Bank Market Power*

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March 2026

Abstract

Local loan markets are often highly concentrated, and small and medium-sized firms may have few alternatives when borrowing from banks. Do banks enjoy market power in lending, and what are its macroeconomic consequences? We propose a measurement strategy that uses credit-register data to quantify bank market power and develop a general equilibrium model to assess its aggregate effects. Our empirical approach decomposes loan interest rates into firm and bank fixed effects and interprets bank fixed effects as deviations from the law of one price. Using the Italian credit register, we find that bank fixed effects account for 15-20% of the variation in interest rates and are strongly correlated with local market shares. We then build a macroeconomic model in which firms are matched at random with banks, who face leverage constraints and compete oligopolistically. We show that the model can fit well key statistics about bank-firm relationships, loan demand elasticities, and the dispersion of interest rates in our data. We use the model to measure the output costs of bank market power and how it shapes the transmission of macroprudential policies.

*First draft: March 2026. **Preliminary and incomplete, please do not circulate.** The views and opinions in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy or the Eurosystem. We thank Markus Brunnermeier, Erik Hurst, and seminar participants at Frontiers of Macroeconomics, Stanford and the European Central Bank. Alexander Gilsa Hansen provided excellent research assistance. All errors are our own. Luigi Bocola thanks the National Science Foundation for generous funding.

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1 Introduction

In many countries, local loan markets are highly concentrated, and firms often have few alternatives to bank borrowing when managing their day-to-day operations. These observations lead to natural questions: Do banks enjoy market power in lending? How large are the associated rents, and to what extent do they depress economic activity? These questions are central for understanding the cost of credit faced by firms, the transmission of financial shocks, and the role of policies that affect the structure of the banking sector.

In this paper, we contribute to this debate in two ways. First, we develop a methodology to quantify deviations from perfect competition in loan markets using administrative data on loan prices. We decompose the interest rates that firms pay on loans as the sum of two components, a firm and a bank fixed effect. The bank fixed effect is identified from the dispersion in interest rates across lenders for loans taken by the same borrower and, as such, captures deviations from the law of one price. We document, by applying this methodology to the European credit register, that bank fixed effects are economically large. In addition, we show that they are strongly related to standard measures of market power: banks that charge high interest rates are also those with a large share of loans in their local market. The second contribution of the paper is to extend a baseline macro-finance model, in the tradition of Gertler and Karadi (2011) and Gertler and Kiyotaki (2010), to allow for bank market power. We fit the model using estimates of loan demand elasticities and of the distribution of bank-firm relationships and show that it predicts well several patterns in the observed distribution of interest rates. We then use the model to assess the economic costs induced by bank market power and to study how financial policies affect bank competition.

Our empirical analysis combines two complementary sources of administrative data. First, we use AnaCredit, the harmonized euro-area credit register, which provides rich loan-level information on interest rates, loan and borrower characteristics, but is only available for a relatively short time period. Second, we use the Italian credit register and complementary sources to obtain a longer time series of bank-firm relationships, interest rates for different types of loans, and detailed characteristics of borrowers and lenders. Taken together, these sources provide detailed information on prices and quantities, while allowing us to study both cross-sectional and time-series variation in the pricing of bank credit.

Our empirical strategy proceeds in two steps. In the first step, we residualize interest rates on short-term lending facilities with respect to the bank's assessment of the borrower's credit risk, including default probabilities and recovery values for any pledged collateral.[1] This allows us to isolate variation in credit prices that is not directly accounted for by risk or contract composition. Consistent with recent studies that use credit-register or supervisory loan data for other countries,

[1] Our benchmark analysis focuses on overdraft accounts because they are comparatively homogeneous contracts: they are callable and do not have an explicit maturity. In the paper we show that our results are quantitatively similar if we were to use other categories of short-term lending.

e.g., Cavalcanti et al. (2023), Faria-e-Castro et al. (2025b), and Ferreira and Kozeniauskas (2025), we find substantial dispersion in interest rates even after conditioning on these indicators.[2]

In the second step, we regress the residualized interest rates on a firm and a bank fixed effect. The firm component captures systematic differences in borrowing rates across firms, while the bank component captures systematic differences in the interest rates charged by banks on the same firm.[3] The identification of the bank fixed effect comes from firms that borrow from multiple lenders at the same time: once these overlapping lending relationships generate a connected network, we can recover bank fixed effects relative to one another from within-firm comparisons of borrowing rates. In our setting, the bank fixed effects can be estimated from a simple cross-section, since we observe many firms borrowing from multiple lenders at the same time.

We begin by applying this framework to AnaCredit, focusing on overdraft accounts of Italian firms outstanding in the third quarter of 2019. We document that the bank fixed effect accounts for 17% of the dispersion in residualized interest rates—equivalent to roughly half of the share of variance in interest rates accounted for by our indicators of default risk and recovery values. These effects remain economically important even when controlling for factors that might otherwise account for heterogeneity in loan pricing. For example, a possible explanation for the dispersion in interest rates is that overdraft rates depend on other characteristics of the contract, such as the committed amount, whether the interest is fixed or variable, or the date of inception, or on characteristics of the bank-firm match, such as the length of the relationship. We show that all these factors, while important for driving the cross-sectional dispersion in interest rates, have little impact on the share of variance accounted for by the bank fixed effect.

We then turn to the longer Italian credit-register sample to study how these forces evolved over time. We find that the importance of bank fixed effects declined during the 2000s and then rose again after the financial crises of the 2010s, a pattern consistent with a period of stronger competitive pressure followed by post-crisis consolidation in banking.[4] In addition, we show that across provinces, banks with larger market shares tend to charge higher interest rates, even after controlling for bank balance-sheet characteristics and time effects. This evidence supports the interpretation of bank fixed effects as capturing economically meaningful differences in market power.

[2]In our residualization step, we find that default probability and loses upon default explain 26% of the cross-sectional dispersion in interest rates in overdraft accounts. This is somewhat higher than that found in other studies, which typically pool all types of loans. Using Brazilian data, Cavalcanti et al. (2023) show that observable measures of risk explain about 24% of the variation in loan spreads. In Faria-e-Castro et al. (2025b), default probability and loss-given-default explains (together with other loans' characteristics and sector-time fixed effects) only 19% of the dispersion.

[3]Our definition of a bank is the interaction between a banking group (e.g. *UniCredit*) and a province (e.g. Rome), thus allowing branches of the same group in different locations to have different fixed effects.

[4]See for example De Bonis et al. (2014) for an analysis up to 2014. The European Central Bank has instead documented that euro-area banking markets became more concentrated after the global financial crisis, with about one-third of banking groups disappearing (European Central Bank, 2021).

While this evidence points to a significant deviation from the law of one price, it is silent about how large the underlying rents are and about the associated economic costs. To make progress on this dimension, we develop a dynamic model with a banking sector that can generate cross-sectional dispersion in interest rates and use it to measure the efficiency costs of market power in banking. Our model builds on the macro-banking framework of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011): banks issue deposits to households, subject to a leverage constraint, and invest these funds in firms that need to borrow to finance working capital. The key innovation relative to the existing literature is to assume that financial services provided by banks are imperfect substitutes, and that firms are randomly matched to a subset of banks. Conditional on these matches, banks interact strategically under oligopolistic competition when setting interest rates.

In equilibrium, the interest rate charged by a bank to a firm is a markup over the bank's marginal cost of funds. As in standard variable-markup models, these markups are heterogeneous across banks and firms. When a firm borrows from many atomistic lenders, the elasticity that each lender faces is related to how substitutable loan services are. When a firm is instead matched with just one lender, the elasticity is related to the speed at which the firm reduces production when facing higher interest rates. To the extent that the former is larger than the latter, our model predicts that loan markups will be larger for banks with large market shares. This also implies that firms matched with only a few banks will typically face higher markups. The marginal cost, in turn, reflects both the rate at which banks borrow and the scarcity of deposits relative to the loans they want to extend. While the former is common across banks, the latter may be heterogeneous because banks' leverage constraints bind differently across institutions.

We discipline the model parameters via indirect inference, matching, among other targets, the average number of banks from which firms borrow, the distribution of bank market shares, and reduced-form estimates of the elasticity of loan demand with respect to interest rates. Specifically, we apply the methodology of Amiti and Weinstein (2018) to the Italian credit register to isolate idiosyncratic changes in a bank's lending rate that are unrelated to loan-demand factors, and we study how loans adjust to such shocks. We estimate a semi-elasticity of -19 in levels and -12 when loans are measured as a fraction of total firm borrowing.[5] To match these values, the model requires loan demand to be fairly elastic for an "atomistic" bank ($\eta = 4.5$), while the elasticity faced by a monopolistic lender is much smaller because it is pinned down by the firm's intensive-margin response through working-capital demand. These values, together with the distribution of bank-firm relationships and the size distribution of banks, discipline the average markup in our model and how it varies across banks and firms.

[5]These estimates are consistent with recent work. Using U.S. supervisory loan data, Dempsey and Faria-e-Castro (2025) estimate an overall semi-elasticity of loan demand close to -20. Using euro-area credit-register data, Altavilla et al. (2022) estimate an elasticity of substitution across banks in the range of 7 to 23. Our estimate of -19 for loan levels is therefore close to the former, while our estimate of -12 for loan shares lies comfortably within the range reported by the latter.

We test the model's predictions by asking whether it can reproduce key features of the observed interest-rate distribution. We show that interest rates in our economy admit a log-linear representation in a firm and a bank fixed effect, like the one we estimate in the data. Firms that are matched with few banks end up facing high interest rates in equilibrium, as the banks they borrow from exploit their market power and charge high markups. The bank fixed effect, in turn, is driven by the sum of the markup and of the marginal cost of that specific bank relative to the average across banks. We show that the estimated model is not only consistent with the observed cross-sectional dispersion in interest rates, but is also consistent with the decomposition we estimate in the Italian data: about 20% of the cross-sectional dispersion captured by the bank fixed effect, and the latter are strongly correlated with bank market shares. This provides support for the mechanism through which heterogeneity in bank costs and markups jointly shape the observed cross-section of credit prices.

After validating the model, we turn to counterfactual analysis. First, we ask what would happen if banks were forced to price their loans at marginal cost. This exercise is useful from a measurement perspective because it allows us to translate the deviations from the law of one price observed in the credit register into an output metric. When banks price at marginal cost, there are two key forces operating in the short run: a reduction in the average interest rate paid by firms and a compression of its dispersion. The first effect increases output through the standard working-capital channel, with lower interest rates increasing labor demand and economic activity. The second channel increases output by reducing misallocation, as equally productive firms in our economy pay different interest rates. We show that the overall gains from the elimination of markups are sizable, with output increasing by 1.3% on impact. Most of these effects are due to the reduction in the average markup rather than to the misallocation channel.

In the long run, however, part of these gains is eroded. Because banks price at marginal cost, they accumulate less capital over time. As capital helps banks overcome their leverage constraints, the economy with zero markups converges to a steady state in which financial constraints on banks are tighter. Thus, while eliminating bank market power reduces the distortions coming from loan markups, it increases over time the marginal cost of borrowing for banks. This force pushes output downward. Eventually, this mechanism erodes most of the gains from eliminating bank market power, with output increasing by only about 0.5% in the long run.

In a second counterfactual, we use the model to study the interaction between macroprudential policy and bank competition. Changes in lending standards affect banks asymmetrically depending on the tightness of their leverage constraints. Because less-capitalized banks are more likely to be constrained in our framework, a uniform relaxation in lending standards has larger effects on them, reshaping market shares and, in turn, the distribution of loan markups. In our quantitative exercise, about half of the decline in interest rates following a relaxation of capital requirements comes from this endogenous change in markups rather than from a direct reduction in marginal

costs. These effects speak to the anti-competitive consequences of macroprudential policy that are often discussed by policymakers, and show how the structure of credit markets can shape the transmission of regulatory interventions.

