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Asymmetric information and capital regulation in SME lending: a structural model of bank and non-bank competition

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Abstract

We analyse how risk-based capital requirements shape competition and credit allocation in the UK unsecured Small and Medium-sized Enterprises (SME) lending market using confidential loan-level data. Motivated by empirical patterns, we develop and estimate a structural model with screening, asymmetric information, and imperfect competition, in which banks and non-bank lenders differ in regulatory treatment. We estimate lender-specific costs and screening precision, and show how these features jointly account for the observed lender market shares across borrower risk and loan size segments. Our results indicate that regulation interacts with heterogeneity in information processing and costs to shape equilibrium pricing and credit allocation, with non-bank lending reflecting not only regulatory differences but also comparative advantages in screening technology. Our model provides a quantitative framework for evaluating regulatory policy in markets with both regulated and non-regulated intermediaries.

Key words: Small business lending, asymmetric information, non-bank financial intermediaries, screening, capital regulation.

JEL classification: G20, G21, G23, G28.

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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 includes differentially regulated banks and non-banks, heterogeneous screening technologies and cost structures, connecting regulation, screening, and pricing decisions in a unified setting. We focus on the UK's unsecured SME lending market, and estimate the model using confidential loan-level data from a leading UK credit reference agency covering the main bank and non-bank SME lenders. We obtain preliminary estimates of lender-specific screening precision and costs, along with demand elasticities.

We document three sets of descriptive evidence that motivate our structural approach. First, we find strong evidence that lenders screen on soft information: even conditional on a rich set of firm observables, there is substantial residual dispersion in interest rates. Moreover, consistent with models of private information, we document a positive correlation property (Chiappori and Salanié, 2000): conditional on observables, higher interest rates predict higher ex-post default rates. We then document heterogeneity across lender types in the extent of this correlation. Our regression analysis shows that the sensitivity of pricing to risk factors captured by default but orthogonal to observables—the unobserved component of risk—varies significantly across banks and non-banks, suggesting core differences in how risk is processed.

Second, we observe distinct market positioning: non-banks serve a borrower pool with significantly higher default rates and charge an interest rate premium compared with banks. Finally, and most notably, we analyze the intensive margin. We document that, conditional on observables, default is positively correlated with loan size. Furthermore, while banks are active in the small loan segment, we observe a sharp contraction in their large loan exposures: banks rarely issue large unsecured loans, and when they do, default rates are significantly lower than default rates of non-bank loans. This prudence is mirrored in the pricing as well. By analyzing the sensitivity of rates to ex-post default conditional on observables across lender types and loan sizes, we find that relative to non-banks, banks retain significantly higher pricing sensitivity to unobserved risk in large exposures. Taken together, these different pricing strategies and allocation patterns are driven by the interplay between differences in screening ability and risk-based regulation on bank credit exposures. Our structural analysis is designed to disentangle these mechanisms.

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 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 intensive margin of loan size. A well-known challenge in estimating demand for products involving personalized pricing is that only the *accepted* loan is observed, while the other competing offers in the borrower's choice set remain unobserved. The standard approach in the literature approximates these missing loan interest rate offers using a regression framework, but this method is not well suited to the SME context for two reasons. First, our descriptive evidence indicates that pricing is highly individualized, driven by heterogeneous screening and asymmetric regulatory exposures across lender types. Moreover, reliance on firm fixed effects to generate price variation fails to capture the supply-side heterogeneity inherent in our setting; it cannot distinguish between a borrower's inherent risk and a specific lender's assessment of that risk. Second, implementing such regressions requires data on multiple loans per firm. For smaller SMEs, this is rarely the case due to the inherent challenges in accessing credit, where securing even a single loan can be significant hurdle. Our setting is no exception. To overcome these issues, we jointly estimate the demand and supply sides. Our model incorporates the required supply-side heterogeneity, allowing us to simulate the menu of offers while explicitly accounting for lenders' distinct screening and pricing incentives.

Our structural estimation quantifies key parameters governing demand, supply-side cost structures, and information processing. On the demand side, we estimate an average own-price elasticity of 1.7 for banks and 3 for non-banks. This which indicate that a 10% increase in the interest rate results in a 17% and 30% decline in market share, respectively. Turning to the supply side, we identify a distinct cost asymmetry. Non-banks, lacking access to cheap deposits, face a higher marginal cost of 9.14 driven by larger funding expenses. In contrast, banks benefit from a lower average marginal cost of 3.21, which includes both their funding costs and the impact of regulation. The balance sheet capacity component, which incorporates risk-based capital regulation, accounts for around half of the bank's total marginal cost for safe borrowers. Finally, we find that non-banks possess a more precise screening technology, and that the requested loan size serves as a relatively weak signal compared to the private screening outcomes of each lender.

Related Literature This paper contributes to the literature on the transmission of 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 employs a structural model to quantify the impact of capital regulation in the UK mortgage market. We complement this work by extending the structural approach to the unsecured SME credit sector. This setting presents distinct modeling challenges. While mortgage pricing is typically standardized around observable collateral values (such as Loan-to-Value ratios), the SME market is characterized by a high degree of information asymmetry. Quantifying the impact of risk-based capital regulation in this context therefore necessitates a framework that explicitly incorporates screening of borrower default risk.

Second, our work is connected to the empirical literature on information asymmetry in credit markets, building on the seminal work of Stiglitz and Weiss (1981).[1] Crawford, Pavanini and Schivardi (2018) develops a structural model of small business lending to analyze the interplay between adverse selection and market power in the Italian SME market. Our approach differs from theirs in that we allow lenders to have heterogeneous screening capabilities. This feature is crucial in our setting, not only because it captures the plausible operational differences between banks and non-banks, but also because it is required to identify the effects of bank capital regulation. By introducing these lender-specific technologies and regulatory differences, we are able to quantify how regulation interacts with information asymmetries. Methodologically, our work also relates to Matcham (2025), who develops a structural model of screening for the UK consumer credit market, though we focus specifically on the impact of regulation on SME lenders. Additionally, Stillerman (2024) develops a model of SME lending with screening to study SBA guarantees in the US, but abstracts from the impact of regulation on lending. More broadly, our work connects to the literature utilizing industrial organization methods to analyze financial markets.[2] Our paper extends this agenda by quantifying the interaction between regulation and screening in the market for unsecured small business credit.

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

[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 have examined household finance, including the mortgage market (Benetton, Gavazza and Surico, 2025; Fisher et al., 2024) and pension systems (Hastings, Hortaçsu and Syverson, 2017). Similarly, Koijen and Yogo (2016) apply these tools to the insurance sector.

Finally, this paper contributes to the vast literature on lending by non-bank financial institutions (NBFIs).[3] This literature studies the interaction of NBFIs 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.

2 Institutional Setting and Data

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

[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.

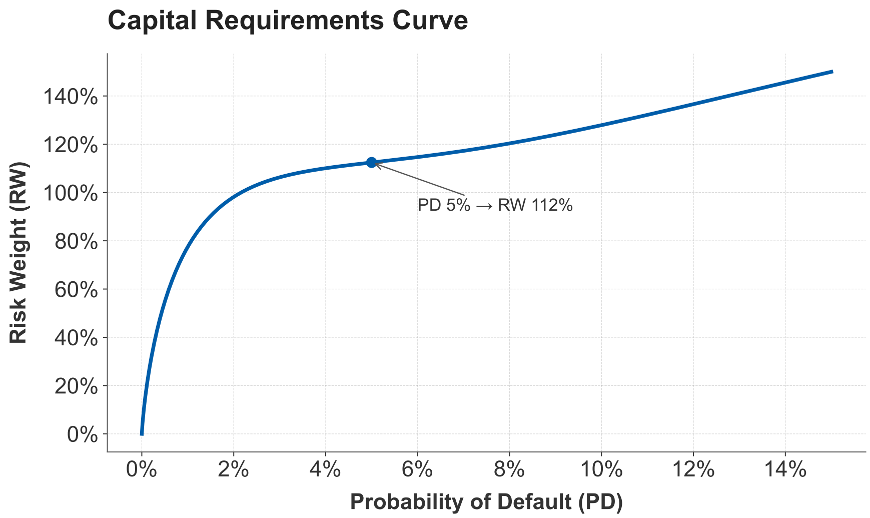
A key factor underlying these financing challenges is asymmetric information. Relative to large corporations, SMEs typically lack audited financial statements and standardized disclosure, making borrower quality more difficult for lenders to assess. This opacity increases the uncertainty surrounding 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`.

