. 0.45). This reversal is consistent with the institutional evidence in Gomes et al. (2025), which reports that bank loan applications above a threshold of approximately £50,000 require in-person underwriting and additional analyst scrutiny, while non-banks rely on the same online application process irrespective of loan size. Finally, both lender types possess private signals that are substantially more precise than the public signal derived from loan size residuals (0.07), implying that the lenders' private screening signals, rather than the public signal inferred from loan size, are the primary source of information about borrower type in this market.

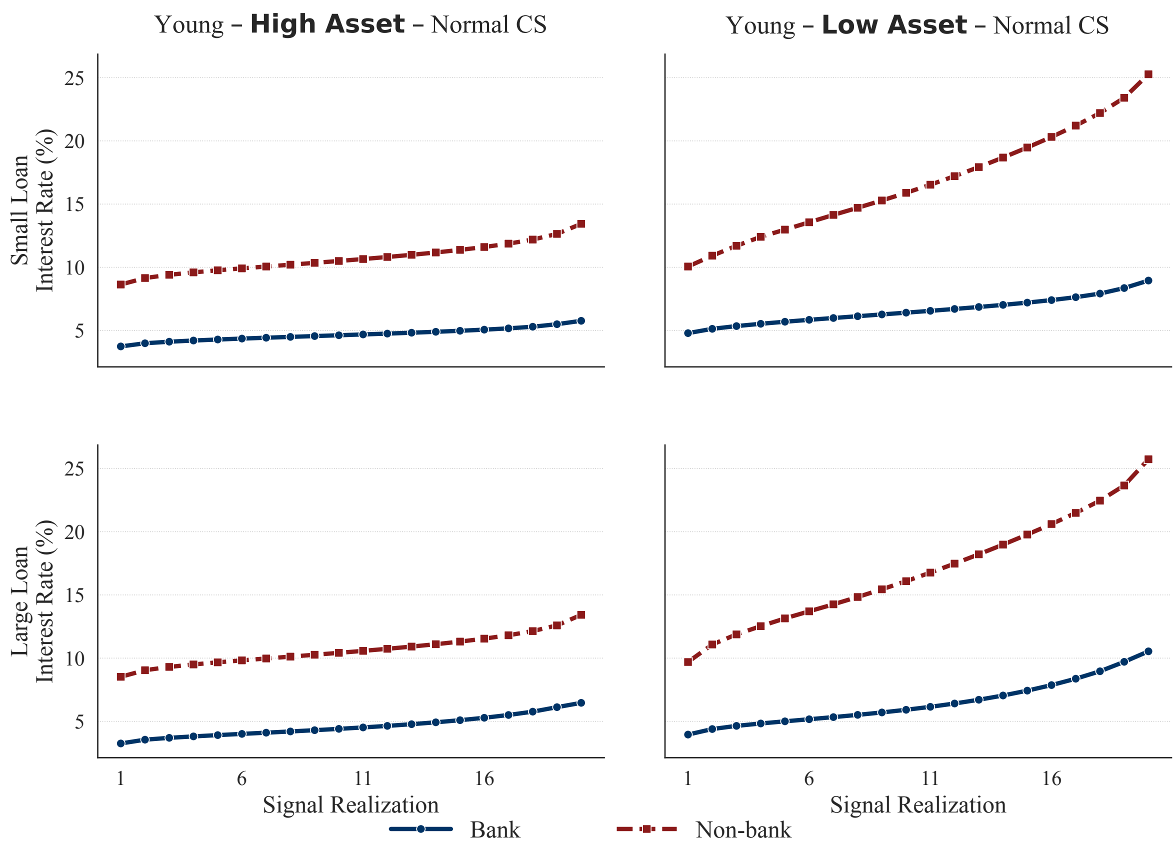
Equilibrium Pricing Mechanics. To illustrate the model's mechanics, Figure 9 presents a representative example of the equilibrium pricing schedules. This visualization isolates the distinct impacts of our three structural components: unobserved private information, observable borrower characteristics, and loan size.

First, the variation within each plot (moving along the x-axis) captures the pricing of unobserved risk. As the private signal deteriorates (moving to the right), both lenders increase interest rates to compensate for the higher expected probability of default. The steepness of these schedules reflects the sensitivity of each lender's pricing to changes in the private signal, which depends jointly on the precision of the lender's screening technology, the elasticity of its cost structure with respect to risk, and the intensity of strategic competition with the rival.

Second, comparing the columns highlights the effect of observable characteristics. Moving from the left column (High Asset) to the right column (Low Asset) reveals an upward shift in the pricing schedules for both lenders, illustrating how observable risk acts as a baseline risk adjuster: a borrower with fewer assets is perceived as riskier ex-ante, causing both lenders to reset their pricing intercepts higher before processing any private signal. The shift is also accompanied by a steepening of both schedules. Because the default probability is mapped through the cumulative normal, low-asset borrowers operate on a steeper portion of the cumulative distribution function, so the same change in the private signal translates into a larger change in default probability, and therefore in price.