Related literature. Several recent papers use credit register data to document salient features of the cross-sectional distribution of loan rates paid by firms. This includes Cavalcanti et al. (2023) for Brazil, Altavilla et al. (2024) for the euro area, Faria-e-Castro et al. (2025a) and Amiti et al. (2026) for the United States and Ferreira and Kozeniauskas (2025) for Portugal. A common finding in this literature is that there is sizable dispersion in borrowing rates across firms even after controlling for observable indicators of credit risk. Among these papers, the one closest to ours empirically is Ferreira and Kozeniauskas (2025), who also estimate "AKM-style" regressions for observed loan rates with firm and bank fixed effects identified from firms borrowing from multiple lenders. Consistent with our analysis, they find that bank-side heterogeneity accounts for 10-15% of the observed dispersion in interest rates.[6]

Our contribution to this literature is threefold. First, we explicitly connect dispersion in bank fixed effects to deviations from the law of one price in loan markets, and show that this statistic is informative about the degree of bank market power.[7] Second, we show that a model with sticky firm-bank relationships and variable bank markups can account well for the cross-sectional dispersion in interest rates observed in the data. Third, we combine this measurement with our model to quantify the macroeconomic costs of monopolistic rents in loan markets.

A second strand of the literature studies the macroeconomic effects of bank dynamics through the lens of dynamic general equilibrium models, building on the foundational frameworks of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). More recently, the high concentration of the banking industry has led researchers to incorporate bank market power into these frameworks. Jamilov and Monacelli (2025) develop a model of heterogeneous financial intermediaries with market power in deposit markets, while Ulate (2021), Bianchi and Bigio (2022) and Wang et al. (2022) study how bank market power shapes the transmission of monetary policy. Dempsey (2025) studies how heterogeneous banks compete both with one another and with the bond market, and Aguirregabiria et al. (2025), Maingi (2026), and Bordeu et al. (2026) analyze how bank market structure shapes the spatial allocation of credit. Most closely related to our paper, Corbae and d'Erasmo (2021) and Villa (2025) develop quantitative models of banking industry dynamics with oligopolistic competition to study business cycles and the effects of macroprudential policies. We contribute to this literature by developing a model of oligopolistic competition among non-atomistic banks and showing that, given plausible values of loan-demand elasticities and concentration measures,

[6] This figure is the closest one to our approach, in which the bank fixed effect is identified exclusively from the dispersion in lending rates applied to the same borrower at the same time.

[7] Our analysis corroborate this result by documenting that the bank fixed effects correlate with concentration measures in loan markets.

it can fit well key features of the cross-sectional dispersion in interest rates observed in the credit register.

An influential view considers monopolistic rents important for supporting long-term relationships between banks and firms, which in turn can foster lending to small and young firms whose prospects are uncertain and hard to monitor. In Petersen and Rajan (1995) banks are more willing to finance young and credit-constrained firms in concentrated markets because they can better internalize the future rents generated by a lending relationship. There is substantial evidence documenting the importance of relationship lending in credit markets, see for example the empirical analysis of Crawford et al. (2018) or the recent quantitative analysis in Beraldi (2025). It is important to point out that our counterfactuals only assess the efficiency gains coming from eliminating bank markups—not the indirect effects that weaker bank-firms relationships would have on bank lending. In this respect, our approach closely mirrors that of Hsieh and Klenow (2009), Baqaee and Farhi (2020), and Edmond et al. (2023), who assess the efficiency losses due to monopolistic rents in product markets without considering the effects that eliminating those rents would have on other margins, e.g., innovation activity.[8]

Finally, our paper relates to a growing literature on market power across different markets and its welfare consequences. In an influential paper, De Loecker et al. (2020) document a substantial increase in markups in the United States since 1980, while Edmond et al. (2023) study the welfare costs of markup distortions. In labor markets, Yeh et al. (2022) measure markdowns and Berger et al. (2022) quantify the welfare cost of labor market power. In banking, Drechsler et al. (2017) and Begenau and Stafford (2018) study market power in deposit markets, while Benetton et al. (2025) analyze market power in mortgage lending. Our paper instead focuses on loan markets, where we quantify rents associated with lender market power and assess their macroeconomic costs.

Layout. The remainder of the paper is organized as follows. Section 2 presents the data and the empirical evidence Section 3 describes the general equilibrium model. Section 4 presents the quantitative analysis, including the estimation of the model and the main counterfactual exercises. Section 5 concludes.

2 Empirical Evidence

This section presents the main empirical findings of the paper. Section 2.1 describes data sources, definitions and sample selection. Section 2.2 describes the empirical model that we use to decompose interest rates into a firm fixed effect and a bank fixed effect, and presents the results of this

[8] Our work is therefore related to a literature measuring the welfare cost of markdowns and labor market power (Berger et al., 2022).

decomposition. Section 2.3 analyzes further the bank fixed effects, showing that they correlate with measures of market concentrations.

2.1 Data

We perform our analysis using two main datasets. Our baseline analysis uses AnaCredit, the harmonized credit register for the euro area. This register provides detailed information on all loans issued by credit institutions in the euro area above €25,000, starting from 2018-M9.[9] We then complement this analysis with information from the Italian Credit Register. While this register is less detailed than AnaCredit (it provides information at the firm rather than loan level), it gives us a longer time-series and provides information on small banks.

AnaCredit covers all loans above €25,000 euros extended by credit institutions in the euro area and records, at the loan level, the contractually agreed interest rate and interest rate type, the outstanding and committed amounts, and key loan characteristics including loan type, loan purpose, date of inception, maturity, and allocated collateral value. AnaCredit also reports a bank assessment of the firm probability of default, defined as the one-year probability that a debtor will fail to meet its obligations. This figure is primarily aligned with the Internal Ratings-Based (IRB) approach for credit risk, as established in the Capital Requirements Regulation (CRR) and is only reported when the filing institution has opted for and IRB approach on the specific loan issued. AnaCredit also directly reports firm-level information on total revenues, assets and number of employees.

The second dataset, covering the 2005–2019 period, is built by matching several administrative sources. The core comes from the Italian Credit Register and the TAXIA archive on interest rates, supplemented with balance sheet data on borrowers from Cerved and on lenders from the Supervisory Files (COREP) on banks and banking groups.

The Italian Credit Register, managed by the Bank of Italy, is a comprehensive database recording the debts of households and firms toward the banking and financial system. It collects information submitted by virtually all banks and credit intermediaries in Italy. It contains detailed quarterly information on credit issued by banks and other credit intermediaries above a minimum threshold of €30,000, covering both disbursed and undisbursed credit.[10] Information is reported at the firm-bank level, and all loans that a firm has taken from a specific bank are aggregated into three categories: *rischi a revoca* (revolving loans), *rischi autoliquidanti* (loans backed by account receivables), and *rischi a termine* (fixed-term loans). Bank of Italy provides intermediaries with

[9] Not all banks participate into the program. National Central Banks can let financial institutions (temporarily) opt out from reporting information if the total outstanding amount of loans is less than (4%) 2% of the national figure.

[10] When a borrower is classified as a bad debtor, based on an assessment of their overall financial situation rather than isolated late payments, the reporting threshold drops to €250.

information on their customers' total indebtedness, loan types, and repayment behavior. Intermediaries can also query the register about prospective borrowers to assess creditworthiness.

TAXIA complements the Credit Register with information on interest rates for borrowers with at least €75,000 in overall granted or disbursed credit by institution. It is reported by all but the smallest banks, and its coverage is highly representative — reporting banks account for roughly 80 percent of outstanding credit. For each of the three loan categories in the credit register, TAXIA records the actual interest amount paid by debtors in each quarter and the computational principal, as computed by the bank, on which the effective interest rate is applied to compute the actual interest paid by debtors to a given bank. Effective interest rates are hence computed as the ratio between interest paid and the relevant computational principal for each quarter. The interest paid is recorded net of commissions and fees.

CEBI (Centrale dei Bilanci) is a proprietary database compiled by an external risk-analytics firm, CERVED, providing detailed firms' balance sheet and income statement information at the yearly frequency and expected default probability at 1, 3 and 5 years horizons. Its coverage is substantial: total credit to Cerved firms represents approximately three-quarters of loans by Italian banks to the nonfinancial corporate sector. Balance sheet information on lenders comes from the Supervisory Files on banks and banking groups, containing virtually all information present on Balance Sheet and Income Statements as well as Prudential reporting documents (COREP).

All data sources are matched based on the year-quarter of observation, the credit institution unique charter code (ABI), and the firm unique VAT code. For our baseline analysis, we will focus on overdrafts accounts.[11] These are the vast majority of revolving credit for Italian firms, and they are considered superior for analyzing interest rate policies compared to other instruments because they have fairly standardized basic features, are short-term, and often have variable rates or frequently updated fixed rates, unlike long-term fixed loans. This is especially important when using the Italian credit register because all term loans issued are aggregated up at the firm level without information on maturity, date of inception, or referent rate used at the time of inception. As a result, dispersion in interest rates for term loans would be rather confused by variation in these characteristics across firms. As a robustness, however, we will repeat our analysis for different types of loans when using AnaCredit, since in those cases we have information at the loan level.

Sample selection. Our baseline sample consists of loans issued by firms headquartered in Italy. We exclude micro firms (fewer than five employees), firms with missing information on key variables, and outliers. Specifically, we drop observations in which loan utilization exceeds total firm assets or in which operating income is very negative. We winsorize interest rates at ±2.5 percent and loan utilization at ±1 percent to limit the influence of extreme observations.

[11] Overdraft accounts are defined as revolving credit facilities that allow account holders to withdraw more money than is available in their current or cash management accounts, up to a pre-approved limit.

Table 1: Summary Statistics

	Obs.	Mean	p5	p25	p50	p75	p95
Firm employment	52,397	61.41	6	9	14	27	121
Firm assets	52,397	2.74e+07	311,150	980,000	2,398,000	6,667,000	4.54e+07
Firm revenue	52,397	1.98e+07	402,000	1,038,000	2,394,000	6,684,573	4.73e+07
No. banks per firm	52,397	1.39	1	1	1	2	3
Age of relationship	52,397	3.15	1	2	3	4	5
Prob. of default	52,397	0.048	0.002	0.006	0.016	0.035	0.170
Collateral	52,397	9,366.49	0	0	100	158.04	496.96
Interest rate	84,505	6.50	0.59	3.00	5.25	8.63	15.29
Loan size	84,505	80,201.08	47	4,493	22,548	67,481	338,728
Loan commitment	84,505	166,193.37	73	14,705	39,453	99,634	499,984

Notes: The sample consists of overdraft accounts outstanding in 2019:Q3 for firms headquartered in Italy, excluding micro firms (fewer than five employees). Interest rates and loan utilization are winsorized at ±2.5% and ±1%, respectively. Monetary values are in euros.

Summary statistics. Table 1 reports summary statistics for the overdraft accounts in 2019:Q3. The sample contains 52,397 firm observations and 84,505 loan observations. The average firm in the sample employs approximately 61 workers and holds assets of about 27.4 million euros. The median firm is substantially smaller, with 14 employees and assets of 2.4 million euros, reflecting the prevalence of small and medium-sized enterprises in the Italian economy.

A key feature of the sample is that most firms borrow from a small number of banks. The average number of banking relationships per firm is approximately 1.4, and the median is 1, indicating that the majority of firms in the sample maintain a single banking relationship. However, around 40% of firms in our sample have at least two overdraft accounts open at different banks. This is important because, as we will discuss later, the bank fixed effect is identified from firms that borrow from more than one bank.