2.2 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 are a measure of 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 minimum.

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

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.

3 Empirical Patterns on 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: while banks offer cheaper credit, they cater to safer borrowers. In contrast, non-banks provide broader credit access, including riskier firms, but charge a significant interest rate premium. These patterns motivate the specific demand and supply features we incorporate into the structural model in Section 4.

We document four key empirical patterns. First, (1) market activity is sharply segmented by loan size: banks are highly active in the small-loan segment but become less willing to take risk when issuing large loans, exhibiting significantly lower realized default rates in this segment. Second, even after controlling for observable characteristics, we find that: (2) loan prices are positively correlated with ex-post default, consistent with private information screening; (3) non-banks serve a pool with higher residual risk, reflecting distinct underlying risk profiles; and (4) loan size is positively correlated with ex-post default.

3.1 Market Segmentation and Loan Size

We begin by documenting the sharp segmentation of lending activity based on loan size. Table 2 reports the market share and realized default rates for banks and non-banks across different loan size categories. The data reveals a clear divergence in lending behavior: banks are the dominant providers of credit in the small-loan segment, but their market share contracts significantly as loan size increases. Conversely, non-banks capture a growing share of the market for larger loans.

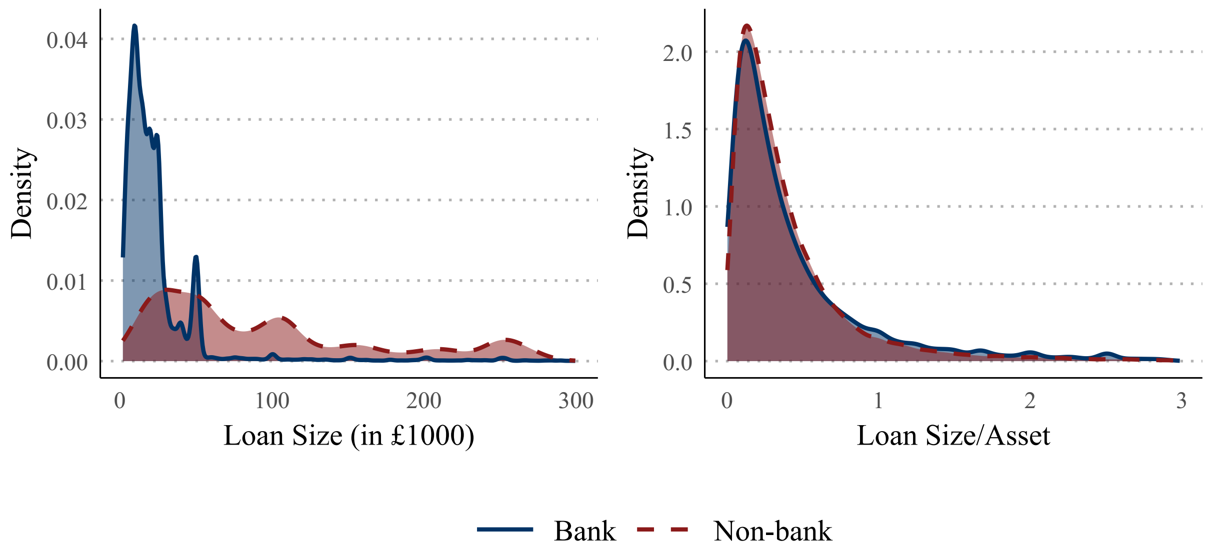
Table 2: Market Segmentation and Performance by Loan Size

	Small Loans		**Large Loans**	
Lender	Bank	Non-bank	Bank	Non-bank
Market Share (%)	57	43	10	90
Default Rate (%)	2.00	3.81	0.61	2.87

Notes: Market shares and realized default rates by lender type. Small and Large loans are split by the sample median loan size ($\approx$ £$50,000$).

Table 2 also highlights an important difference in performance. For both bank and non-bank loans, we observe a negative relationship between size and risk: realized default rates are significantly lower for relatively large loans compared to small loans, especially for banks.

Figure 2: Loan Size Segmentation: Nominal vs. Relative.



Note: This figure plots the density of loan amounts (Panel (A)) and loan-to-asset ratio (Panel (B)) for banks (solid line) and non-banks (dashed line). It shows how non-bank portfolios are skewed toward larger nominal sizes, and that the relative exposure, normalized by firm size, is nearly identical across lender types.

This indicates that banks exercise much stricter selection as exposure size grows, resulting in a significantly safer borrower pool in the large-loan segment.

To understand whether this segmentation is driven by leverage risk or loan size, Figure 2 plots the densities of loan characteristics for both lender types. Panel A displays the distribution of loan amounts, confirming that non-bank portfolios are skewed toward larger absolute loan sizes. However, 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; they are willing to fund high loan-to-asset ratios provided the absolute loan size is small. 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.

3.2 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:

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

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; $\mathbb{1}_{it}^{\text{Large}}$ equals one if the loan to firm i at time t exceeds the sample median; and $\mathbb{1}_{ijt}^{\text{Default}}$ indicates whether that specific loan eventually defaulted. 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 loan size buckets (s). The vector X_{it} controls for firm attributes (dummies for above-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