Third, comparing the rows reveals how loan size shapes the equilibrium. Larger loans carry a higher balance-sheet capacity cost for banks, and because this cost is linked to the risk weight (and therefore to the bank's assessed default probability), the bank's pricing schedule becomes more convex in the signal on large loans. This effect is most visible in the bottom-right panel (large loan, low asset), where the bank's schedule curves upward sharply at deteriorating signal realizations: as the signal worsens, the assessed default probability rises, the risk weight rises, and the regulatory capital charge rises non-linearly, all of which the bank must price in. The non-bank, whose cost structure does not depend on loan size, exhibits no comparable shift in convexity across the loan-size dimension.

Figure 9: Equilibrium Pricing Functions by Lender Type



Note: This figure plots an illustrative example of equilibrium interest rate schedules from the simulation. The x-axis represents the rank of the borrower's private signal (unobserved risk), where a lower rank indicates a safer signal. The columns distinguish between borrowers with different observable asset levels, while keeping Age fixed at 'Young' and Credit Score fixed at 'Normal'. The rows compare small versus large loan sizes.

7 Counterfactual Analysis

7.1 Bank Capital Regulation

We use the estimated model to evaluate how changes in bank capital regulation affect the equilibrium allocation of credit in the unsecured SME lending market. We focus on shocks to the regulatory minimum capital requirement, $\bar{\rho}_B$, varying it by ± 1 and ± 2 percentage points around the calibrated baseline. Note that at baseline, the bank holds a buffer of 3.33 percentage points above the regulatory minimum ($\rho_B = 16.30\%$, $\bar{\rho}_B = 12.97\%$). The shocks operate exclusively through the shadow cost function $C(\rho_B - \bar{\rho}_B)$ and propagate to bank pricing, market shares, and the composition of borrowers across lenders. This experiment admits a short-run policy interpretation, under the premise that a regulatory shock to $\bar{\rho}_B$ takes time to be absorbed through the bank's capital adjustment decisions and that the bank cannot frictionlessly raise equity in the immediate aftermath.

Table 10 summarizes the equilibrium effects of the four counterfactual scenarios. Panels A and B report the changes in rates, marginal costs, and markups through two complementary measures. Panel A averages outcomes over the grid points of the lenders' pricing functions in the (observable group, signal) space, weighting each grid cell equally; Panel B averages over the population of actually originated loans, weighting by the equilibrium distribution of borrowers across lenders. Both panels reveal a pronounced asymmetry between tightening and loosening. This reflects the convexity of the shadow cost function in the bank's distance from the regulatory minimum: tightening pushes the bank closer to the constraint, where the marginal cost rises steeply, while loosening moves it into the already-flat region of the cost curve. A +2pp tightening raises the bank's average originated rate by approximately 83 bp, while a −2pp loosening lowers it by only 10 bp. The non-bank's response remains modest across all scenarios.

The allocation panels confirm that tightening contracts the market substantially on both margins. Under a +2pp shock, the extensive margin falls by 2.4 pp, indicating that some borrowers exit the market entirely in favor of the outside option, while the intensive margin shifts by 7.6 pp away from the bank toward the non-bank. The effects on realized default rates, reported in Panel D, are small in magnitude and consistent in sign with the composition shifts described below.

The remainder of this subsection unpacks the mechanism behind these aggregate effects in two steps: the response of the bank's pricing function to the shock, and the decomposition of

Table 10: Counterfactual Effects of Changes in the Regulatory Minimum Capital Requirement

	Shock to $\bar{\rho}_B$ (relative to baseline)			
Outcome	**$-$2pp**	**$-$1pp**	**+1pp**	**+2pp**
Panel A: Pricing Strategies (bp; average over pricing function grid)				
Bank				
Average rate	-8.30	-5.55	+14.96	+86.99
Average marginal cost	-8.95	-6.10	+16.52	+93.54
Average markup	+0.72	+0.47	-1.22	-6.26
Non-bank				
Average rate	-0.08	+0.02	+0.12	+1.32
Average marginal cost	+0.10	+0.08	-0.26	-1.11
Average markup	-0.45	-0.36	+0.50	+3.12
Panel B: Realized Outcomes (bp; average over originated loan population)				
Bank				
Average rate	-10.20	-6.35	+15.40	+82.86
Average marginal cost	-11.15	-6.81	+18.19	+95.50
Average markup	+1.24	+0.96	-2.33	-11.63
Non-bank				
Average rate	+1.81	+2.11	+2.49	+4.71
Average marginal cost	+0.54	+0.65	+0.88	+1.93
Average markup	-0.90	-0.88	+0.08	+2.52
Panel C: Allocation (pp)				
IM: Bank share (vs. non-bank)	+1.021	+0.767	-1.320	-7.629
EM: Borrowing share (vs. outside option)	+0.223	+0.125	-0.562	-2.449
Panel D: Default Rates (bp)				
Average default rate, bank	-0.31	+0.78	-0.31	-1.57
Average default rate, non-bank	+0.95	+1.16	+1.58	+3.33