The average interest rate on overdraft accounts is 6.50 percent, with substantial dispersion: the 5th percentile is 0.59 percent and the 95th percentile is 15.29 percent. The spread between the 25th and 75th percentiles is approximately 5.6 percentage points. This dispersion is the empirical phenomenon we seek to explain and decompose.

2.2 AKM decomposition

This section studies the driving forces of interest rate dispersion across bank–firm pairs. We proceed in two steps. We begin by quantifying how much of the observed cross-sectional dispersion in loan rates can be explained by the most natural competitive determinant of pricing, namely default risk and recovery values in the event of default. We then turn to a statistical decomposition of the residual variation into firm and bank components. This decomposition allows us to quantify the dispersion in interest rates across banks lending simultaneously to the *same* firm, and as such it will be informative about deviations from the law of one price in loan markets.

Default risk. The most natural explanation for interest rate dispersion is default risk. Even under competitive loan pricing, interest rates would vary across loans because they reflect differences in the probability of default and in the recovery value conditional on default. Our first step therefore quantifies how much of the cross-sectional dispersion in loan rates can be accounted for by these two forces. To do so, we estimate:

$$r_{lib,t} = \alpha + \delta'_{pd}\, pd_{lib,t} + \delta'_{col}\, collateral_{lib,t} + \hat{r}_{lib,t}, \tag{1}$$

where $r_{lib,t}$ denotes the interest rate on loan l of firm i with bank b at time t, $pd_{lib,t}$ and $collateral_{lib,t}$ are fixed effect based on the deciles of the distribution of reported default probabilities and collateral values. Importantly, the default probability is observed at the firm–bank level, since it is reported by each bank for each borrowing firm. We also use information on the reported value of pledged collateral, which affects recovery values in the event of default.

We estimate equation (1) in the cross section of loans and find that default risk and collateral jointly explain 26 percent of the cross-sectional variation in interest rates. Thus, while these variables have substantial predictive power, the majority of the observed dispersion remains unexplained. One potential concern is that bank-specific measures of default probability may introduce bias into the estimated role of default risk. To address this issue, we replicate the analysis using external credit ratings from TAXIA and find that these ratings have even less predictive power than the bank-reported probability of default. This finding is in line with the evidence in Cavalcanti et al. (2023), Ferreira and Kozeniauskas (2025), Amiti et al. (2026), and Faria-e-Castro et al. (2025a), who document for other countries that a large fraction of interest rate dispersion cannot be explained by default risk.

AKM decomposition. Having established that a substantial share of interest rate dispersion is not explained by default risk and collateral, we next decompose the remaining variation into firm and bank components. Specifically, we estimate a two-way fixed effects regression in the spirit of Abowd et al. (1999):

$$\hat{r}_{lib,t} = \alpha_{b,t} + \alpha_{i,t} + \varepsilon_{lib,t}, \tag{2}$$

where $\alpha_{b,t}$ is the bank fixed effect and $\alpha_{i,t}$ is the firm fixed effect. We define a bank as a bank–province pair, where the province is the province in which the firm is headquartered.[12] By doing so, we are allowing the same banks to systematically charge different interest rates in different markets.

Intuitively, the firm fixed effect is identified from the average interest rate paid by a given firm, while the bank fixed effect is identified from differences in the rates charged by different banks

[12]Provinces are administrative units roughly comparable to a U.S. county. According to the Italian Antitrust Authority, the relevant market in banking for antitrust purposes is the province (Guiso et al., 2012). Italy is divided into 110 provinces.

to the same firm. For this purpose, we restrict the estimation of equation (2) to firms that have at least two simultaneous lending relationships with different banks. In contrast to the standard worker–firm setting, where identification relies on workers switching employers over time, here we observe within-period borrowing relationships between the same firm and multiple banks, which provides direct cross-sectional variation for identifying bank fixed effects.

Because these fixed effects are identified only up to a constant, estimation is typically restricted to connected sets. A connected set is a subset of firms and banks that are linked through observed borrowing relationships, so that fixed effects can be compared across all units in the set. In our application, different provinces form disconnected sets because we allow for bank–province fixed effects and assign province information based on the province in which firms are headquartered. We therefore take the largest connected set within each province and normalize the fixed effects within province so that either the average firm fixed effect or the average bank fixed effect is equal to zero. We discuss below how results may be sensitive to this normalization.

The main object of interest is the relative importance of firm and bank fixed effects in explaining residual interest rate dispersion. In particular, we focus on:

$$\frac{\mathrm{Var}(\alpha_{b,t})}{\mathrm{Var}(\hat{r}_{lib,t})}, \tag{3}$$

that is, the share of the variance of residual interest rates accounted for by bank fixed effects. Estimating this statistic from the fitted fixed effects may, however, lead to biased estimates because of limited-mobility bias (Andrews et al., 2008; Bonhomme et al., 2023; Kline, 2024). The intuition is that, when bank fixed effects are imprecisely estimated, they may absorb idiosyncratic noise, artificially inflating the estimated variance of bank effects. This concern is likely less severe in our setting because, at a given point in time, we observe the same firm borrowing simultaneously from multiple banks. In labor market applications, by contrast, one would need to observe the same worker employed by multiple firms at the same time for an analogous source of within-period variation, which is infeasible; as a result, the standard AKM estimator instead relies on workers switching jobs over time.

Nonetheless, to address any residual concern related to limited-mobility bias, we report results for a high-mobility subsample. In practice, we restrict attention to bank–province pairs for which we observe at least 15 firms that also borrow from at least one other bank, that is, at least 15 movers.[13]

Results. Table 2 reports the variance decomposition under the benchmark specification and three alternative specifications. Column (1) reports the benchmark AKM decomposition. Firm

[13] Bonhomme et al. (2019) show that the standard AKM estimator may create problems when the true model is not log-additive in the two fixed effects. Our model implies a log-additive decomposition of interest rates.

fixed effects account for 62 percent of residual interest rate dispersion, while bank fixed effects account for 17 percent. The remaining variation is captured by the residual component, and the covariance between firm and bank fixed effects is small and negative.

Column (2) asks to what extent the dispersion in bank–province fixed effects simply reflects geographical differences in lending rates across provinces. To address this question, we absorb province fixed effects and recompute the decomposition. Since each province is a connected set, this is equivalent to the bank-province fixed effect so that they have mean zero within each province.[14] The variance of bank fixed effects remains sizable and equal to 10 percent of total residual interest rate dispersion. Thus, while geography matters, a large share of the bank component does not reflect pure geographical variation but rather differences across banks within the same province or differences across provinces within the same banks.

Column (3) further controls for observable loan characteristics. In particular, we add fixed effects for the type of rate, whether the rate is fixed or variable, the reference rate, the purpose of the loan, the committed amount, and the amount utilized, using bins for continuous variables where appropriate. These controls have predictive power for loan pricing, but they are largely orthogonal to the estimated bank fixed effects. This finding suggests that the bank component does not primarily reflect specialization in particular loan contracts within the broad loan category we study. Even after controlling for this rich set of loan characteristics, bank fixed effects still explain 16 percent of residual interest rate dispersion.

Finally, Column (4) addresses two additional competing explanations for interest rate dispersion. First, the price charged on a given loan may depend on the length of the underlying bank–firm relationship, as emphasized by Crawford et al. (2018) and Beraldi (2025). Second, loan pricing may reflect cross-subsidization across different contracts held by the same firm with the same bank, for example if overdrafts, working capital loans, and long-term loans are jointly priced. To account for these possibilities, we add controls for the length of the relationship and for the number of credit instruments within the same firm–bank match. These additional controls leave the results essentially unchanged.[15]

Time variation. We turn to the Italian Credit Register (TAXIA) to study how the dispersion in bank fixed effects has evolved over time. While we use AnaCredit for our baseline results, AnaCredit does not allow us to go back before 2018. By contrast, TAXIA covers a much longer period and, importantly, still allows us to observe firms borrowing from multiple banks in each year. This makes it possible to estimate the ratio $\mathrm{Var}(\alpha_b)/\mathrm{Var}(i_{fb})$ separately year by year.

[14] In the baseline specification we normalized the firm fixed effect to have mean zero within each province, but the mean bank-province fixed effect for each province was equal to the average interest rate in that province.

[15] Beraldi (2025) documents robust evidence that accounting for relationship lending is essential to explain how interest rates vary over time within a given firm-bank pair. Our evidence suggests that relationship lending has little explanatory power in the cross-section.

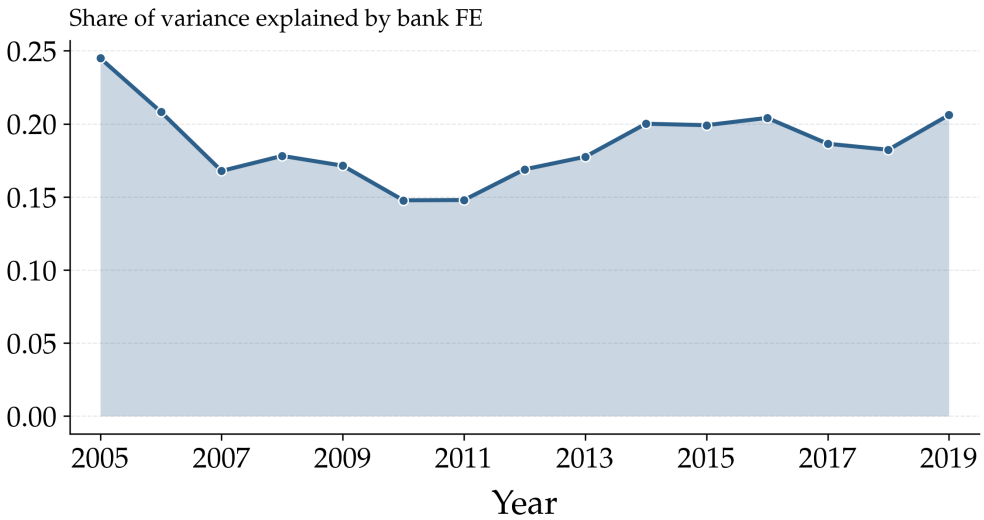
Table 2: AKM Variance Decomposition

	Benchmark	Province FE	Loan Controls	Relationship + Loan
Standard deviation	2.87	2.87	2.87	2.87
Variance share: firm FE	0.62	0.62	0.52	0.52
Variance share: bank FE	**0.17**	**0.10**	**0.16**	**0.16**
Variance share: residual	0.24	0.24	0.22	0.22
Variance share: COV firm–bank FE	−0.02	−0.02	−0.03	−0.03
N	48,335	48,335	47,891	47,891

Notes: The table reports the variance decomposition of residual interest rates $\hat{r}_{lib,t}$ estimated from equation (2). All variance components are expressed as fractions of total residual variance $\text{Var}(\hat{r}_{lib,t})$. Column (1) reports the benchmark specification. Column (2) absorbs province fixed effects to isolate the component of bank–province fixed effects that is orthogonal to pure geographical variation in lending rates. Column (3) adds loan-level controls for the type of rate, whether the rate is fixed or variable, the reference rate, the purpose of the loan, the committed amount, and the amount utilized, using fixed effects for bins of continuous variables where appropriate. Column (4) further adds controls for the length of the bank–firm relationship and for the number of credit instruments within the same firm–bank match.

The results are plotted in Figure 1. A first observation is that the estimated contribution of bank fixed effects is relatively stable over time. Relative to AnaCredit, however, TAXIA delivers somewhat larger estimates of the variance explained by bank fixed effects on average. At the same time, the series exhibits meaningful variation. In particular, the ratio declined during the 2000s and through the onset of the Great Recession, before increasing again thereafter.[16]

Figure 1: AKM Decomposition Over Time



Notes: The figure plots the ratio $\text{Var}(\alpha_b)/\text{Var}(\hat{r})$ estimated annually from the Italian credit register (TAXIA) over time.