Table 3: Loan Pricing and Private Information

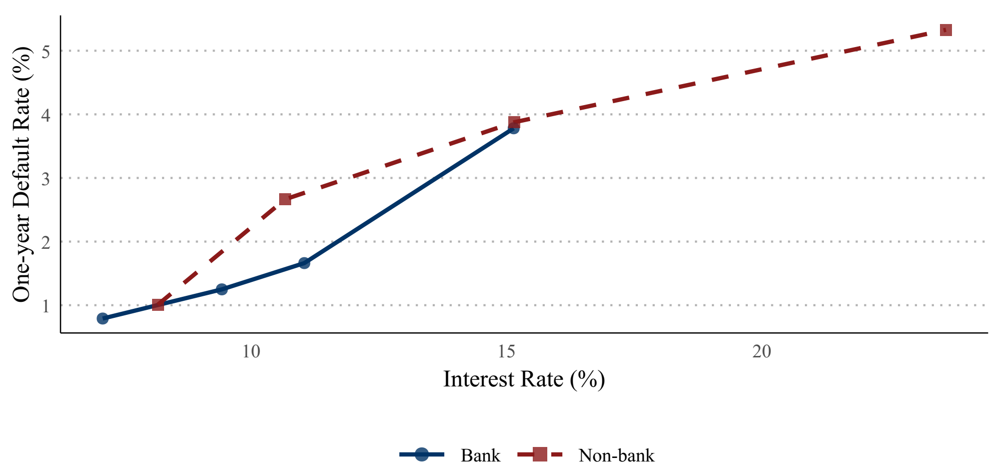
	Interest Rate (%)			
	(1)	(2)	(3)	(4)
Firm Controls				
Young Firm	1.037***	1.021***	1.045***	1.086***
	(0.045)	(0.045)	(0.045)	(0.044)
Small Asset (Below Med.)	1.405***	1.388***	0.689***	0.598***
	(0.049)	(0.048)	(0.047)	(0.047)
Credit Score (Normal)	-0.997***	-0.973***	-0.900***	-0.864***
	(0.049)	(0.049)	(0.048)	(0.047)
Credit Score (Safe)	-1.732***	-1.694***	-1.538***	-1.468***
	(0.058)	(0.058)	(0.057)	(0.056)
Lender & Outcome				
$\mathbb{1}_j^{\text{Bank}}$	-6.407***	-6.337***	-6.928***	
	(0.074)	(0.072)	(0.095)	
$\mathbb{1}_{ijt}^{\text{Default}}$		2.566***	4.099***	4.079***
		(0.189)	(0.409)	(0.408)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Default}}$		-0.929***	-2.447***	-2.380***
		(0.317)	(0.496)	(0.484)
Loan Size Effects				
$\mathbb{1}_{ijt}^{\text{Large}}$			-1.747***	-1.636***
			(0.072)	(0.072)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Large}}$			0.361***	0.949***
			(0.103)	(0.093)
$\mathbb{1}_{ijt}^{\text{Default}} \times \mathbb{1}_{ijt}^{\text{Large}}$			-2.463***	-2.393***
			(0.452)	(0.451)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Default}} \times \mathbb{1}_{ijt}^{\text{Large}}$			**1.571*****	**1.481*****
			(0.560)	(0.563)
Observations	67,083	67,083	67,083	67,082
R^2	0.450	0.454	0.465	0.473
Quarter fixed effects	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Maturity fixed effects	✓	✓	✓	✓
Lender fixed effects				✓

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. $\mathbb{1}_j^{\text{Bank}}$, $\mathbb{1}_{it}^{\text{Large}}$, and $\mathbb{1}_{ijt}^{\text{Default}}$ are indicator variables for banks, large loans, and ex-post default, respectively. Firm controls include categorical dummies for age, asset size, and credit score. The omitted category defines an old firm with above median assets and a risky credit score, borrowing from a non-bank. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that the baseline model captures standard risk-based pricing.

Column (2) introduces the one-year default indicator and its interaction with the lender type to test for private information screening. We find that, conditional on these observable categories, firms that default ex-post pay significantly higher interest rates than firms that do not default ex-post. This positive "information premium" confirms that both banks and non-banks possess screening-derived information that allows them to identify and price risk. Within our regression framework, this result implies that lenders are pricing risk factors that are orthogonal to firm observables, such as the credit score and the comprehensive set of fixed effects. To visualize this, Figure 3 implements a positive correlation test (Chiappori and Salanié, 2000), plotting the predicted probability of default against interest rates while controlling for observables, showing a positive relationship for both lender types.

FIGURE 3: Positive Correlation Test (Interest Rates vs. Default).



Notes: This figure plots the relationship between the annualized interest rate and the predicted probability of ex-post default, 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).

Column (3) adds the loan size dimension, interacting the default indicator with both lender type and the "Large Loan" dummy. This specification allows us to compare the relative screening sensitivity of the two lenders across loan size segments. We find a positive coefficient on the triple interaction term. This indicates that the pricing dynamic shifts significantly as exposure size grows: while non-banks may screen aggressively in the small segment, relative to non-banks, banks retain significantly higher pricing sensitivity to unobserved risk in large exposures. This suggests that banks' lower willingness to extend large loans (Fact 1) is accompanied by a pricing sensitivity that is more consistent with realized default rates, ensuring that higher ex-post risk is matched by significantly higher ex-ante prices. Column (4) shows that the addition of lender fixed effects does not alter the main coefficients of interest meaningfully, suggesting little role for within lender type heterogeneity. Finally, across all specifications, the model explains approximately 47% of the variation in interest rates ($R^2 \approx 0.47$). The large unexplained variation in interest rates is consistent with a market characterized by highly individualized pricing, where borrower-lender interactions play an important role.

3.3 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:

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

where $\mathbb{1}_{ijt}^{\text{Default}}$ is a dummy variable equal to 1 if firm i defaulted within one year of origination 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.

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

Table 4: Residual Risk: Ex-Post Default Analysis

	Default Dummy (×100)		
	(1)	(2)	(3)
Firm Controls			
Young Firm	0.652***	0.649***	0.647***
	(0.157)	(0.158)	(0.158)
Small Asset (Below Med.)	0.760***	0.815***	0.898***
	(0.174)	(0.192)	(0.191)
Credit Score (Normal)	-0.996***	-1.002***	-1.001***
	(0.168)	(0.169)	(0.170)
Credit Score (Safe)	-1.617***	-1.630***	-1.649***
	(0.202)	(0.206)	(0.208)
Lender Type Effect			
$\mathbb{1}_j^{\text{Bank}}$	-2.158***	-2.090***	
	(0.151)	(0.201)	
Loan Size Interaction			
$\mathbb{1}_{ijt}^{\text{Large}}$		0.160	0.128
		(0.229)	(0.228)
$\mathbb{1}_j^{\text{Bank}} \times \mathbb{1}_{ijt}^{\text{Large}}$		-0.097	-0.440
		(0.286)	(0.390)
Observations	67,083	67,083	67,082
R^2	0.011	0.011	0.011
Quarter fixed effects	✓	✓	✓
Region fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Maturity fixed effects	✓	✓	✓
Lender fixed effects			✓

Notes: This table reports OLS estimates of the Linear Probability Model in Equation 2. The dependent variable is the ex-post default indicator scaled by 100. $\mathbb{1}_j^{\text{Bank}}$ and $\mathbb{1}_{it}^{\text{Large}}$ 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 above median assets and a risky credit score, borrowing from a non-bank. Standard errors are clustered at the Region × Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 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 large loan dummy—the point estimate is negative (-0.097). This directional result suggests that the lower default rate of banks is not merely an artifact of the small-loan segment. If anything, the bank performance advantage appears to widen slightly for large exposures, 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.

3.4 Determinants of Loan Size

Finally, we investigate the determinants of loan size to characterize the equilibrium allocation of credit exposures. We estimate a linear probability model where the dependent variable is the indicator for a large loan:

[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.

$$\mathbb{1}^{\text{Large}}_{it} \times 100 = \alpha + \beta_1 \mathbb{1}^{\text{Default}}_{ijt} + \Gamma X_{it} + \Phi_{F.E.} + \epsilon_{ijt} \ , \quad (3)$$

where $\mathbb{1}^{\text{Large}}_{it}$ is an indicator variable equal to 1 if the loan originated to firm i by lender j in quarter t is classified as a "Large Loan", which are loans above the median sample size. The specification includes our standard set of firm controls and fixed effects. The results are reported in Table 5.

TABLE 5: Determinants of Loan Size

	Large Loan Dummy ($\times$100)	
	(1)	(2)
Firm Controls		
Young Firm	-1.560***	-1.584***
	(0.392)	(0.394)
Small Asset (Below Med.)	-47.71***	-47.73***
	(0.645)	(0.643)
Credit Score (Normal)	5.474***	5.521***
	(0.389)	(0.388)
Credit Score (Safe)	9.385***	9.468***
	(0.547)	(0.547)
Outcome		
$\mathbb{1}^{\text{Default}}_{ijt}$		5.137***
		(1.010)
Observations	67,083	67,083
R^2	0.435	0.436
Quarter fixed effects	✓	✓
Region fixed effects	✓	✓
Industry fixed effects	✓	✓
Maturity fixed effects	✓	✓

Notes: This table reports OLS estimates of the Linear Probability Model in Equation 3. The dependent variable is an indicator for Large Loans, scaled by 100. $\mathbb{1}^{\text{Default}}_{ijt}$ is an indicator variables for ex-post default. 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 above median assets and a risky credit score. Standard errors are clustered at the Region $\times$ Sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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.