Note: This table reports the counterfactual effects of changes in the regulatory minimum capital requirement, $\bar{\rho}_B$. Each column shows the change in equilibrium outcomes when $\bar{\rho}_B$ is shifted by the indicated amount relative to the calibrated baseline, with all other model primitives held fixed. Positive shocks correspond to a tightening of capital regulation, and negative shocks to a loosening. Panel A reports changes in equilibrium rates, effective marginal costs, and effective markups averaged over the grid points of the lenders' pricing functions, defined in the (signal, observable characteristics, loan size) state space. Cells in which a lender exits the market are excluded from these averages. Panel B reports the same outcomes averaged over the simulated population of originated loans, which captures both the change in pricing functions and the selection of borrowers across lenders. Panel C reports changes along two allocation margins: the intensive margin gives the share of originations captured by banks (relative to non-banks), and the extensive margin gives the share of agents who choose to borrow (relative to the outside option of no borrowing). Panel D reports changes in realized default rates on originated loans, weighted by the equilibrium loan-size distribution within each lender. Panels A, B, and D are reported in basis points (bp); Panel C is reported in percentage points (pp).

the realized equilibrium rate change into a pricing component and a composition component.

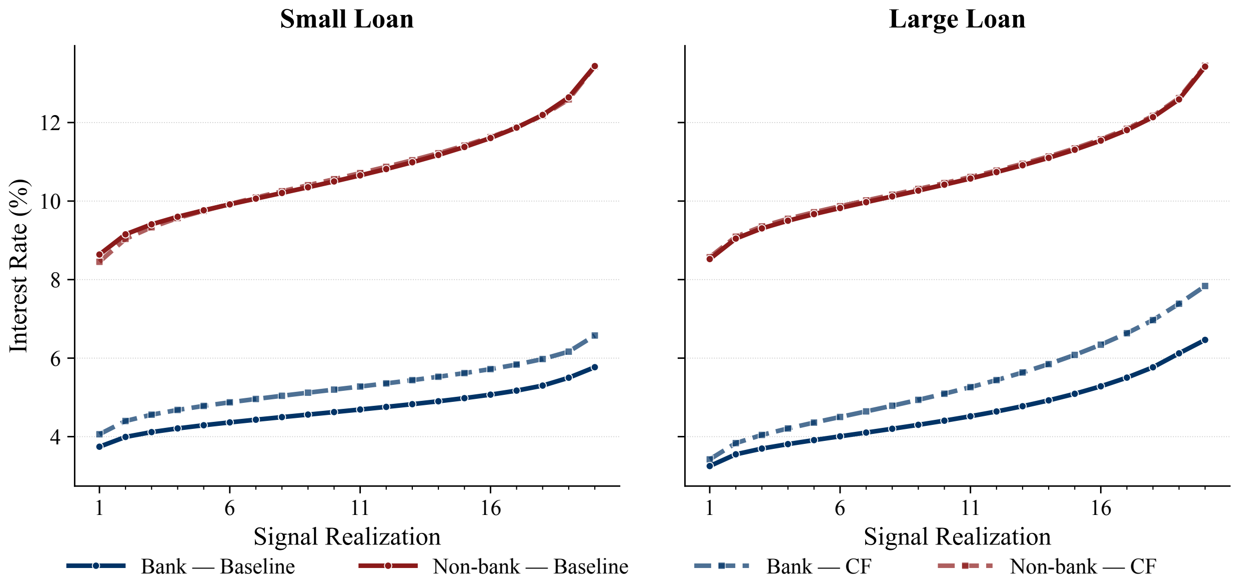
Pricing function response. Figure 10 traces the equilibrium pricing functions under the +2pp counterfactual for a representative borrower segment. The bank's pricing function shifts upward at every signal realization, and the shift widens as the signal worsens. This convexity arises from the structure of the model: the shadow cost $C(\rho_B - \bar{\rho}_B)$ is convex in the assessed risk weight, which itself rises sharply at higher assessed default probabilities. The upward shift is also larger for large loans than for small loans at risky signals, for two reasons. First, a larger loan reduces the bank's capital buffer ratio more than a smaller loan does, and the shadow cost is convex in this buffer reduction. Second, the bank's screening technology is more precise on large loans, so a bad signal updates the bank's posterior probability of default further upward on large loans than on small loans, which compounds the regulatory charge through the risk weight.