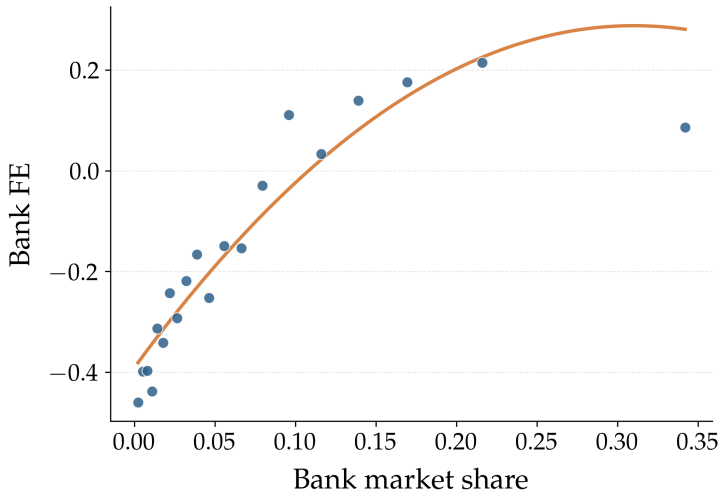
[16]This pattern is consistent with a period of stronger banking competition prior to the financial crisis, followed by a re-concentration of the banking sector as weaker institutions exited and surviving banks gained market share.

2.3 Bank fixed effects and market concentration

A natural question is whether the bank fixed effects reflect market power or instead capture other bank-specific characteristics, such as differences in monitoring technology or funding costs. To shed light on this interpretation, we study the relationship between bank fixed effects and local market concentration.

Figure 2 provides a first piece of evidence. It plots bank fixed effects against provincial market shares in a binscatter, without conditioning on any bank-level controls. The relationship is strongly positive and nonlinear: banks with a larger share of the loan market in a given province charge systematically higher rates, conditional on firm characteristics.

Figure 2: Bank Fixed Effects and Local Market Share



Notes: This figure presents a binscatter plot of the estimated bank fixed effect coefficients from regression (4) against the bank's market share, and the fitted quadratic line from Table 3.

The positive relationship in Figure 2 could, however, reflect bank-specific heterogeneity in marginal funding costs rather than market power. A bank with a high cost of funds will charge high rates, and if such banks also tend to have large market shares, the observed correlation between fixed effects and market shares could simply capture cost heterogeneity rather than differences in markups. To address this concern, we regress the estimated bank fixed effect on market share, allowing for a quadratic relationship and progressively adding controls that proxy for variation in marginal funding costs. Importantly, the fixed effects included in this regression are second-stage bank fixed effects in the bank-year panel and should not be confused with the AKM bank effects that are the dependent variable in the regression. In particular, we include year fixed effects and a vector of time-varying bank balance-sheet characteristics X_{bt} — interest expense, operating costs, provisions, impairments, and capital, all measured as a share of total assets. Formally, we estimate

$$\alpha_{bt} = c + \beta_1 s_{bt} + \beta_2 s_{bt}^2 + \mu_b + X_{bt}'\gamma + \delta_t + \varepsilon_{bt}, \tag{4}$$

Table 3: Regression of Bank Fixed Effects and Local Market Share

	(1)	(2)	(3)	(4)
$\hat{\beta}_1$ (market share)	4.38^{***}	1.67^{***}	2.03^{***}	1.47^{***}
	(0.22)	(0.33)	(0.34)	(0.36)
$\hat{\beta}_2$ (market share^2)	-7.05^{***}	-2.21^{***}	-2.27^{***}	-1.67^{***}
	(0.57)	(0.70)	(0.70)	(0.72)
Bank FE		✓	✓	✓
Time FE			✓	✓
Bank controls				✓
Observations	19,571	19,429	19,429	19,155
R^2	0.03	0.54	0.54	0.55

Notes: Dependent variable is the bank fixed effect α_{bt} from equation (2), estimated at the bank-year level. Market share is the fraction of total provincial loan volume. Bank controls include interest expense, operating costs, provisions, impairments, and capital (all as a percentage of total assets). Standard errors clustered at the bank level in parentheses. $^{***}p < 0.01$.

where α_{bt} denotes the AKM bank effect estimated at the bank-year level, s_{bt} is bank b's provincial market share in year t, μ_b are bank fixed effects in this second-stage panel regression, and δ_t are year fixed effects. The quadratic term s_{bt}^2 captures the concavity visible in Figure 2. The bank fixed effects μ_b absorb time-invariant differences across banks, while the time-varying controls X_{bt} capture changes in balance-sheet conditions that may affect the shadow cost of funds.

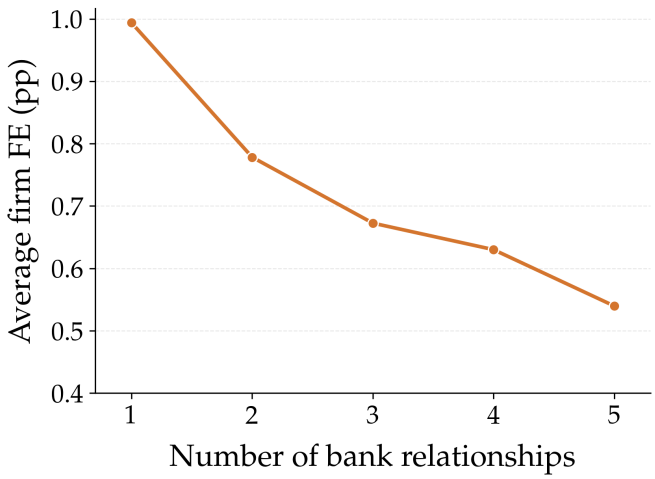
Table 3 reports the results. Column (1) shows the unconditional relationship. Column (2) adds bank fixed effects. Column (3) further adds year fixed effects. Column (4) adds the bank-level controls X_{bt}. Both $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ are stable across specifications, confirming a positive and concave relationship between market share and bank fixed effects. The coefficients decline only modestly as controls are added and remain large and precisely estimated throughout. This suggests that the positive association between bank fixed effects and market shares is not driven by heterogeneity in marginal funding costs alone.

Firm fixed effects and the number of banking relationships. The market power interpretation also implies a prediction about the *firm* fixed effect. Firms matched with a larger set of banks can substitute more effectively among them, which reduces the average markup they face and therefore lowers their firm fixed effect. Conversely, firms with access to only one bank have no outside option and pay a higher average rate, even after controlling for credit risk and collateral. Bank market power therefore shapes both components of the AKM decomposition.

Figure 3 documents this pattern. It plots the average firm fixed effect against the number of banking relationships. The pattern is sharply negative: firms borrowing from more banks have systematically lower firm fixed effects. The gradient is steepest between one and two banks, consistent with the largest marginal gain from having any outside option at all. The pattern is not

mechanically driven by firm size or credit risk, as these are absorbed in the first step. It therefore constitutes direct evidence that bank market power shapes the dispersion of rates across firms, not only across banks. Importantly, the number of banking relationships is not the only driver of the firm fixed effect: the identity of those banks—their sizes and funding costs—also matters, as the model in Section 3 makes precise.

Figure 3: Firm Fixed Effects and Number of Banking Relationships



Notes: The figure plots the average firm fixed effect α_i from equation (2) against the number of distinct banking relationships maintained by the firm in 2019. Firm fixed effects are residualized with respect to default risk and collateral in the first step. The negative gradient reflects the competition mechanism: firms with access to more banks face more elastic loan demand and pay lower average markups.

3 Model

Our model builds on the macro-banking framework of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), augmented with oligopolistic competition in the loan market through a random matching process between firms and banks. We consider an economy populated by a representative household, a continuum of firms, and a finite number of banks. Time is discrete and the horizon is infinite. We start by describing the environment, then define the equilibrium, and end by characterizing the optimal interest rates set by banks and showing how the structural elasticities map to the reduced-form elasticities we later estimate in the data.

3.1 Environment

Households. The representative household maximizes expected discounted utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[C_t - \frac{\chi N_t^{1+\psi}}{1+\psi} \right], \tag{5}$$

where C_t is consumption, N_t is labor supply, $\beta \in (0,1)$ is the discount factor, $\chi > 0$ scales the disutility of labor, and $\psi > 0$ is the inverse Frisch elasticity of labor supply. The household supplies labor to firms, holds deposits a_t in banks, receives dividends from banks when they exit, and collects profits from firms. We normalize the price of consumption to 1. The budget constraint is given by

$$C_t = w_t N_t + \Pi_t + a_t i_{at}, \tag{6}$$

where w_t is the real wage and Π_t denotes the aggregate level of dividends distributed in period t. The latter includes all firm profits together with the dividends distributed from banks. The interest rate on deposits is denoted by i_{at}.

Firms. There is a unit measure of firms. Each firm $f \in (0,1)$ produces a perfectly substitutable good using labor as the sole input of production. We assume each firm's production function features decreasing returns to scale, $\sigma \leq 1$:[17]

$$y_f = n_f^{\sigma}, \tag{7}$$

where n_f denotes the amount of labor firm f uses, and y_f its production.

Production requires working capital. A fraction γ of the wage bill must be paid upfront using credit from banks. We denote by ℓ_f the overall loan amount of firm f. The working capital requirement is given by

$$\ell_f \geq \gamma w n_f. \tag{8}$$

We assume each firm f has access to a random subset $B(f) \subseteq \mathcal{B}$ of banks, where $\mathcal{B}$ denotes the set of all banks in the economy. We assume that a firm is matched with each individual bank with probability ξ. This matching process is iid across relationships and across firms. The expected number of available banks per firm therefore equals ξN_B, where N_B is the number of banks in the economy. Loan services from different banks are imperfectly substitutable. In particular, we assume that the overall loan amount of firm f is a CES aggregator across all individual loans.

[17] For ease of notation, we omit the time subscript in the firm block.

That is,

$$\ell_f = \left(N_{Bf}^{-\frac{1}{\eta}} \sum_{b \in B(f)} \ell_{fb}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{9}$$

where $\eta > 1$ is the elasticity of substitution across banking relationships, and N_{Bf} denotes the number of banks firm f is connected with.

Imperfect substitutability across banking relationships captures, in reduced form, frictions that make loans from different banks only partially interchangeable from the firm's perspective. These frictions may reflect relationship-specific information, differences in contract terms or lending technologies, and adjustment costs in reallocating borrowing across lenders. As a result, substitution across banks is feasible but limited, so each bank faces a downward-sloping residual demand and retains some degree of market power over the firm.

We assume that each bank the firm is matched with offers an interest rate specific to that firm which we denote by i_{fb}. The firm takes as given the interest rates offered by its entire banking network, and decides the amount of borrowing from each bank. In summary, the firm's problem is given by

$$\begin{aligned} \pi_f = \max_{\{n_f, \ell_f, \{\ell_{fb}\}_{b \in B(f)}\}} \quad & n_f^{\sigma} - w n_f - \sum_{b \in B(f)} \ell_{fb} i_{fb}, \\ \text{s.t.} \quad & \gamma w n_f \leq \ell_f, \\ & \ell_f = \left(N_{Bf}^{-\frac{1}{\eta}} \sum_{b \in B(f)} \ell_{fb}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}. \end{aligned} \tag{10}$$

Banks. There is a finite number of banks in the economy. Banks are denoted by $b \in \mathcal{B}$. The net worth of bank b at the start of period t is denoted by k_{bt}. Each bank finances their loan portfolio through a combination of equity (k_{bt}) and household deposits (a_{bt}), so that

$$\int \ell_{fbt} df \leq k_{bt} + a_{bt}. \tag{11}$$

Banks are subject to a leverage constraint (capital requirement) that limits the ratio of loans to equity:

$$\frac{k_{bt}}{\int_f \ell_{fbt} df} \geq \theta, \tag{12}$$

where $\theta \in (0, 1)$ is the required capital ratio. This constraint can be interpreted in reduced form as capturing regulatory capital requirements, incentive constraints arising from limited commitment, or increasing marginal funding costs associated with higher leverage.