Crucially, however, we find a significant relationship between ex-post default and loan size. The coefficient on $\mathbb{1}_{ijt}^{\text{Default}}$ is positive and significant. This implies that, conditional on all observable characteristics (age, assets, and credit score), loans that eventually default are significantly more likely to be large. This positive correlation between unobserved riskiness (revealed only ex-post) and loan size indicates that in equilibrium, unobserved risk maps into larger exposures, a feature we explicitly incorporate into the theoretical model in Section 4.

4 Model

Motivated by the empirical patterns documented in Section 3, we develop a model of the SME unsecured lending market to quantify the equilibrium effects of risk-based capital regulation. The framework explicitly captures the interplay between information asymmetry, screening and regulation, highlighting how these forces shape the competitive dynamics between banks and non-banks. We abstract from within lender type heterogeneity, based on evidence from Table 3 and Table 4, and model the supply side considering one bank and one non-bank.

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.

4.1 Borrower Setup

Borrowers, indexed by i, are heterogeneous in two dimensions: a vector of observable characteristics X_i and a scalar unobservable risk type θ_i. Borrowers seek an unsecured term loan from a lender $j \in \mathcal{J} = \{B, N\}$, where B denotes the bank and N denotes the non-bank financial institution. Borrowers also have access to an outside option (no borrowing), denoted by $j = 0$.

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

$$\ell_i = \beta^\ell X_i + \beta^\ell_\theta \theta_i + \epsilon^\ell_i \, , \tag{4}$$

where ϵ^ℓ_i is an idiosyncratic shock to credit demand. In this specification, $\beta^\ell X_i$ accounts for the baseline correlation between firm observables (such as asset size) and investment scale. Importantly, the term $\beta^\ell_\theta \theta_i$ incorporates a structural link between unobserved risk and loan size—consistent, for instance, with distressed firms requiring larger liquidity buffers. This formulation is directly motivated by the pattern documented in Fact 4, which reveals that, conditional on observable attributes, latent risk is positively correlated with the demand for larger exposures.

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:

$$U^F_{ij} = \beta^F X_i + \beta^F_\theta \theta_i + \delta^F_j + \epsilon^F_{ij} \, , \tag{5}$$

where ϵ^F_{ij} is an ex-post idiosyncratic shock. 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:

$$PD_{ij}(X_i, \theta_i) = \Phi\left(\beta^F X_i + \beta_\theta^F \theta_i + \delta_j^F - U_0^F\right) \ , \tag{6}$$

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 the anticipated repayment burden, the borrower chooses the lender that maximizes their ex-ante utility. The indirect utility from accepting a loan from lender j is defined as:

$$U_{ij}^D = -\alpha_i r_{ij} + \beta^D X_i + \delta_j^D + \epsilon_{ij}^D = V_{ij}^D + \epsilon_{ij}^D \ , \tag{7}$$

where δ_j^D represents the vertical quality of lender j (e.g., speed or convenience), and ϵ_{ij}^D is a demand shock. Crucially, the price sensitivity parameter, α_i, is heterogeneous and defined as:

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

This functional form allows the borrower's price elasticity to vary along two dimensions. First, γ_ℓ governs the scale effect; a positive coefficient would imply that borrowers demanding larger loans are more sensitive to interest rates (e.g., due to higher debt service costs). Second, the parameter γ_θ determines the correlation between risk and price sensitivity. If $\gamma_\theta > 0$, the model features an adverse selection mechanism where riskier borrowers are less sensitive to price increases, causing the pool of applicants to deteriorate as rates rise.

Finally, we normalize the utility of the outside option to $U_{i0}^D = \epsilon_{i0}^D$. Assuming the demand shocks ϵ_{ij}^D follow a Type I extreme value distribution, the probability that borrower i chooses lender j takes the standard multinomial logit form:

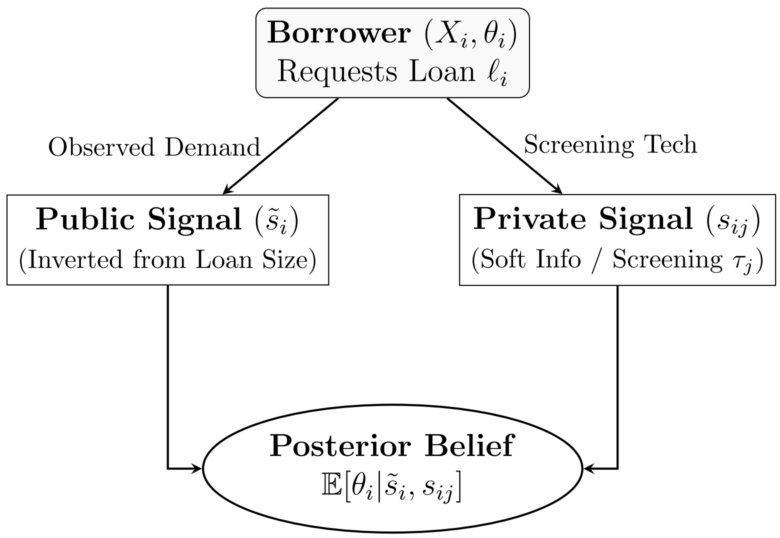
$$Q_{ij} = \frac{e^{V_{ij}^D}}{1 + \sum_{k \in \mathcal{J}} e^{V_{ik}^D}} \ , \tag{8}$$

where $\mathcal{J} \equiv \{B, N\}$ denotes the subset of lenders.

4.2 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 4:

FIGURE 4: Information Structure and Bayesian Updating



Notes: This figure displays the information structure of the model, characterized by Bayesian updating on observable and unobservable characteristics.

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

$$\tilde{s}_i \equiv \frac{\ell_i - \beta^{\ell} X_i}{\beta^{\ell}_{\theta}} = \theta_i + \tilde{\epsilon}_i \, . \tag{9}$$

Second, lender j acquires a private screening signal s_{ij}. This signal captures "soft information" generated through the lender's specific due diligence technology—such as interviews, relationship history, or proprietary data analysis. We model this as:

$$s_{ij} = \theta_i + \epsilon^{s}_{ij} \, , \tag{10}$$

where $\epsilon_{ij}^s \sim \mathcal{N}(0, \tau_j^{-1})$. The parameter τ_j denotes the precision of lender j's screening technology. A higher τ_j implies a more accurate screening process that reduces residual uncertainty about the borrower's true quality.

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.

4.3 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 innovation of our framework is that we resolve this intractability by incorporating horizontal differentiation. The presence of the idiosyncratic taste shock ϵ_{ij}^D (which generates the smooth Logit demand system) "smoothes" the competition. This ensures the existence of an equilibrium even in the presence of asymmetric regulatory costs.

4.3.1 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_{-N}. Because the probability of winning the loan, Q_{iN}, depends on the competitor's offer, which is a function of s_{-N}, the non-bank must integrate over the distributions of both variables. The maximization problem considers both repayment and default scenarios and is given by:

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

where PD_{iN} represents the borrower's true probability of default given type θ_i. The parameter c_N denotes the marginal cost of loan origination.[9] The outer integral over s_{-N} 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_{-N} and priced

[9] We implicitly assume that such marginal cost incorporates funding costs for non-banks, which would capture the rate of return offered to investors to obtain loanable funds, since non-banks do not face balance sheet capacity constraints.

high. By integrating over s_{-N}, the lender adjusts its bid to account for this winner's curse in the competitive process.