Equilibrium response and the role of selection. To distinguish the contribution of price changes from that of compositional reallocation, Figure 11 decomposes the bank's change in the average originated rate, Δr, using the bank's twelve observable groups (combinations of asset size, firm age, and credit score) as the partition. Letting ω_g denote the share of bank originations in observable group g and $\bar{r}_g$ denote the average originated rate among bank borrowers in group g, both computed empirically over the simulated population, the decomposition can be written as

$$\Delta r \;=\; \underbrace{\sum_g \omega_g^{\text{base}}\,\Delta\bar{r}_g}_{\text{Within}} \;+\; \underbrace{\sum_g \Delta\omega_g\,\bar{r}_g^{\text{base}}}_{\text{Between}} \;+\; \underbrace{\sum_g \Delta\omega_g\,\Delta\bar{r}_g}_{\text{Interaction}}, \tag{18}$$

where $\Delta x \equiv x^{\text{CF}} - x^{\text{base}}$ for any object x. The within component fixes the observable-group shares at their baseline values and captures the change in rates within each group, isolating the pricing-function channel. The between component fixes rates at their baseline values

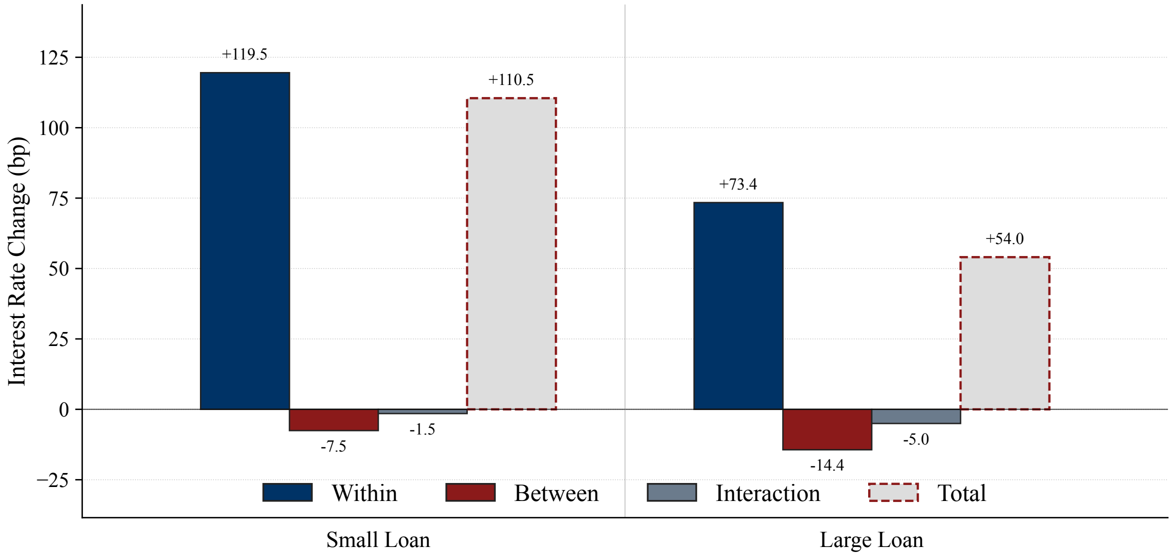
Figure 10: Pricing Function Response to a Capital Requirement Shock (+2pp)



Notes: This figure plots equilibrium interest rate schedules at baseline (solid lines) and under a +2 percentage point counterfactual increase in the regulatory minimum capital requirement $\bar{\rho}_B$ (dashed lines). The schedules are reported separately for banks (blue) and non-banks (red) as a function of the lender's private signal realization, for small loans (left panel) and large loans (right panel). Higher signal indices correspond to less favorable signals (higher assessed default probability). Schedules are shown for a representative borrower segment: high-asset, young firms with a normal credit score. The qualitative patterns shown here are similar for other borrower segments.

and captures the change in the composition of bank originations across observable groups, isolating the selection channel. The interaction is the residual cross-term. The within component is large and positive in both size segments (+119.5 bp for small loans and +73.4 bp for large loans), reflecting the bank's upward repricing within each observable group, evaluated at the baseline weights of bank-originated loans. The between component is negative in both segments and substantially more negative for large loans (−14.4 bp) than for small loans (−7.5 bp): high-risk-weight borrowers face the largest pricing-function increases and substitute disproportionately toward the non-bank or the outside option, leaving the bank's pool tilted toward safer observable groups in equilibrium. This compositional reallocation is more pronounced on large loans.

FIGURE 11: Decomposition of the Bank's Rate Response to a Capital Requirement Shock by Loan-Size Segment (+2pp)



Notes: This figure decomposes the bank's change in the average interest rate, Δr, separately for small loans and large loans, under a +2 percentage point counterfactual increase in the regulatory minimum capital requirement $\bar{\rho}_B$. Within each loan-size segment, the decomposition partitions Δr along the bank's twelve observable demographic cells, defined as the combinations of asset size, firm age, and credit score. The *within* component captures the change in average rates within each demographic cell, holding each cell's share of bank originations fixed at its baseline value. The *between* component captures the effect of the shift in these demographic market shares, evaluated at baseline rates. The *interaction* is the residual cross-term. The three components sum to the *total* change, shown with a light gray fill and dashed mahogany edge to indicate that it is a summary rather than an independent component. All quantities are reported in basis points.