Each bank is matched with a fraction ξ of firms. Because there is a continuum of firms, the

matching process does not lead to any uncertainty from the bank's perspective, nor any uncertainty at the aggregate level. The only shock banks are subject to is an "exit" shock. With probability $1-\phi$, the bank survives the period and retains its profits:

$$k_{bt+1} = \int_{f:b\in B_t(f)} (1+i_{fbt})\ell_{fbt}df - (1+i_{at})a_{bt}. \tag{13}$$

With probability ϕ, the bank exits, remits its remaining net worth to the household as a dividend, and is replaced by a new bank with initial net worth k_0. This random exit process gives the model a well-defined stationary distribution of bank sizes.

Banks compete à la Bertrand. Importantly, the matching between firms and banks is predetermined at the start of each period and fixed for the duration of the period, so the oligopolistic competition in interest rates is static conditional on the network. A bank b decides on the interest rate they offer firm f at time t, i_{fbt}, taking as given the interest rates set by all of its competitors. Denote the residual loan demand the bank faces from a firm by $\ell(i_{fb}, i_{f-b})$, where i_{f-b} denotes the interest rates set by all other firms matched with firm f. The bank chooses these interest rates to maximize their end-of-period net worth:

$$\begin{aligned} \widetilde{k}_{bt+1} = \max_{\{a_{bt},\{i_{fbt}\}\}} \quad & \int_{f:b\in B(f)} (1+i_{fbt})\ell(i_{fbt}, i_{f-bt})df - (1+i_{at})a_{bt}, \\ \text{s.t.} \quad & \int_{f:b\in B(f)} \ell(i_{fbt}, i_{f-bt})df \leq k_{bt} + a_{bt}. \end{aligned} \tag{14}$$

3.2 Equilibrium

Given an initial distribution of bank net worth $\{k_{b0}, \widetilde{k}_{b0}\}$, an equilibrium consists of sequences of quantities $\{N_t, C_t, \Pi_t, a_{bt}, \{\ell_{fbt}\}, \{k_{b,t+1}\}, \{\widetilde{k}_{b,t+1}\}, \{\pi_f\}\}$ and prices $\{w_t, i_{at}, \{i_{fbt}\}\}$ for all banks b and firms f such that:

1. Consumption and labor solves the household's problem, given the real wage and interest rate on deposits.

2. For all firms, loans and employment maximize their profits, given the real wage and the vector of interest rates they are offered from banks.

3. For all banks, their interest rates, loans, and deposits maximize their end-of-period net worth, taking as given the real wage, the banking network, and all interest rates charged by their competitors.

4. Aggregate dividends in the economy satisfy

$$\Pi_t = \int \pi_{ft} df + \sum_b \left(k_{bt} - \widetilde{k}_{bt} \right) \tag{15}$$

5. All markets clear. Specifically, aggregate labor demand equals labor supply, aggregate deposit demand equals deposit supply, and consumption demand equals aggregate output produced.

3.3 Loan Demand and Interest Rate Determination

We now characterize firms' demand for loans from each bank and the resulting interest rate setting problem faced by banks.

Loan demand. Fix a firm f and take as given the vector of interest rates i_{fb} it faces. The firm chooses its loans to minimize total borrowing costs for a given level of total loans ℓ_f. Standard cost minimization with a CES aggregator implies that loan demand from bank b is given by

$$\ell_{fb} = \frac{1}{N_{Bf}} \left(\frac{i_{fb}}{i_f} \right)^{-\eta} \ell_f, \tag{16}$$

where

$$i_f = \left(\frac{1}{N_{Bf}} \sum_{b \in B(f)} i_{fb}^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{17}$$

is the firm-specific CES loan rate index.

The working capital constraint (8) binds in equilibrium, implying $\ell_f = \gamma w n_f$. Substituting into the firm's problem yields the optimal labor demand, $n_f = \left(\frac{\sigma}{w(1+\gamma i_f)} \right)^{\frac{1}{1-\sigma}}$. Combining expressions, the demand faced by bank b from firm f can be written as

$$\ell_{fb} = \frac{1}{N_{Bf}} \left(\frac{i_{fb}}{i_f} \right)^{-\eta} \gamma w \left(\frac{\sigma}{w(1+\gamma i_f)} \right)^{\frac{1}{1-\sigma}}. \tag{18}$$

This expression highlights two key margins: (i) substitution across lenders, governed by η, and (ii) the overall scale of borrowing, which depends on the composite loan rate i_f through firms' labor demand.

Bank pricing. Consider bank b setting the rate i_{fb} for a given firm f, taking as given the rates charged by competing banks and the aggregate conditions. The bank chooses i_{fb} to maximize profits from this relationship:

$$\max_{i_{fb}} \quad (i_{fb} - \lambda_{bt}), \ell(i_{fb}, i_{f-b}), \tag{19}$$

where λ_{bt} denotes the marginal cost of funding for the bank. This marginal cost is given by the Lagrange multiplier on the bank's balance sheet constraint in the bank's problem (14), and reflects the shadow value of internal funds, incorporating both the deposit rate and the leverage constraint.

Solving this profit maximization problem, we obtain the standard markup formula:

$$i_{fb} = \frac{\varepsilon(i_{fb}, i_{f-b})}{\varepsilon(i_{fb}, i_{f-b}) - 1} \lambda_{bt}, \tag{20}$$

where

$$\varepsilon(i_{fb}, i_{f-b}) \equiv -\frac{\partial \ell(i_{fb}, i_{f-b})}{\partial i_{fb}} \frac{i_{fb}}{\ell(i_{fb}, i_{f-b})} \tag{21}$$

is the elasticity of residual loan demand faced by bank b from firm f.

In our setup, the demand elasticity $\varepsilon(i_{fb}, i_{f-b})$ is endogenous and depends on the firm's loan expenditure share with bank b in the following way:

$$\varepsilon(i_{fb}; i_f) = \underbrace{\eta\,(1 - s_{fb})}_{\text{credit substitution}} + \underbrace{\frac{1}{1-\sigma} \cdot \frac{\gamma i_f}{1 + \gamma i_f} \cdot s_{fb}}_{\text{credit demand}}, \tag{22}$$

where $s_{fb} = \frac{\ell_{fb} i_{fb}}{\ell_f i_f}$ denotes the expenditure share of bank b in firm f's total loan expenditure. The coefficient $\frac{1}{1-\sigma}$ in the second term follows directly from the firm's labor demand schedule: the elasticity of labor demand with respect to its interest rate index equals $\frac{1}{1-\sigma} \frac{\gamma i_f}{1+\gamma i_f}$.

The first term, $\eta(1 - s_{fb})$, captures the credit substitution channel: when bank b raises its rate, firm f reallocates borrowing toward other banks in $B(f)$. This effect is proportional to $1 - s_{fb}$: a bank with a larger expenditure share faces less elastic substitution demand, because the firm has less scope to shift borrowing toward alternative lenders. The second term captures the credit demand channel: a higher rate charged by bank b raises the firm's average funding cost i_f, which reduces labor demand and therefore total borrowing through the working capital constraint. This effect is proportional to s_{fb} and becomes stronger when a larger fraction of the wage bill must be financed externally, that is, when γ is higher.

The decomposition in (22) implies that a bank's expenditure share matters for the markup it charges. A bank accounting for a larger share of a firm's borrowing faces, all else equal, a less elastic residual demand curve and therefore optimally sets a higher markup. In particular, the credit substitution term $\eta(1 - s_{fb})$ declines with s_{fb}: as the bank's share increases, the firm can substitute away from it less easily. By contrast, the credit demand term increases in s_{fb}, but its slope is typically smaller when γ is moderate. Hence, whenever the substitution channel dominates, the overall elasticity declines with market share, generating a positive relationship between expenditure share and the interest rate markup.

The demand elasticity faced by the oligopolistic banks resembles the demand elasticity with

oligopolistic competition in Atkeson and Burstein (2008). In their setup, aggregate consumption is nested CES across sectors and firms within each sector, and the demand elasticity faced by each firm is a weighted average between the within-nest and across-nests elasticities, with weights equal to the firm's market share in its sector. Similar to their setup, the elasticity in the credit substitution channel is the elasticity of substitution across lenders and the weights equal the bank's market share. However, in our setup, the second term comes from the firm's demand elasticity for loans and not from an outer nest, and depends on the composite interest rate faced by the firm.

3.4 Discussion

Before turning to the quantitative analysis, let us discuss some of our modeling assumptions.

We assume that loan services from different banks are imperfect substitutes, with substitutability governed by the CES parameter η. This assumption captures, in reduced form, a variety of frictions that make loans from different banks only partially interchangeable: relationship-specific information, differences in contract terms and lending technologies, and adjustment costs in reallocating borrowing across lenders. An alternative approach would be to microfound the imperfect substitutability through an explicit model of search frictions or switching costs. We view the CES formulation as a parsimonious representation that allows us to focus on the interaction between market structure and financial frictions, which is the main object of interest.

We assume that banks compete in interest rates (Bertrand-Nash) and that each bank sets a single interest rate per firm. The Bertrand assumption reflects the fact that interest rates are the primary dimension along which banks differentiate their loan offers. The restriction to linear pricing rules out quantity discounts, two-part tariffs, and other forms of nonlinear contracts. Allowing for nonlinear pricing would give banks additional instruments to extract surplus and would likely increase banks' rents, but at a considerable cost in tractability given the oligopolistic setting.

Bank-firm matching is assumed to be random and independent of bank characteristics. In practice, matching is likely influenced by geography, relationship lending, and information frictions. We view random matching as a tractable approximation that captures the key feature of the data, namely that most firms borrow from a small number of banks, while remaining agnostic about the specific determinants of match formation. An important consequence of this assumption is that the banking network is exogenous: firms cannot respond to high markups by seeking new banking relationships, and banks cannot compete for new customers. Allowing firms to endogenously form and sever banking relationships would introduce a dynamic competition margin that disciplines markups over time. We abstract from this margin to keep the model tractable and to isolate the static forces that drive interest rate dispersion in the cross section.

Finally, our analysis focuses on market power in lending and assumes that the deposit market is competitive. This is a modeling choice, not a statement about reality: a large literature, including

Drechsler et al. (2017), documents significant market power in deposit markets. Allowing for deposit market power will introduce another source of heterogeneity in banks' funding costs. We leave this extension for future work.

4 Quantitative Analysis

In this section, we estimate the model using data from the credit register and show that the estimated model can successfully match key moments of the data, including the AKM decomposition, without targeting them. Then, we use the calibrated model to study the macroeconomic implications of bank market power and the role that market power plays in shaping the effects of macroprudential policy.