4.3.2 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).[10]

We incorporate balance sheet capacity by following Buchak et al. (2024), which encompasses banks' preference for larger buffers, and introduce a convex cost function of the distance between the bank's actual capital ratio and the regulatory minimum:

$$C(\rho_B) = \kappa(\rho_B - \bar{\rho})^{-\phi} \tag{11}$$

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.

To bridge the gap between the bank's aggregate regulatory constraints and individual

[10]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.

loan pricing, we draw on the insights of Stein (2002) regarding the trade-off between decentralized information production and hierarchical capital allocation. Motivated by this perspective, we view the bank as an organization where local business units possess superior information about borrowers, while headquarters manages the aggregate balance sheet. To coordinate these distinct functions, we assume the bank employs an internal capital market that transmits the shadow cost of balance sheet capacity to the unit level. This mechanism encourages the unit to internalize 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, 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. 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:

$$\mathcal{C}_{iB}^{cap} = C(\rho^{\text{post}}) - C(\rho^{\text{pre}}) = \kappa \left[\left(\frac{\rho_B \eta_B}{\underbrace{\eta_B + RW_{iB}\ell_i}_{\text{Increased RWA}}} - \bar{\rho} \right)^{-\phi} - (\rho_B - \bar{\rho})^{-\phi} \right], \tag{12}$$

Intuitively, this formulation implies that the shadow cost of balance sheet capacity is strictly increasing in both the loan size ℓ_i and the risk weight RW_{iB}. Both a larger loan volume and a higher risk assessment accelerate the dilution of the unit's allocated capital buffer; this pushes the local capital ratio closer to the regulatory minimum $\bar{\rho}$, thereby triggering a progressively higher marginal cost.

Under these assumptions, the full maximization problem for the Bank ($j = B$) is:

$$\max_{r_{iB}} \iint Q_{iB}(\cdot) \left[\ell_i \Big((1 - PD_{iB}) r_{iB} - PD_{iB} - c_B \Big) - \mathcal{C}_{iB}^{\text{cap}}(\cdot) \right] dF_{\theta_i|\mathcal{I}iB, s-B} \, dF_{s_{-B}|\mathcal{I}_{iB}}, \tag{13}$$

where the term $\mathcal{C}_{iB}^{cap}$ is a function of the loan size ℓ_i, the Loss Given Default LGD, and the bank's reported probability of default $\overline{PD}_{iB}$, which is defined as the expectation of the default probability PD_{iB} over the business unit's posterior beliefs about θ_i. This reflects the fact that RWAs, and thus capital requirements, are determined by the bank's internal risk assessment, rather than the borrower's unobserved true type.

4.3.3 Optimal Pricing Strategy

Solving the maximization problem for both lenders yields a general first-order condition that characterizes the optimal interest rate r_{ij}. Note that the shadow cost of balance sheet capacity does not apply to the non-bank. The resulting pricing equation decomposes the optimal rate into two distinct components: an effective marginal cost, which incorporates risk and regulation, and a strategic markup, which is determined by competitive pressure:

$$\begin{aligned} r_j(s_{ij}, X_i, \ell_i) = & \frac{\iint Q'_{ij} \left(c_j + PD_{ij} + \mathbb{1}_{j=B} \frac{\mathcal{C}_{ij}^{cap}}{\ell_i} \right) dF_{\theta_i|\mathcal{I}_{ij}, s_{-j}} \, dF_{s_{-j}|\mathcal{I}_{ij}}}{\iint Q'_{ij} \left(1 - PD_{ij}\right) dF_{\theta_i|\mathcal{I}_{ij}, s_{-j}} \, dF_{s_{-j}|\mathcal{I}_{ij}}} \qquad \text{Effective MC} \\ & - \frac{\iint Q_{ij} \left(1 - PD_{ij}\right) dF_{\theta_i|\mathcal{I}_{ij}, s_{-j}} dF_{s_{-j}|\mathcal{I}_{ij}}}{\iint Q'_{ij} \left(1 - PD_{ij}\right) dF_{\theta_i|\mathcal{I}_{ij}, s_{-j}} \, dF_{s_{-j}|\mathcal{I}_{ij}}} \qquad \text{Effective Markup} \end{aligned} \tag{14}$$

We note that Equation (14) does not yield a closed-form analytical solution for r_{ij}, as the demand terms Q_{ij} and Q'_{ij} are endogenous functions of the rate r_{ij} and depend on the rival's simultaneous optimization. Consequently, the equilibrium pricing schedule characterizes a fixed-point problem which we solve using numerical methods.

In addition to the marginal costs of lending, lenders face a fixed cost of loan origination, f_j^c, which encompasses the administrative and operational costs of processing applications, conducting due diligence, and completing credit underwriting. We allow this cost structure to vary by lender type to reflect the institutional features of the UK unsecured SME lending market. For the non-bank lender, we specify a single fixed cost f_N^c, consistent with a uniform online application process. For traditional banks, we model a two-tier structure to capture the nature of their loan application procedures: while small loans can be processed through an online channel, larger facilities require borrowers to submit their application in person. This dual process is reflected by $f_{B,s}^c$ for small loans and $f_{B,\ell}^c$ for large loans, partitioned by the loan-size segment.

These fixed costs govern the extensive margin of lending through a discrete participation decision. Let r_{ij}^* denote the equilibrium interest rate obtained from the fixed-point solution to the lender's pricing problem. Lender j extends an offer to borrower i if and only if the maximised expected variable profit, Π_{ij}^*, exceeds the relevant origination cost:

$$\Pi_{ij}^* \;\geq\; f_j^c(\ell_i) \equiv \begin{cases} f_N^c & \text{if } j = N, \\ f_{B,s}^c & \text{if } j = B \text{ and } \ell_i \leq \bar{\ell}, \\ f_{B,\ell}^c & \text{if } j = B \text{ and } \ell_i > \bar{\ell}. \end{cases} \tag{15}$$

Credit rationing thus arises endogenously: rejections occur whenever the optimal risk-adjusted margin is insufficient to clear the fixed-cost hurdle.

5 Estimation and Results

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

The primary econometric challenge in this setting is the unobservability of the counterfactual offers available to the borrower. This data limitation is pervasive in credit registry analysis, particularly when pricing is individualized. This contrasts with markets such as the UK mortgage sector, where prices are determined by a standardized menu based on a limited set of observable features (e.g., Benetton (2021), Benetton, Gavazza and Surico (2025)). In the presence of individualized pricing, Crawford, Pavanini and Schivardi (2018) provide a powerful solution to this identification problem by predicting unobserved offers using firm fixed effects, exploiting borrowers' multiple banking relationships to recover price heterogeneity.

Our specific context, however, necessitates an alternative approach tailored to the unique structural features of the SME unsecured market. First, the supply side of our market is characterized by significant institutional heterogeneity, where banks and non-banks operate under fundamentally different regulatory and informational constraints. Consequently, the variation in equilibrium prices is driven by complex interactions between lender type and borrower risk, suggesting that price variation is likely richer than what can be captured by a firm fixed effect.

Second, the methodology relying on multiple credit relationships is constrained by the intrinsic nature of our context. As discussed earlier, smaller SMEs seeking unsecured loans face significant frictions in accessing finance; for this segment, obtaining even a single loan can be challenging. Consequently, the multiple simultaneous lending relationships required to identify borrower fixed effects are structurally rare in this market, and our data.

To address these complexities, we leverage the richness of our supply-side model. Rather than inferring unobserved prices through reduced-form projection, we solve the demand and supply systems simultaneously. By explicitly modeling the distinct regulatory constraints and screening technologies of banks and non-banks, we can simulate the equilibrium menu of contracts a borrower would face given their unobserved risk type and observable characteristics. This allows us to recover the latent offer distribution without relying on the existence of multiple banking relationships. In what follows, we detail the simulation-based framework used to estimate the model and present our results.