8 Conclusion

This paper develops and estimates a structural model of competition between banks and non-banks in the UK unsecured SME lending market, with the goal of quantifying how risk-based capital regulation interacts with lender pricing, market allocation, and credit access for small firms. Our analysis begins from three empirical facts that characterize this market. First, lenders price on soft information that is not captured by standard borrower observables, generating substantial residual variation in rates across otherwise comparable firms. Second, non-bank lenders serve a pool of borrowers with systematically higher default risk than the bank's pool, while charging higher interest rates. Third, banks exhibit a pronounced reduction in market share at larger loan sizes and display heightened prudence toward risk in their pricing.

These patterns motivate a structural model that embeds three frictions central to the market: asymmetric private screening technologies between banks and non-banks, a convex shadow cost of regulatory capital that links each loan's price to the bank's buffer position, and endogenous selection of borrowers across lenders. We estimate the structural primitives by Simulated Method of Moments, matching auxiliary regression coefficients, market shares, and default rates from administrative loan-level data.

The parameter estimates illuminate how screening technology and regulatory cost jointly shape market equilibrium. The bank's regulatory capital shadow cost is most prominent on large loans and on borrowers assessed as riskier, while non-banks face a higher marginal cost on average despite not facing the balance-sheet capacity constraint implied by capital regulation, consistent with their lack of access to deposits as a cheap source of funding as well as their higher default rates. The asymmetry in screening precision between the two lender types varies meaningfully across loan-size segments: non-banks are somewhat more precise than banks on small loans, while banks are substantially more precise than non-banks on large loans. This pattern is consistent with non-banks underwriting all applications online, while banks complement online screening on small loans with relationship-based underwriting on large ones.

Counterfactual analysis of changes to the regulatory minimum capital requirement reveals a meaningful asymmetry between tightening and loosening shocks: a +2pp tightening raises the bank's average originated rate by approximately 83 bp, while a −2pp loosening lowers it by only 10 bp. This asymmetry is driven by the convexity of the bank's shadow cost function in its buffer position. The aggregate rate response decomposes into a direct repricing channel within each observable borrower group and a selection channel through which the bank's borrower pool shifts toward safer groups as some risky borrowers substitute toward the non-bank or the outside option. The selection channel is quantitatively smaller but is more pronounced for large loans.

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Appendix

A Regulatory Risk Weight Function

Under the Basel Internal Ratings-Based (IRB) framework, unsecured SME loans that meet specific retail criteria are classified as "Other Retail Exposures".[11] Unlike corporate exposures, the capital requirement for this asset class does not include an explicit maturity adjustment. Instead, the risk weight is determined by a continuous function of the estimated Probability of Default (PD) and Loss Given Default (LGD). The calculation proceeds in three steps. First, the regulator defines the asset correlation factor, R, which determines the sensitivity of the asset's value to systematic risk. For retail exposures, this correlation is negatively related to the probability of default, reflecting the empirical observation that higher-risk borrowers are less correlated with the general business cycle. The asset correlation R is given by:

$$R = 0.03\left(\frac{1-e^{-35\cdot PD}}{1-e^{-35}}\right) + 0.16\left(1-\frac{1-e^{-35\cdot PD}}{1-e^{-35}}\right) \tag{19}$$

Second, the capital requirement K—representing the capital required per unit of exposure to cover unexpected losses at a 99.9% confidence level—is calculated using the Vasicek asymptotic single-risk factor model. The formula subtracts the Expected Loss ($PD \cdot LGD$) from the total conditional expected loss, ensuring that capital is held only for Unexpected Loss:

$$K = LGD \cdot N\left(\frac{G(PD)+\sqrt{R}\cdot G(0.999)}{\sqrt{1-R}}\right) - PD \cdot LGD \tag{20}$$

where $N(\cdot)$ denotes the cumulative distribution function of the standard normal distribution, and $G(\cdot)$ denotes its inverse.

Finally, the regulation incorporates an SME Supporting Factor (SF) designed to encour-

[11] This includes limits on the size of the exposure to a given small business and the granularity on the exposure relative to the overall portfolio, as specified by CRE30, available at `https://www.bis.org/basel_framework/standard/CRE`.