4.1 Loan Demand Elasticities

Loan demand elasticities play a crucial role in the model presented in Section 3, as these elasticities affect markups and interest rates. In this section we will focus on the role played by two distinct structural loan demand elasticities. The total loan demand elasticity $\partial \log(\ell_{fb})/\partial i_{fb}$ captures how firm f's total borrowing from bank b responds to a change in that bank's rate, holding the rates charged by all competing banks fixed. Equations 22 shows that the loan demand elasticity is the sum of two terms, capturing reallocation of credit across banks (i.e., credit substitution) and the change in the overall loan demand from firm f. The second elasticity we focus on is the elasticity of portfolio shares $\partial \log(\ell_{fb}/\ell_f)/\partial i_{fb}$ (i.e., elasticity in shares): it measures how the firm reallocates borrowing across banks within its network, again holding the rates of competing banks fixed. Formally, these structural elasticities can be expressed as:

$$\left.\frac{\partial \log \ell_{fb}}{\partial \log i_{fb}}\right|_{i_{f,-b}} = -\eta(1 - s_{fb}) - \frac{1}{1-\sigma} \cdot \frac{\gamma i_f}{1+\gamma i_f} \cdot s_{fb}, \tag{23}$$

$$\left.\frac{\partial \log(\ell_{fb}/\ell_f)}{\partial \log i_{fb}}\right|_{i_{f,-b}} = -\eta(1 - s_{fb}), \tag{24}$$

where $s_{fb} = \ell_{fb} i_{fb}/(\ell_f i_f)$ is the expenditure share of bank b in firm f's total loan expenditure. The first term in equation (23) captures credit substitution across banks within the firm's set; the second captures the reduction in total loan demand as the firm's average funding cost i_f rises. Each expression is evaluated holding $i_{f,-b}$ fixed—these are partial-equilibrium objects, and the relevant demand elasticities for the bank's first-order condition (20).

Structural versus reduced-form semi-elasticities. When banks behave strategically, the structural elasticity cannot be recovered directly from observed loan-level responses to changes in interest rates, not even when changes in rates are driven by well-identified bank-specific shocks. By construction, the structural elasticity is a partial-equilibrium object: it answers the counterfactual question, how much must bank b change the interest rate i_{fb} it offers to firm f in order to change loan demand by one percent, holding the terms offered by competing banks fixed? In equilibrium, however, a shock to one bank induces competing banks to best respond, which in turn affects the original bank's optimal pricing decision. As a result, the response measured in the data after a bank-level shock is a reduced-form elasticity, which incorporates the full equilibrium adjustment of loan quantities and interest rates across all banks in the market.

Although reduced-form elasticities differ from structural elasticities, the former still contain useful information about the latter (Berger et al., 2022). Our model implies that up to a first order approximation the reduced form elasticity of substitution and the reduced form elasticity of loan demand are equal to:

$$\frac{d\log(\ell_{fb}/\ell_f)}{d\log i_{fb}} = -\eta(1-s_{fb}) + \sum_{b'\neq b}\eta s_{fb'}\frac{d\log i_{fb'}}{d\log i_{fb}} \tag{25}$$

$$\frac{d\log \ell_{fb}}{d\log i_{fb}} = -\varepsilon(i_{fb};i_f) + \sum_{b'\neq b}\Big[\eta-\varepsilon(i_{fb'};i_f)\Big]\frac{d\log i_{fb'}}{d\log i_{fb}} \tag{26}$$

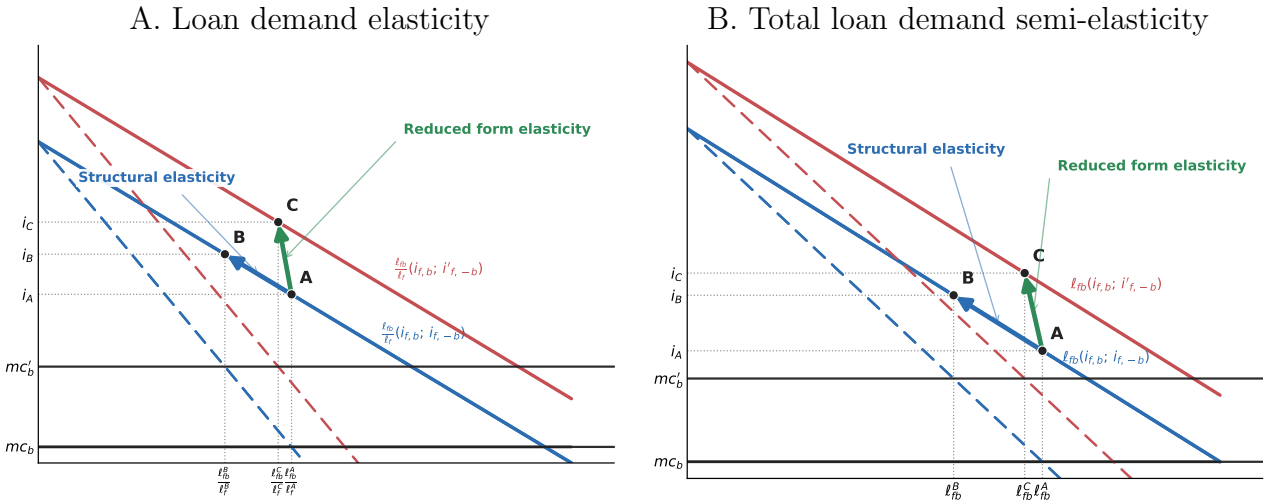
Note that the reduced-form elasticity of substitution is always smaller in absolute value than its structural counterpart. The same applies to the elasticity of loan demand as long as $\eta > \epsilon(i_{fb'}, i_f)$, that is as long as $\eta > \frac{1}{1-\sigma}\frac{\gamma i_f}{1+\gamma i_f}$.

Figure 4 illustrates the wedge for these elasticities. Suppose that the marginal cost of funds of bank b increases from mc_b to mc_b'. In each panel, the blue solid curve traces the structural demand for bank b's loans as a function of i_{fb}, holding competitors' rates fixed at $i_{f,-b}$; the red solid curve is the demand schedule after competing banks have raised their rates to $i'_{f,-b}$ in response to higher marginal costs. Point A is the initial equilibrium.

Panel A focuses on the elasticity of substitution. When the marginal cost of funds for bank b increases, it's optimal for bank b to increase interest rates. Starting from point A, the structural response from point A to point B moves along the blue demand curve: bank b raises its rate and, if the rates of competing banks are held fixed, the firm substitutes its borrowing toward lower-cost alternatives, so bank b's market share would decline substantially.

In practice, firm f may have access to other banks and these banks will not keep their rates fixed, rather they will optimally adjust their rates in response to an increase in i_{fb}. Thus, the loan demand schedule shifts upward, and point C is the new equilibrium resulting from an increase in bank b's marginal cost from mc_b to mc_b'. Since competing banks also raise their rates, the firm's outside option deteriorates, and the demand for bank b's loans shifts upward. Bank b therefore

Figure 4: Structural and Reduced-Form Loan Demand Semi-Elasticities



Notes: Panel A (left) shows the difference between the structural loan demand elasticity of substitution, $\partial \log(\ell_{fb}/\ell_f)/\partial i_{fb}$, which isolates credit substitution across banks, and its reduced-form counterpart. Panel B (right) shows the difference total loan demand semi-elasticity, $\partial \log \ell_{fb}/\partial i_{fb}$, which combines substitution and level effects, and its reduced-form counterpart. In each panel, the blue solid curve is the demand schedule holding competitors' rates $i_{f,-b}$ fixed, while the red solid curve is the demand schedule after competitors have optimally adjusted their rates to $i'_{f,-b}$; and the dashed curves are associated marginal revenues. Point A is the initial equilibrium; B is obtained following an increase in bank b's marginal cost from mc_b to mc'_b along the structural demand; C is the new equilibrium allowing competing banks to best-respond.

raises its rate further yet retains more of its share—the movement from point A to point C is steeper in $(i_{fb},\, \ell_{fb}/\ell_f)$ space than the movement from point A to point B. The structural elasticity in shares thus would exceed the reduced-form estimate in absolute value; using the reduced-form elasticity directly to gauge the substitution channel would understate the substitutability of loan demand.

Panel B depicts the loan demand elasticity. The structural response from point A to point B features a substantial rate increase and a moderate contraction of total lending: holding competitors' rates fixed limits how much the composite loan rate i_f rises, so the scale effect on total firm borrowing is contained. The reduced-form equilibrium is instead point C, on the red demand curve: competing banks also raise their rates. As long as $\eta > \epsilon(i_{fb'}, i_f)$, the loan demand schedule for bank b shifts upward. The structural loan demand elasticity thus would exceed the reduced-form estimate in absolute value; using the reduced-form elasticity directly to gauge the loan demand elasticity would overstate the rigidity of loan demand.

Estimates of reduced-form elasticities. Since the reduced-form loan demand elasticities are informative about the structural elasticities in the model, we adopt an indirect inference approach by estimating reduced form elasticities in the model and in simulated data.

We estimate the two reduced-form semi-elasticities using the Italian credit register. Our focus

Table 4: Estimated Loan Demand Elasticities

	Total (ϵ_{tot})	Substitution (ϵ_{subst})
Estimate	-19.044^{***}	-12.153^{***}
Standard error	(2.056)	(2.003)
Observations	88,521	88,428

Notes: The table reports IV estimates of the total and substitution loan demand elasticities from equations (27) and (28). *** denotes significance at the 1% level.

is on semi-elasticities so that results are independent on the level of interest rates in the data that is associated to default risk. The estimating equations use Δi_{fb}—the change in the interest rate level—so the estimated coefficients are semi-elasticities, measuring the change in log loan demand per unit change in the interest rate:

$$\Delta \log \ell_{fb} = \epsilon_{\text{tot}} \, \Delta i_{fb} + e_{fb}, \tag{27}$$

$$\Delta \log(\ell_{fb}/\ell_f) = \epsilon_{\text{subst}} \, \Delta i_{fb} + e_{fb}. \tag{28}$$

Identification relies on a shift-share instrument following Amiti and Weinstein (2018). For each bank-firm pair (b, f), we construct the instrument as the change in the average rate that bank b charges to all *other* firms in the same province p, excluding firm f itself. Formally, let $\bar{i}_{bt}^{-f}$ denote this leave-one-out average. The instrument isolates bank-level variation in lending rates that is common across the bank's other borrowers and therefore plausibly orthogonal to the idiosyncratic demand conditions facing firm f. To remove common macroeconomic and regional variation, we partial out aggregate year fixed effects and province-year fixed effects before constructing the instrument, so that the identifying variation is purely cross-bank within a province in a given year.

Estimates of reduced-form loan demand elasticities are reported in Table 4. The point estimate for loan demand elasticity implies that when the interest rate charged by bank b to firm f increases by one percentage points, then loan demand of firm f from bank b will fall by 19%. Similarly, the point estimate for the elasticity of substitution implies that when the interest rate charged by bank b to firm f increases by one percentage points, then market share of bank b in the portfolio of loans of firm f falls by 12%. The estimates are broadly consistent with those reported by Dempsey and Faria-e-Castro (2025) and Altavilla et al. (2022). We use these estimates to discipline the demand parameters σ and η in the model using an indirect inference approach: for each candidate parameter vector (η, σ), we simulate a panel of bank-firm relationships from the model and apply the identical Amiti-Weinstein estimation procedure to the simulated data, recovering model-implied reduced-form semi-elasticities. We then choose η and σ to minimize the distance between these model-implied moments and the data estimates in Table 4.

Table 5: Calibrated Parameter Values

Parameter	Description	Value
η	Loan CES index	4.5
σ	Returns to scale	0.98
ϕ	Exit probability	0.12
B	Number of banks	10
k_0	Initial bank net worth	10^{-6}
ξ	Probability of matching with each bank	0.18
θ	Minimum net-worth-to-asset ratio	0.08
β	Discount factor	0.99
ψ	Frisch elasticity	1
χ	Labor disutility	1
γ	Working capital ratio	0.40

4.2 Calibration and Validation

Calibration. The model has eleven parameters: $\Theta = [\psi, \chi, \beta, \gamma, \theta, \xi, B, \phi, k_0, \sigma, \eta]$. Our quantitative strategy consists of choosing Θ to match a set of moments from the Italian credit register.

A first set of common parameters is set equal to standard values in the macroeconomic literature. We set the inverse Frisch elasticity $\psi = 1$ and $\beta = 0.99$. We set $\gamma = 0.40$ following Bocola and Bornstein (2023), who document this ratio of short-term debt to revenues for Italian firms. The capital requirement $\theta = 0.08$ corresponds to the Basel I/II minimum Tier 1 capital ratio applied to corporate loans, which carry a risk weight of one so that the effective requirement equals 8 percent of loan volume. The scale parameter χ in the utility function is normalized to one.