5.1 Estimation Strategy

We estimate the structural parameters Θ using Indirect Inference (Gourieroux, Monfort and Renault, 1993). This method recovers the parameters by minimizing the weighted quadratic distance between the vector of empirical moments, μ^{data}, and the corresponding moments generated by the model simulation, $\mu^{sim}(\Theta)$.

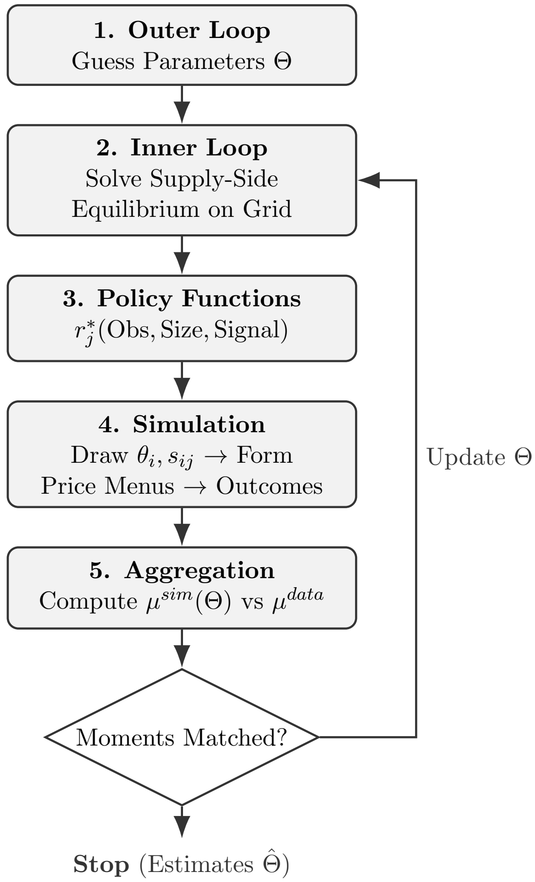
To identify the parameters, we construct a vector of target moments that captures both the conditional correlations of the data and the aggregate market structure. We categorize these moments into three groups.

First, we target the coefficients from the auxiliary regressions outlined in Section 3. This ensures that the structural model reproduces the conditional correlations governing the key equilibrium outcomes: interest rates, loan performance, and loan amounts. Specifically, we include the pricing regression coefficients (Table 3, Column 3), the default probability coefficients (Table 4, Column 1), and the loan size determinants (Table 5, Column 2). These moments discipline the model's ability to replicate the pass-through of observable and unobservable risk factors to contract terms, while explicitly accounting for lender heterogeneity.

Second, to capture the heterogeneity in lender behavior along the intensive margin, we match market shares and realized default rates conditional on loan size segments. These moments are essential for identifying the cost parameters, as they reveal how lender competitiveness and screening performance vary as exposure to loan size increases.

Finally, to capture aggregate substitution patterns and participation margins, we match the market shares calculated across distinct borrower risk profiles. We define the outside

Figure 5: Overview of the Numerical Estimation Algorithm



Notes: This figure displays the algorithm used to solve and estimate the structural model.

option based on the population of SMEs in our sample that maintain an active current account relationship but do not hold any form of formal credit product (including mortgages and other secured loans, or leases).

Numerical Implementation The estimation relies on a nested fixed-point algorithm, illustrated in Figure 5. 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. We do this by iterating on the lenders' first-order conditions (Equation 14) until convergence. This yields the equilibrium policy functions that map borrower observables, loan sizes, and lender signals 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. 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 $\mu^{sim}(\Theta)$. The estimator minimizes the distance between these simulated moments and the empirical targets described above.

5.2 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.

5.3 Estimation Results

Table 6 presents the structural parameter estimates. Figure 6 illustrates the goodness of fit, showing that the model closely tracks the targeted moments. In what follows, we discuss the quantitative implications for borrower demand, lender cost structures, and information frictions.

TABLE 6: Structural Parameter Estimates

Panel A: Demand Parameters

Parameter	**Sym.**	**Est.**
Price Sensitivity	α	20.544
Interaction: Size	γ_ℓ	0.083
Interaction: Risk	γ_θ	3.258
Intercept: Bank	δ_B^D	0.045
Intercept: Non-Bank	δ_N^D	1.796
Observable Controls (β^D):		
Young Firm	β_y^D	0.184
Low Asset	β_{la}^D	0.081
Normal Credit	β_{nc}^D	−0.166
Safe Credit	β_{sc}^D	−0.069

Panel B: Supply & Regulation

Parameter	**Sym.**	**Est.**
Reg. Scale	κ	0.071
Reg. Ref. RWA Size	η	2366.1
Parameter for cap. adequacy	ϕ	−1.094
Funding Cost: Bank	c_B	0.008
Funding Cost: NB	c_N	0.056
Fixed Cost: B (Sm.)	$f_{B,s}^c$	0.003
Fixed Cost: B (Lg.)	$f_{B,\ell}^c$	0.006
Fixed Cost: NB	f_N^c	0.001

Panel C: Default Technology

Parameter	**Sym.**	**Est.**
Intercept: Bank	δ_B^F	−5.943
Intercept: Non-Bank	δ_N^F	−4.856
Risk Sensitivity	β_θ^F	1.523
Observable Controls (β^F):		
Young Firm	β_y^F	0.373
Low Asset	β_{la}^F	0.714
Normal Credit	β_{nc}^F	−0.489
Safe Credit	β_{sc}^F	−1.215