age lending to small businesses. For exposures below €1.5 million, which encompasses the unsecured retail loans in our sample, this factor reduces the capital requirement by approximately 23.81% (setting $SF = 0.7619$). The final Risk-Weighted Assets (RWA) are obtained by converting K into a risk-weight equivalent, scaling by the Exposure at Default (EAD), and applying this discount factor:

$$RWA = K \cdot 12.5 \cdot EAD \cdot SF \tag{21}$$

B Default Regression in the Multi-Lender Subsample

TABLE B.1: Loan Default - Lender Type

	$\mathbb{1}^{D}_{ijt} \times 100$		
	(1)	(2)	(3)
Age Category = Young	1.337	1.579	0.4869
	(1.037)	(1.044)	(1.139)
Asset Category = Below Median	1.128	1.019	1.337
	(1.023)	(1.050)	(1.459)
Credit Score Category = Normal	0.5747	0.6332	-1.666
	(0.8461)	(0.8572)	(1.276)
Credit Score Category = Safe	-0.0368	0.1879	-3.817**
	(1.161)	(1.179)	(1.753)
Bank	-1.793***	-1.736***	-2.309**
	(0.5584)	(0.5559)	(0.9036)
Observations	3,043	3,043	1,808
R^2	0.03585	0.04569	0.45191

Note: This table reports OLS estimates of the Linear Probability Model in Equation 2, in the restricted sample of firms that borrow from multiple lenders. The dependent variable is the ex-post default indicator scaled by 100. $\mathbb{1}^{\text{Bank}}_{j}$ and $\mathbb{1}^{\text{Large}}_{it}$ are indicator variables for banks and large loans, respectively. Firm controls include categorical dummies for age, asset size, and credit score. The regression includes Region, Sector, and Quarterly Time fixed effects. The omitted baseline category defines an old firm with high assets (above median) and a risky credit score, borrowing from a non-bank. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Bank Capital Requirements, Loan Interest Rates, and Loan Sizes

One important ingredient in our setting is the differential regulatory regime that banks and non-banks are subject to. Bank capital regulation imposes maximum levels of (risk-weighted) leverage that banks can sustain, and is set by regulators. The literature has emphasized that these capital requirements are costly for banks, with implications for loan pricing. In our model, these costs also affect the bank's incentives along the intensive margin, since the shadow cost of balance sheet capacity is convex in loan size and in the loan's risk weight.

To examine the extent to which these patterns are present in our data, we make use of confidential data containing bank-specific capital requirements, which are set by regulators, usually at annual frequency. Importantly, these additional capital requirements reflect changes in credit risk and are unknown to the bank before communication by the regulator. This motivates a simple test of how *changes* in capital buffer translate into differential SME loan terms. We define $\Delta \mathit{Capital\ Buffer}_{jt}$ as the change in the bank's excess Tier 1 capital ratio above total tier 1 capital requirements, in percentage points, and estimate the following specification:

$$y_{ijt} = \beta_1 \, \Delta \mathit{Capital\ Buffer}_{jt} + \beta_2 \Delta \mathit{Assets}_{jt-1}(\%) + \beta_3 \Delta \mathit{Deposits}_{jt-1}(\%) + \Gamma_1 X_{jt} + \Phi_{F.E.} + \varepsilon_{ijt} \, , \tag{22}$$

where y_{ijt} is either the interest rate r_{ijt} or the log loan size $\log(\mathit{Loan\ Size})_{ijt}$ on a loan from bank j to firm i in quarter t; $\Delta \mathit{Capital\ Buffer}_{jt}$ represents the change in tier 1 capital buffer; $\Delta \mathit{Assets}_{jt-1}(\%)$ and $\Delta \mathit{Deposits}_{jt-1}(\%)$ are the percent change in total bank assets and total bank deposits, respectively; X_{it} is a vector of time-varying firm-level controls; and $\Phi_{F.E.}$ denotes the fixed effects specified in each column. The results are shown in Table C.1.

The pattern that emerges is consistent with the loan-level shadow cost structure in our structural model. Increases in capital buffers are associated with lower interest rates: across specifications, a 1 percentage point increase in capital buffer is associated with a reduction in SME unsecured loan interest rates of approximately 7-9 basis points. This is consistent with banks operating on a flatter portion of the convex shadow cost schedule when headroom is larger, so that the marginal cost of each new loan is lower.

Table C.1: Capital Headroom, Loan Interest Rates, and Loan Sizes

		r_{ijt}	
	(1)	(2)	(3)
$\Delta Capital\ Buffer_{jt}$	-0.0756**	-0.0819***	-0.0968***
	(0.0289)	(0.0280)	(0.0273)
$\Delta Assets_{jt-1}(\%)$	4.331***	3.233***	3.123***
	(1.301)	(1.154)	(0.8379)
$\Delta Deposits(\%)_{jt-1}$	-0.2386	-0.4458	0.3820
	(1.546)	(1.345)	(1.030)
Observations	29,987	29,987	27,046
R^2	0.40802	0.46745	0.54702
Firm Controls		✓	✓
Bank fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	
Region fixed effects	✓	✓	
Industry fixed effects	✓	✓	
Maturity fixed effects	✓	✓	✓
Quarter-Region-Industry fixed effects			✓