The remaining parameters $[\xi, B, \phi, k_0, \sigma, \eta]$ are jointly estimated by method of simulated moments. While these parameters are jointly estimated, we provide some intuition on how they are identified by the targeted moments. We set $B = 10$ to match the number of banks that account for 99 percent of the market in the sample. The matching probability ξ is disciplined by the average number of banks per firm, which equals 2.1 in the data. The exit probability ϕ and the initial net worth k_0 are jointly identified from the distribution of bank market shares—specifically, the combined loan share of the three largest banks and the five largest banks. To discipline the demand parameters $[\sigma, \eta]$, we target the estimated loan demand semi-elasticities reported in Table 4, using the indirect inference approach described in Section 4.1.

Tables 5 and 6 report the calibrated parameter values and the fit of the model to the targeted moments.

Validation. A remarkable feature of our model is that, despite its parsimonious parameterization, it matches several untargeted moments of interest. In particular, the model replicates key features of the interest rate distribution that were not directly targeted in the calibration, such as

Table 6: Calibration Targets: Data and Model

Calibration target	Data	Model
Semi-elasticity (ϵ_{tot})	-19	-20
Semi-elasticity in shares (ϵ_{subst})	-12	-12
Three largest banks' market share (%)	65	61
Five largest banks' market share (%)	84	84
Ten largest banks' market share (%)	99	100
Std. deviation of interest rates	2.90	2.51
Average number of banks per firm	2.1	2.1

the cross-sectional standard deviation of interest rates after controlling for bank-specific default probabilities. Table 7 reports the results. In the data, the standard deviation of residualized loan rates is 2.49, compared with 2.51 in the model.

Table 7: AKM Decomposition: Data vs. Model

	Data	Model
Standard deviation of i_{fb}	2.49	2.51
Variance($\hat{\alpha}_f$)	0.67	0.57
Variance($\hat{\alpha}_b$)	0.18	0.24
Covariance($\hat{\alpha}_f$, $\hat{\alpha}_b$)	-0.02	0.09

Notes: The table compares the AKM decomposition of loan interest rates i_{fb} from the data and from simulated model data. Variances are of fixed effects are reported as percent of total variance.

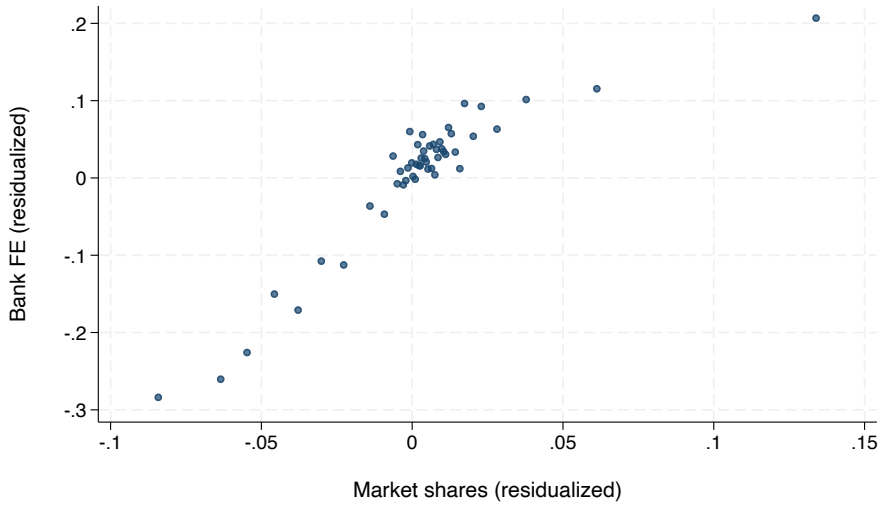
We apply the AKM decomposition (2) to the simulated data using the same estimation procedure as in Section 2. We find that dispersion in bank fixed effects accounts for 24% of the overall dispersion in interest rates, very close to what we document in the data.

In the model, banks are heterogeneous in their marginal cost of funds, and the relevant state variable is the distribution of banks' net worth. While the overall number of banks is fixed, bank dynamics originate from entry and exit, which induce changes in market structure. For example, when a large bank exits, other banks gain market share and are therefore able to charge higher markups.

We estimate in the model how bank fixed effects change over time with changes in bank market shares, controlling for bank marginal cost of funds, bank fixed effects, and time fixed effects, as we do in Section 2. Since in the model banks are heterogeneous only in their net worth, as in Gertler and Karadi (2011), the unconditional correlation between bank fixed effects and market shares would be negative in the cross-section, because the reason large banks have high market shares is that they have a low marginal cost of funds.

Figure 5 plots this relationship between residualized bank fixed effects and market shares in the simulated model data. The positive relationship between residualized bank fixed effects and

Figure 5: Bank Fixed Effect vs. Market Share in the Model



Notes: Binscatter from simulated model data. The bank fixed effect (bank-year) and market share are both residualized on the marginal cost of funds, bank fixed effects and time fixed effects.

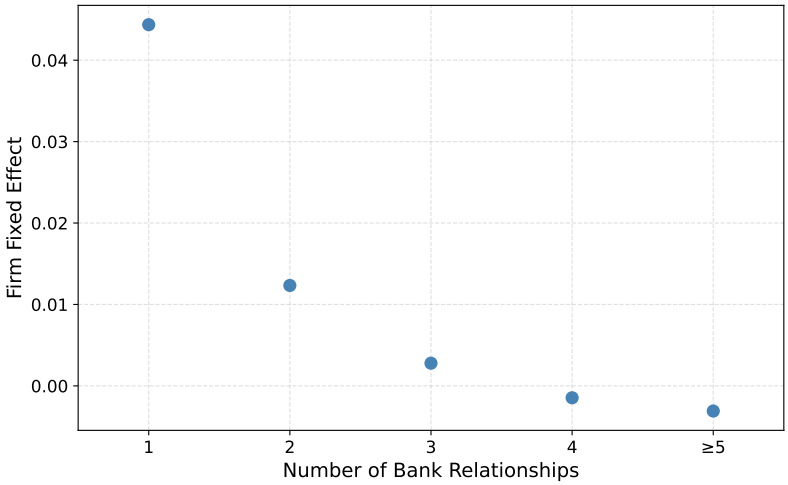
market shares is due to oligopolistic competition, since markups are increasing in market shares. Moreover, the model generates the same gradient between bank fixed effects and market shares that we document in the data (see Figure 2 in Section 2): an increase in bank market share is associated with higher markups in equilibrium.

While it is not surprising that bank fixed effects play an important role in the model, given the rich heterogeneity we allow across banks, we also find that firm fixed effects account for a large share of interest rate dispersion. In particular, firm fixed effects explain 57% of the variance in interest rates in the model, which is close to their contribution of firm fixed effects we documented in the data. In our model firm heterogeneity arises entirely from the set of banks with which a firm is matched. Thus, firm fixed effects are driven by the number of banks each firm is matched with and the identity of these banks. For instance, we would expect firms who borrow from only one bank to pay higher rates on average relative to firms who can borrow from more banks.

Figure 6 shows that firm fixed effects decrease with the number of banks each firm is matched with. The negative correlation in the model is qualitatively consistent with what we documented in the data (Figure 3): firms with access to more lenders pay lower rates on average.

Notably, the number of banking relationships is not the only determinant of the firm fixed effect, as there is substantial dispersion within each group. This dispersion reflects differences in the funding costs of the banks the firm is matched with. A firm whose banking network consists of two banks with a high marginal cost of funds may face higher borrowing costs than a firm with access to only one bank with a very low marginal cost of funds.

Figure 6: Model: Firm Fixed Effect vs. Number of Banking Relationships



Notes: Binscatter from simulated model data of the average firm fixed effect against the number of banking relationships N_{Bf}.

4.3 Macroeconomic Effects of Bank Market Power

The first main counterfactual exercise aims to quantify the macroeconomic costs of bank market power. In the calibrated model, banks face downward-sloping loan demand curves and therefore charge interest rates in excess of their marginal cost of funds. These markups are heterogeneous across bank-firm pairs: a firm matched with a single large bank, or with fewer competing lenders, faces a more inelastic residual demand and thus pays a higher markup than a firm with access to several competing lenders. Heterogeneous markups across firms translate into heterogeneous effective borrowing costs i_f across firms. Because firms operate under decreasing returns to scale in production, heterogeneity in borrowing costs across firms distort the allocation of productive inputs. Specifically, a firm facing a higher average loan rate incurs a higher marginal cost of production and consequently employs fewer workers and produces less output than an equally productive firm facing a lower rate. This misallocation reduces aggregate output relative to a frictionless benchmark in which all firms face the same effective cost of credit.

To quantify these effects, we compare the baseline economy to a counterfactual in which each bank sets its loan rate equal to its marginal cost of funds, so that $i_{fb} = mc_b$ for all bank-firm pairs (b, f). An important subtlety in this exercise is that the elimination of markups does not necessarily imply lower equilibrium interest rates.[18]

The main reason why lower markups might not lead to lower rates in equilibrium is that the marginal cost of funds mc_b is endogenously determined by the distribution of bank net worth in equilibrium. When banks are constrained to price at marginal cost, their profits fall. Lower profits

[18]Similarly, if a share of markups would capture rents due to asymmetric information or cost of information acquisition, removing markups might not necessarily lead to lower rates in equilibrium, as banks might not be willing to supply loans.

imply a slower accumulation of net worth over time, which increases the likelihood that banks face binding leverage constraints. A tighter constraint raises the shadow cost of funds, pushing mc_b upward and partially offsetting the direct benefit of eliminating the markup. The net effect on equilibrium interest rates therefore reflects the balance between the static reduction arising from the elimination of markups and the dynamic increase arising from the endogenous deterioration of bank capitalization.

A secondary reason why removing markups might not lead to lower rates is the presence of supply constraints. Indeed, even if we abstract from changes in the distribution of bank net worth, some banks might hit the financial constraint and in that case the level of loans would be pinned down by the available net worth, with interest rates being pinned down by the loan demand schedule given the amount of loans the bank can issue at the constraint. In this case removing markups would not increase the amount of loans issued, but may only affect the allocation of loans issued across different firms.

To trace the dynamic effects of removing markups, we design the counterfactual exercise as follows. We initialize both the baseline economy and the counterfactual at the stationary distribution of bank net worth from the calibrated model, and we impose competitive pricing—$i_{fb} = mc_b$ for all (b, f)—from period $t = 0$ onward. At $t = 0$, the two economies share an identical distribution of bank net worth, so that any difference in aggregate output is driven entirely by the elimination of markups, with the financial structure of the banking sector held constant across the two economies. As time progresses, the distributions of bank net worth diverge: banks in the counterfactual accumulate less net worth due to lower profits, gradually tightening their leverage constraints and causing the marginal cost of funds to rise relative to the first period of the experiment.

The removal of markups affects aggregate output through two distinct channels. The first is the *level-of-loans channel*: on impact, the elimination of markups reduces loan rates, stimulating firm borrowing and employment and raising aggregate output. Over time, however, declining bank net worth raises the marginal cost of funds, partially eroding the initial rate reduction and attenuating the output gain. The second channel is *resource misallocation*: since firms pay heterogeneous effective borrowing costs i_f, they face different marginal costs of production and therefore optimally choose different input levels. To formalize this, note that aggregate output can be decomposed as:

$$\log Y = \log N - \log \left(\int \frac{1}{N} \left(\frac{\sigma}{w[1 + \gamma i_f]} \right)^{\frac{\sigma}{1-\sigma}} df \right), \tag{29}$$

where the first term reflects the contribution of aggregate employment and the second term is a misallocation wedge arising from the cross-firm dispersion in effective borrowing costs i_f. A reduction in this dispersion—which follows from eliminating heterogeneous markups—compresses the misallocation wedge and provides an additional source of output gain beyond the level-of-loans channel. Intuitively, the dispersion in i_f across firms reflects differences in the composition of each

firm's lending network: a firm matched with a single large bank that charges a high markup will face a higher average loan rate than a firm with access to multiple competing lenders.