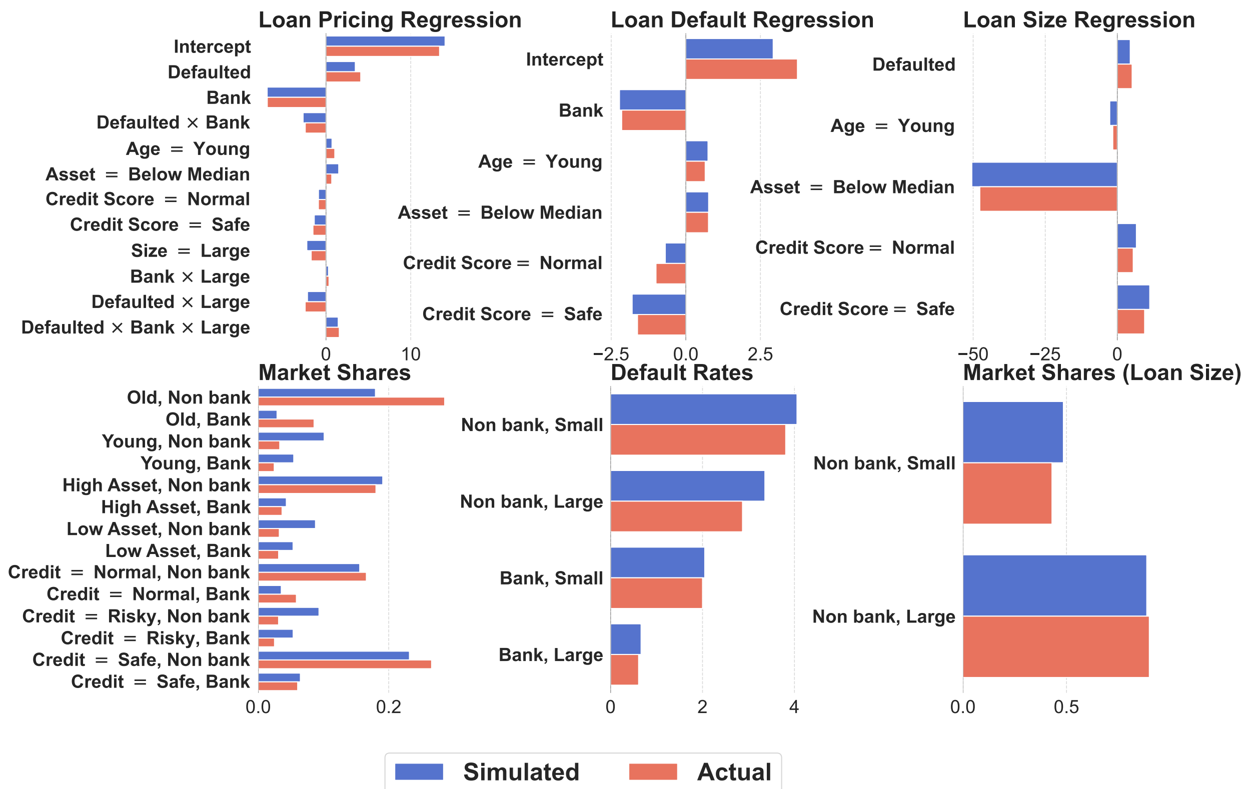
Panel D: Information & Loan Size

Parameter	**Sym.**	**Est.**
Signal Noise: Bank	$\sigma_{s,B}$	2.298
Signal Noise: NB	$\sigma_{s,N}$	1.451
Size Shock SD	σ_ϵ	6.158
Loan Size Controls (β^ℓ):		
Young Firm	β_y^ℓ	0.463
Low Asset	β_{la}^ℓ	6.078
Normal Credit	β_{nc}^ℓ	−0.203
Safe Credit	β_{sc}^ℓ	−0.002
Large Dummy	β_{lg}^ℓ	0.173

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 20% and 17.8%, 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.

Demand Estimates The demand parameters (Panel A) imply an average own-price elasticity of 3 for non-banks and 1.7 for banks. In economic terms, these values indicate that a

FIGURE 6: Model Fit: Simulated vs. Data Moments



Note: This figure compares the targeted moments in the data (red bars) against the simulated moments generated by the model (blue bars) using the estimated parameters reported in Table 6.

10% increase in the interest rate results in a 30% and 17% decline in market share, respectively. Our estimated elasticities are higher than those reported by Benetton and Buchak (2024) for US SME revolving credit. This difference is consistent with the fundamental distinction between the two products. As Benetton and Buchak (2024) note, firms often acquire credit cards for transactional purposes (payments) rather than financing, making them less sensitive to rates they do not anticipate paying. In contrast, the unsecured term loans in our setting represent a deliberate, upfront borrowing decision. Furthermore, because the baseline interest rates for unsecured SME loans in our sample are significantly higher than (Benetton and Buchak, 2024), a proportional increase represents a larger absolute cost. The combination of these factors naturally induce greater price sensitivity.

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 14, 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 9.14% for non-banks and 3.21% for banks. 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 banks earn a slightly higher average effective markup than non-banks (5.22% versus 4.56%). This gap is largely compositional: non-banks serve a greater share of large loans, which carry lower markups due to the higher price sensitivity of borrowers in that segment. Disaggregating by loan size confirms this interpretation. Within each size category, the effective markup differential between lender types is negligible (5.5% versus 5.6% for small loans; 3.9% for both lender types in large loans). The magnitude of our markup estimates is slightly below, but broadly consistent with, those reported in Benetton and Buchak (2024).

Our estimate of η (2366) defines the effective scale of the regulatory constraint in terms of RWAs. When adjusted for the average risk weight observed in our simulations, this translates to a raw portfolio exposure of approximately £2.6 million. Assuming an average loan size of £25,000, this implies a "span of control" of almost 100 loans per regulatory unit. Regarding the shape of the balance sheet capacity cost function, our estimate of the curvature parameter ϕ imply a slightly more convex cost structure than Buchak et al. (2024).

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

Lender/Size	**Mean**	**SD**	**Median**	**p10**	**p90**
Non-Bank (All)	9.14	2.85	8.44	6.35	12.85
Small Loans	10.25	3.56	9.05	6.75	14.79
Large Loans	8.53	2.14	7.97	6.22	11.88
Bank (All)	3.21	1.24	3.13	1.67	4.92
Small Loans	3.51	1.15	3.48	2.09	5.16
Large Loans	1.81	0.31	1.89	1.35	2.20

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.

Table 8: Comparison of Information Precision

Information Source	**Noise (σ)**	**Precision ($1/\sigma^2$)**
Non-Bank Private Signal	1.45	.69
Bank Private Signal	2.29	0.43
Public Signal (Loan Size Residual)	6.15	0.16

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. The estimated noise of the private signal for non-banks ($\sigma_{s,N} \approx 1.45$) is significantly lower than that for banks ($\sigma_{s,B} \approx 2.29$). Table 8 translates these estimates into precision ($1/\sigma^2$). The results imply that non-banks possess a screening technology that is almost 1.6 times more precise than the screening technology of banks (.69 vs. 0.43). This suggests that in the market for small unsecured SME loans, the alternative data and algorithmic scoring models typically employed by non-banks provide a sharper signal of borrower type than the traditional screening mechanisms used by banks. Finally, both lenders possess information that is orders of magnitude more precise than the public signal derived from loan size residuals (0.16), confirming that private information — rather than observable characteristics — is the primary driver of adverse selection in this market.

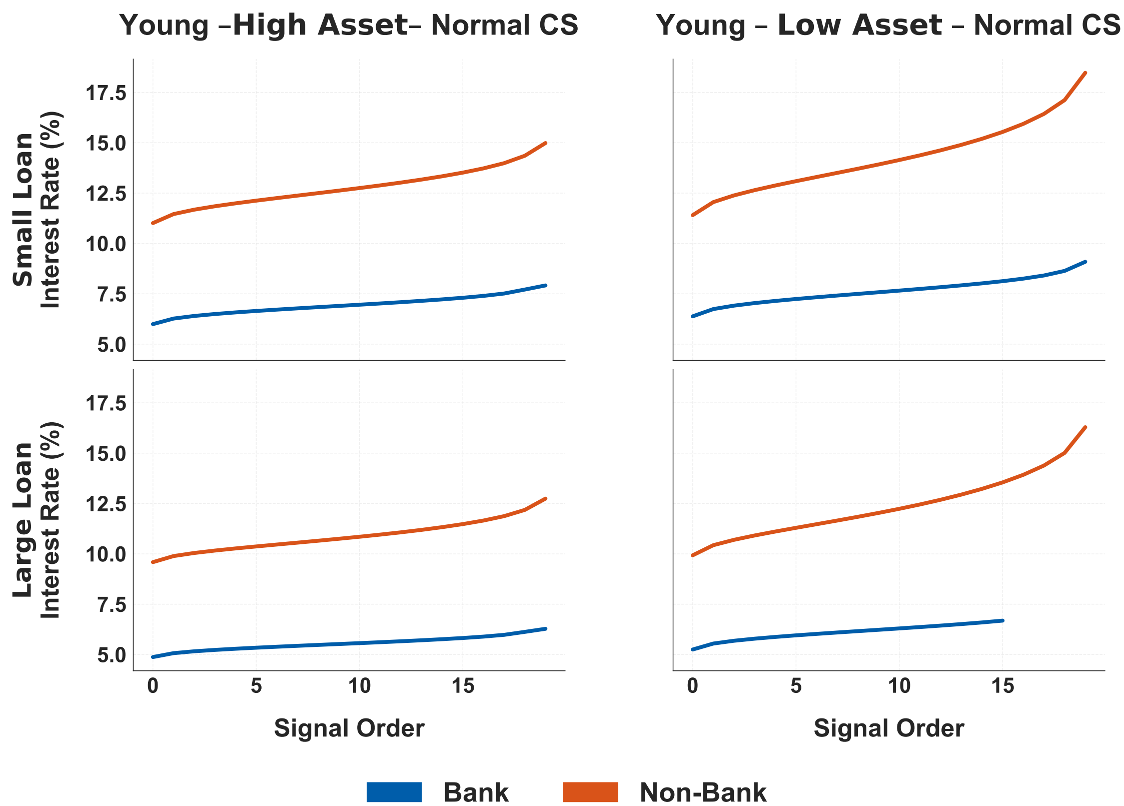
Equilibrium Pricing Mechanics. To illustrate the model's mechanics, Figure 7 presents a representative example of the equilibrium pricing schedules. This visualization isolates the distinct impacts of our three structural components: unobserved private information, observable borrower characteristics, 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 curves reflects the sensitivity of each lender's pricing to marginal changes in the private signal, a function of three interacting factors: the precision of their screening technology, the elasticity of their cost structure with respect to risk, and the intensity of strategic competition with their 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 a distinct upward shift in the pricing schedules for both lenders. This illustrates how "hard information" acts as a baseline risk adjuster: a borrower with fewer assets is perceived as riskier ex-ante, causing both the Bank and Non-Bank to reset their pricing intercepts to a higher level before processing any private signals.