Note: This table presents estimates of Equation 22. The unit of observation is the loan-origination at monthly frequency. The dependent variable alternates between $\log(\ell_{ijt})$, the log of the originated loan amount, and r_{ijt}, the interest rate on a loan originated by bank j to firm i in month t. Δ*Capital Buffer*$_{jt}$ represents the change in tier 1 capital buffer, computed as total Tier 1 Equity minus Total Bank-Specific Tier 1 Capital Requirements, including Pillar I and Pillar II. $\Delta Assets_{jt-1}(\%)$ and $\Delta Deposits_{jt-1}(\%)$ are the percent change in total bank assets and total bank deposits, respectively. Firm-level controls include credit risk category, firm age category and firm asset size category. Standard errors clustered at the Bank × Region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Extended Pricing Regression with Lender-Type Interactions

To capture how the pricing of observable firm characteristics differs between banks and non-banks, we estimate an extended version of the pricing regression in Equation 1 that interacts each firm-level control with the bank indicator $\mathbb{1}_j^{\text{Bank}}$:

$$r_{ijt} = \delta_1 \mathbb{1}_j^{\text{Bank}} + \delta_2 \mathbb{1}_{ijt}^{\text{Default}} + \lambda \mathbb{1}_{ijt}^{\text{Default}} \times \mathbb{1}_j^{\text{Bank}} + \Gamma_1 X_{it} + \Gamma_2 \left(X_{it} \times \mathbb{1}_j^{\text{Bank}} \right) + \Phi_{F.E.} + \epsilon_{ijt} \,, \quad (23)$$

where X_{it} is the same vector of firm controls (above-median age, above-median assets, and credit score categories) used in the main pricing regression. The coefficients Γ_2 capture how the pricing of each firm characteristic varies between banks and non-banks. The estimates are reported in Table D.1.

The interaction coefficients reveal that banks price observable risk characteristics differently from non-banks. The negative coefficient on Bank $\times$ Young indicates that banks apply a smaller age premium than non-banks, while the positive coefficients on Bank $\times$ Credit Score (Normal) and Bank $\times$ Credit Score (Safe) indicate that banks compress the credit-score discount relative to non-banks. The asset-size interaction is small and not statistically significant. We target the full vector of coefficients from Column (5) in the structural estimation.

TABLE D.1: Extended Pricing Regression with Lender-Type Interactions

	Interest Rate (%)
Firm Controls	
Young Firm	1.198***
	(0.058)
Small Asset (Below Med.)	1.409***
	(0.062)
Credit Score (Normal)	−1.316***
	(0.068)
Credit Score (Safe)	−2.067***
	(0.074)
Lender & Outcome	
$\mathbb{1}_j^{\text{Bank}}$	−6.523***
	(0.105)
$\mathbb{1}_{ijt}^{\text{Default}}$	2.527***
	(0.191)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Default}}$	−0.789**
	(0.320)
Bank × Firm Controls	
$\mathbb{1}_j^{\text{Bank}}\times$ Young Firm	−0.530***
	(0.072)
$\mathbb{1}_j^{\text{Bank}}\times$ Small Asset (Below Med.)	0.022
	(0.099)
$\mathbb{1}_j^{\text{Bank}}\times$ Credit Score (Normal)	0.909***
	(0.090)
$\mathbb{1}_j^{\text{Bank}}\times$ Credit Score (Safe)	1.274***
	(0.111)
Observations	64,711
R^2	0.454

Notes: This table reports OLS estimates of the extended pricing regression in Equation 23, which interacts firm-level controls (age, asset size, and credit score) with the bank indicator $\mathbb{1}_j^{\text{Bank}}$. The dependent variable is the annualized interest rate in percentage points. $\mathbb{1}_j^{\text{Bank}}$ and $\mathbb{1}_{ijt}^{\text{Default}}$ are indicator variables for banks and default within one year of origination, respectively. The omitted category defines an old firm with above-median assets and a risky credit score, borrowing from a non-bank. The regression includes Region, Sector, Quarter, and Maturity fixed effects. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E Moral Hazard

Our model assumes there is no moral hazard, that is, a direct causal effect of changes in interest rates on default. To understand the validity of this assumption, we exploit the fact that certain bank loans have floating interest rates, which increased substantially during the post-pandemic interest rate hike in the UK.