Figure 7 plots the percentage deviation of output in the counterfactual relative to the baseline economy as a function of time, together with a decomposition into the two channels described above. On impact, eliminating bank market power raises aggregate output by 1.3 percent relative to the baseline level. This initial gain reflects the direct reduction in loan rates that follows from the elimination of markups, while the distribution of bank net worth remains identical across the two economies at $t = 0$. Over time, however, the reduction in bank profits leads to a gradual erosion of net worth in the counterfactual economy, tightening leverage constraints and causing the marginal cost of funds to rise relative to the first period of the experiment. As a consequence, the output gain diminishes over time: after twenty years, output in the counterfactual remains above the baseline, but the magnitude of the gain is substantially smaller than the effect on impact. This result highlights that an evaluation of the macroeconomic costs of bank market power based solely on static considerations or on observed markups would substantially overstate the long-run benefits of its elimination, and that accounting for the endogenous adjustment of the banking sector's capitalization is essential for a quantitative assessment.

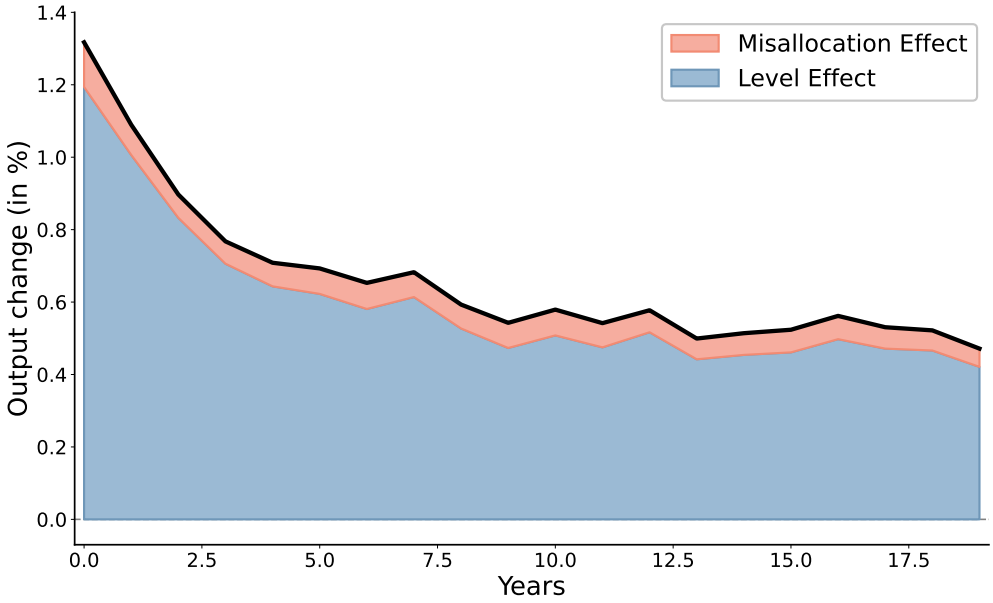
The decomposition in Figure 7 further reveals the relative importance of misallocation channel that, while present, is quantitatively modest relative to the level-of-loans channel. The majority of the output effect—both on impact and over time—operates through the average level of borrowing costs across firms rather than through the cross-firm dispersion in rates. This finding is consistent with Faria-e-Castro et al. (2025a), who document a small role for credit misallocation in normal times.

4.4 Macroprudential Policies and Bank Market Structure

Minimum capital requirements have been a cornerstone of banking regulation since the introduction of the Basel Accord framework in the 1980s. More recently, capital requirements have become a central instrument in the macroprudential policy toolkit, with the objective of strengthening the resilience of the banking system to aggregate shocks and limiting the procyclicality of credit. The costs and benefits of such requirements have been studied extensively; Jiménez et al. (2017), Corbae and d'Erasmo (2021), Bonaccorsi di Patti et al. (2023), and Plosser and Santos (2023), among others, document that changes in capital requirements have quantitatively significant effects on bank lending and real economic activity.

Our model offers a new perspective on assessing the aggregate cost of capital requirements. We argue that macroprudential policies can substantially alter the market structure of the banking sector—specifically, the distribution of market shares across banks—and that such changes in market structure have quantitatively important implications for the aggregate cost of borrowing

Figure 7: Decomposition of Output Effects: Average Rate vs. Misallocation



Notes: The figure plots the percentage deviation of aggregate output in the counterfactual economy—in which all banks price at marginal cost—relative to the baseline, as a function of time. We compute $2 \times M$ simulations of length T. In the first M simulations we set $i_{fb} = mc_b$. The figure plots the difference in logs between the first and second set of simulations, averaging across M. The total output effect is decomposed into two channels: the *level-of-loans channel* and the *misallocation channel*.

and for aggregate output. This channel operates through the link between bank size, market power, and the incidence of the leverage constraint.

To study these effects quantitatively, we consider a counterfactual economy in which the minimum capital ratio θ takes a lower value. We compare the baseline economy—in which $\theta = 0.08$—to a counterfactual with a more relaxed requirement, $\theta = 0.04$. As in Section 4.3, we implement the change at $t = 0$ in a counterfactual economy initialized at the stationary distribution of bank net worth from the calibrated baseline, and we compare the subsequent evolution of the two economies over time.

Before turning to the quantitative results, it is useful to describe the main mechanisms. A relaxation of the capital requirement reduces the shadow cost of the leverage constraint, allowing banks to expand their balance sheets by issuing more deposits and extending more loans.[19] The aggregate supply of credit therefore expands. However, the response is heterogeneous across banks. The largest banks are, in equilibrium, unconstrained: their accumulated net worth exceeds the regulatory minimum by a sufficient margin that their leverage constraint does not bind. A relaxation of the capital requirement therefore does not directly expand their lending capacity; they could in principle issue more loans, but they optimally choose not to do so because they face downward-sloping loan demand curves and any further expansion would require lowering their rate

[19]The present analysis focuses on the costs of regulatory constraints and abstracts from their potential benefits in terms of limiting systemic risk and ensuring bank solvency.

and compressing their markup. By contrast, smaller banks whose leverage constraints are binding respond directly to the relaxation: for these banks, the total volume of loans is determined by the supply constraint rather than by the profit-maximizing choice along the demand curve, so that an expansion of the constraint translates into an expansion of lending.[20] The net effect is therefore a reallocation of market share from large banks—which are unconstrained—to small banks—which were previously constrained—and a reduction in aggregate market concentration.

Table 8: Effects of Reducing Capital Requirement from 8% to 4%

	1 year	5 years	20 years
Output	+0.40%	+0.62%	+0.69%
Average rate	−0.43 pp	−0.77 pp	−0.82 pp
of which: cost of funds	−0.21 pp	−0.41 pp	−0.45 pp
of which: markups	−0.22 pp	−0.36 pp	−0.37 pp
Market share of three largest banks	−7 pp	−10 pp	−10 pp
Market share of five largest banks	−5 pp	−8 pp	−8 pp

Notes: The table reports the effects of reducing the minimum capital ratio θ from 8 to 4 percent. All entries are deviations from the baseline equilibrium. "Average rate" refers to the average loan rate across all bank-firm pairs. "Cost of funds" and "Markups" decompose the change in the average rate into contributions from changes in marginal funding costs and changes in markups, respectively. Bank concentration is measured by the combined loan market share of the three and five largest banks, respectively.

Table 8 reports the quantitative effects of this experiment. Output rises by 0.40 percent at the one-year horizon and by 0.69 percent in the long run. The average loan rate falls by 0.43 percentage points on impact and by 0.82 percentage points in the long run. These aggregate effects are consistent with the mechanism described above: the relaxation of the capital requirement allows small banks to expand their lending, which stimulates firm borrowing, employment, and output, while the increase in credit supply exerts downward pressure on loan rates.

The most notable finding concerns the decomposition of the change in the average loan rate. Decomposing the average loan rate as the sum of the average marginal cost of funds and the average markup,

$$\bar{i} = \overline{mc} + \bar{\mu}, \tag{30}$$

the table reports the contribution of each component separately. Roughly half of the total decline in the average loan rate is attributable to a reduction in the average markup—that is, to a reduction in bank market power—rather than to a reduction in the marginal cost of funds. The mechanism operates through the change in market structure described above: the relaxation of capital requirements disproportionately expands the lending capacity of small banks, which face more elastic loan demand and therefore charge lower markups. As small banks gain market share, the average markup in the economy falls. This reallocation is confirmed by the last two rows of

[20] The allocation of loans across firms by a given constrained bank is nonetheless shaped by the firm-specific loan demand schedule and, in particular, by the firm-specific loan demand elasticity.

Table 8: the combined market share of the three largest banks falls by 7 percentage points at the one-year horizon and by 10 percentage points in the long run, reflecting a persistent fall in concentration of the banking sector. Since banks are non-atomistic and their market power is directly related to their market share, a less concentrated banking sector charges lower markups and thereby reduces loan rates.

Table 8 also reveals that the output gains are increasing over time: from 0.40 percent at the one-year horizon to 0.62 percent at the five-year horizon and 0.69 percent in the long run. This pattern reflects the gradual adjustment of the distribution of bank net worth in response to the regulatory change. At $t = 0$, all banks begin from the same distribution of net worth as in the baseline, so the initial effect is driven entirely by the direct relaxation of binding constraints for small banks. Over time, however, the distribution of net worth adjusts: small banks that were previously constrained now accumulate net worth at a faster pace and progressively gain market share from large banks. This reallocation of market share from large banks—which charge high markups—toward small banks—which charge lower markups—amplifies the competitive channel over time and explains why both the output gains and the decline in average markups are larger at longer horizons than on impact.

5 Conclusion

This paper studies bank market power in local loan markets and its macroeconomic consequences. We propose a measurement strategy based on an AKM decomposition of loan interest rates from administrative credit registers and use the resulting bank fixed effects as a structural measure of deviations from the law of one price. Applied to Italian credit register data, we find that bank fixed effects explain 10 to 17 percent of residual interest-rate variation—roughly half the contribution of default risk and collateral—and are strongly correlated with local market shares even after controlling for bank funding costs. The AKM decomposition also reveals a pronounced negative gradient between firm fixed effects and the number of banking relationships, consistent with oligopolistic pricing: firms with fewer lenders face higher average markups.

To assess the aggregate implications, we develop a dynamic general equilibrium model with oligopolistic competition, random matching between firms and banks, and leverage constraints. The model fits the empirical distribution of bank-firm relationships, loan demand elasticities, and the pattern of interest rate dispersion observed in the credit register. Out of sample, it replicates the qualitative structure of the AKM regression in the data.

Our counterfactual experiments produce three main findings. Eliminating bank market power raises output by 1.3 percent in the short run, declining to 0.4 percent in the long run: the gap reflects the role of profits in sustaining bank capitalization, which creates a dynamic tension between the short-run gains from competition and the long-run fragility of an undercapitalized banking sector. Most of the output effect operates through the average level of rates rather than through cross-firm misallocation. Finally, macroprudential policy interacts with market structure: roughly half of the interest rate decline following a loosening of capital requirements comes from an endogenous compression of markups as small banks gain market share, rather than from lower funding costs alone. Together, these results highlight the importance of modeling the industrial organization of banking jointly with financial frictions.

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