Third, comparing the rows reveals how the drivers of market segmentation evolve with loan size. The higher price sensitivity associated with larger loans pushes rates down for both lender types and flattens the pricing schedules relative to the small-loan segment. However, the effect is asymmetric across lenders: because larger loans carry a greater balance-sheet cost of regulation for banks, their pricing schedules retain somewhat more convexity than those of non-banks, whose cost structure is largely insensitive to loan size. Furthermore, the combination of higher fixed costs for large bank loans and the elevated regulatory capital charge makes bank rejections increasingly likely in this segment, shrinking the set of signals under which the bank finds it profitable to lend. This is particularly visible for Young – Low Asset – Normal Credit Score borrowers, for whom the already-thin margins on high-risk

Figure 7: 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. The blue line represents Banks, and the orange line represents Non-Banks.

profiles leave little room to absorb the additional cost burden of a larger loan.

6 Conclusion

This paper quantifies how risk-based capital requirements affect competition between banks and non-bank lenders and, in turn, access to credit for SMEs. We address this question by developing and estimating a structural model that captures the interaction between asymmetric information, lender heterogeneity, and differential regulatory treatment.

We document three key empirical facts that define this market. First, lenders price on soft information not captured by observables. Second, non-bank lenders serve a pool of borrowers with systematically higher default risk. Third, banks exhibit a pronounced reduction in lending for larger exposures and display strong pricing sensitivity to unobserved risk.

To account for these patterns, the structural estimates highlight the quantitative importance of capital requirements in shaping bank pricing and equilibrium competition. Capital requirements affect the effective cost of lending for banks, with higher charges associated with larger exposures and riskier loans. These regulatory effects interact with a funding asymmetry: consistent with institutional features, banks benefit from a substantial funding cost advantage relative to non-banks, reflecting access to low-cost deposit financing.

At the same time, our results indicate that the expansion of non-bank lending cannot be explained solely by differences in regulatory treatment. To match observed pricing behavior and market participation in higher-risk segments, the model identifies superior screening as a key offsetting force. We estimate that non-bank lenders exhibit substantially higher screening precision than banks, enabling them to price risk effectively in segments where bank lending is more constrained.

Taken together, the findings characterize the UK unsecured SME lending market as one in which funding differences, information processing, and regulation jointly determine equilibrium outcomes. Future work can build on this structural understanding to evaluate how different policy tools affect lending rates, borrower allocation, and aggregate access to credit for SMEs.

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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:

$$R = 0.03\left(\frac{1-e^{-35\cdot PD}}{1-e^{-35}}\right) + 0.16\left(1 - \frac{1-e^{-35\cdot PD}}{1-e^{-35}}\right) \tag{16}$$

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:

$$K = LGD \cdot N\left(\frac{G(PD) + \sqrt{R}\cdot G(0.999)}{\sqrt{1-R}}\right) - PD \cdot LGD \tag{17}$$

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:

$$RWA = K \cdot 12.5 \cdot EAD \cdot SF \tag{18}$$

B Additional Figures and Tables

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. *Bank* is an indicator variable for banks. 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 and Loan Interest Rates

One important ingredient in our setting is the differential regulatory regime that banks and non-banks are subject to. This includes bank capital regulation, which 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.

To understand the extent to which this also happens 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 do 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 requirements relative to total capital translate into differential SME loan interest rates. We define $\Delta Capital\ Buffer_{jt}$ as the change in excess tier 1 capital on top of total capital requirements, normalized by total assets, and estimate the following specification:

$$r_{ijt} = \beta_1 \Delta Capital\ Buffer_{jt} + \Gamma_1 X_{jt} + \varepsilon_{ijt} \, , \tag{19}$$

Where r_{ijt} is the interest rate on a loan from bank j to firm i in quarter t, $\Delta Capital\ Buffer_{jt}$ represents the change in capital buffers, normalized by total assets, and X_{jt} is a vector of time-varying bank level controls. The results are shown in Table C.1. Across all specifications we find that changes in capital requirements affect loan interest rates, with estimates suggesting that a 1 percentage point increase in the total buffer held by a bank increases SME unsecured loan interest rates roughly by 7 basis points.

Table C.1: Capital Requirements and Loan Interest Rates

	r_{ijt} (1)	(2)	(3)
$\Delta Capital\ Buffer_{jt}$	-0.0696***	-0.0729**	-0.0714**
	(0.0259)	(0.0276)	(0.0292)
$Log(Assets)_{jt-1}$	0.2244	0.1380	0.5148*
	(0.2791)	(0.2920)	(0.2926)
$\Delta Assets_{jt-1}(\%)$	3.703**	4.423***	5.455***
	(1.549)	(1.432)	(1.631)
$\Delta Deposits(\%)_{jt-1}$	-2.104	-2.821*	-3.671**
	(1.673)	(1.545)	(1.641)
$Credit\ Risk\ Category : Normal_{jt}$	-0.8581***	-0.7565***	-0.8063***
	(0.0459)	(0.0411)	(0.0460)
$Credit\ Risk\ Category : No\ Score_{jt}$	-0.5412***	-0.4845***	-0.4955***
	(0.0772)	(0.0751)	(0.0937)
$Young_{jt}$	1.229***	1.007***	1.027***
	(0.1055)	(0.1001)	(0.1192)
Observations	36,434	36,434	32,895
R^2	0.23625	0.26145	0.34016
Bank fixed effects	✓	✓	✓
Quarter fixed effects	✓	✓	
Region fixed effects		✓	
Industry fixed effects		✓	
Firm Size fixed effects		✓	
Quarter-Region-Industry-Firm Size fixed effects			✓

Note: This table presents estimates of equation 19. The unit of observation at the loan-origination month level. The dependent variable r_{ijt} represents the interest rate on a loan originated by bank j to firm i in month t. $\Delta Capital\ Buffer_{jt}$ represents the change in capital buffers, normalized by total assets, and X_{jt} is a vector of time-varying bank level controls. Capital buffers are calculated as total Tier 1 Equity minus Total Bank Specific Capital Requirements, including Pillar I and II. The coefficient of interest, β_1, captures the impact of changes in the capital buffer on loan interest rates. Standard errors are clustered at the Bank $\times$ Region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.