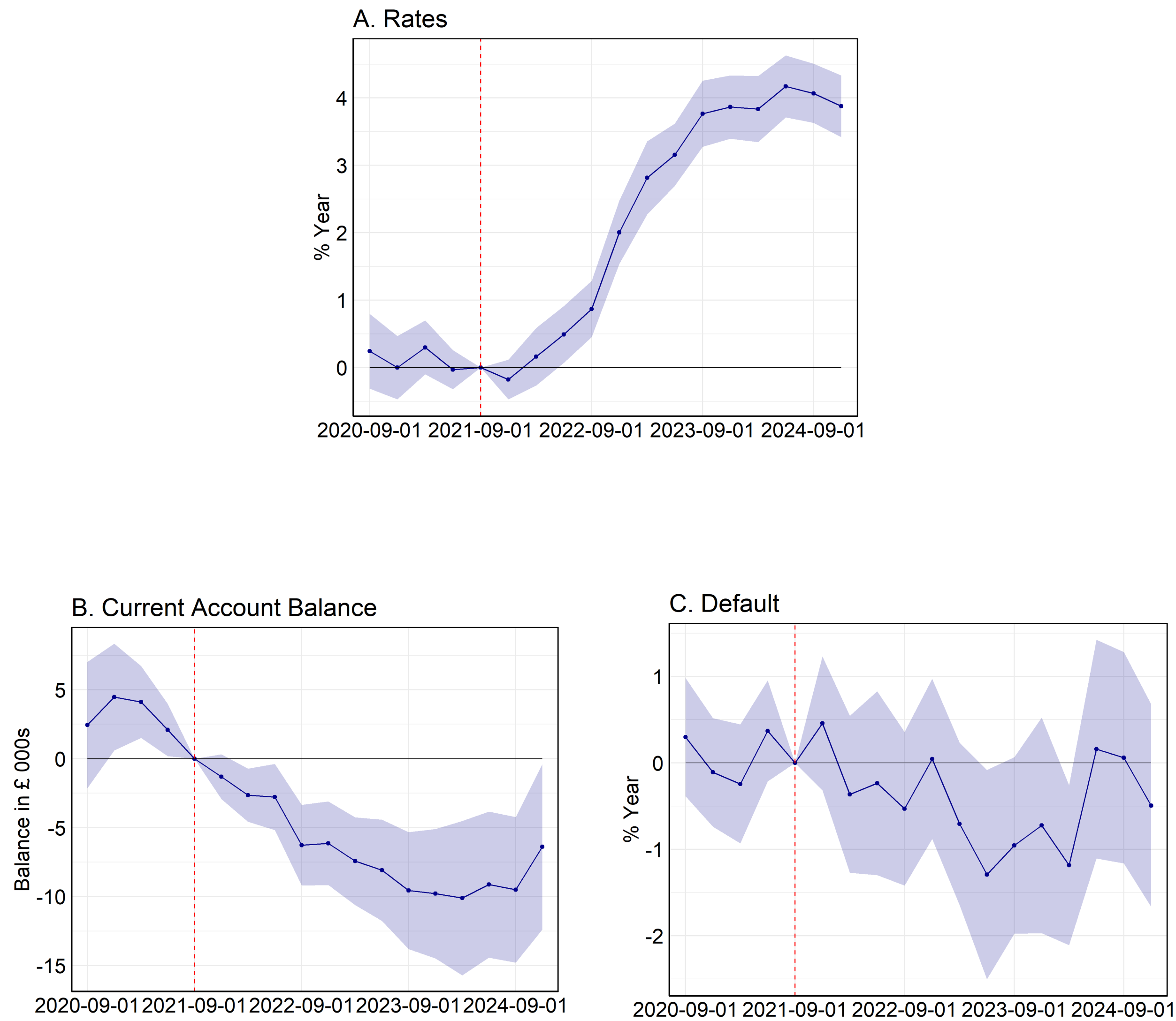
Specifically, using a firm-quarter panel, for each firm i that borrows from a bank j that issues floating rate loans, we define a dummy $Floating_i$ which equals to 1 if firm i has *any* floating rate loans issued before July 2021. We then compare outcomes of firms with and without floating rate loans using a differences-in-differences type setting:

$$y_{it} = \alpha_i + \alpha_t + \sum_{\tau \neq 0} \delta_\tau \times Floating_i + \epsilon_{it} \tag{24}$$

Where y_{it} is an outcome for firm i in quarter t, and α_i and α_t are firm and time fixed effects, respectively. The coefficients of interest δ_τ correspond to the difference between the values of y_{it} in period τ relative to the baseline period of 2021Q3, right before the start of the interest rate hike. We use three different outcomes to assess how floating rate borrowers experience differences in their cash-flows compared with fixed rate borrowers during the interest rate hike: interest rate payments, net current account balances and default. The results are shown in Figure E.1.

Panel A shows that firms with floating rate loans experience large increases in their effective monthly interest rates compare with fixed rate borrowers, relative to the differences in September 2021, right before the interest rate hike. Such increase in interest rate expenses is associated with a decrease in net current account inflows, suggesting firms do spend more resources paying for rising monthly installments. However, despite the large increase in interest rates faced by floating rate borrowers, we see no differences in performance over time, with default rates across both groups evolving similarly after the interest rate hike. This suggests a limited role for interest rates in *causing* default.

Figure E.1: Floating rate versus fixed rate borrowers



Notes: This figure displays the point estimates of δ_τ from estimating specification 24, using three different outcomes: average effective monthly interest rates in quarter t (Panel A); total net current account balances in quarter t in thousands of £ (Panel B), and a default dummy which equals 1 if any outstanding loan to firm i has been flagged as under default in quarter t (Panel C). Standard errors are clustered at the region-industry level. Error bands correspond to 95% confidence intervals.