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Pricing Risk or Rationing Credit? Bank Behaviour in a Tightening Monetary Cycle

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Abstract

This paper examines how banks adjusted the pricing and quantity of credit to borrower risk during the ECB's monetary tightening cycle that began in mid-2022. Using loan-level data from AnaCredit combined with banks' internal probabilities of default (PD), we estimate how the sensitivity of lending terms to firm risk evolves under tighter monetary conditions. We find pronounced non-linearities in risk pricing: although banks charge higher spreads to riskier borrowers, the marginal increase in spreads flattens for high-PD firms, and this effect intensifies during the tightening period. In contrast, the sensitivity of loan amounts to borrower risk rises sharply after July 2022, consistent with a shift toward quantity-based rationing. This shift is strongest among better-capitalized banks. Overall, when borrowing costs rise, banks shift from pricing risk through spreads to restricting credit, altering the transmission of monetary policy through bank intermediation.

JEL Classification Codes: E52, G21, D82

Keywords: loan pricing, credit allocation, credit rationing, monetary policy

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1 Introduction

Pricing and allocating credit risk are core functions of financial intermediaries and central to how shocks are transmitted to firms and the real economy. A large literature documents that banks adjust loan rates and credit quantities in response to borrower risk, and that these adjustments depend on both bank balance sheet conditions and the broader macro-financial environment (Jiménez et al., 2012; Ioannidou et al., 2015; Altavilla et al., 2020; Andersen et al., 2024). Yet we know relatively little about how banks choose between pricing and quantity adjustments when monetary conditions tighten, especially across the full distribution of borrower risk. Understanding this margin of adjustment is important not only for assessing bank risk management but also for evaluating how monetary policy affects credit allocation and firm financing conditions.

This paper provides new evidence on this mechanism by examining how euro area banks adjusted the sensitivity of lending spreads and loan amounts to borrower risk during the ECB's monetary tightening cycle that began in mid-2022. Using loan-level data from AnaCredit matched with banks' internal probabilities of default (PD), we quantify how risk enters bank lending decisions and how this sensitivity changes in tighter financing conditions. This dataset allows us to observe both fine-grained variation in borrower risk and banks' contemporaneous adjustments in loan terms, enabling a detailed examination of the pricing–allocation trade-off.

Our findings reveal two main results. First, risk-based pricing is highly non-linear: although banks charge higher spreads to riskier firms, the marginal increase in spreads flattens sharply for high-PD borrowers, consistent with upper bounds on risk-based pricing documented in classic credit rationing theory (Stiglitz and Weiss, 1981). This flattening becomes more pronounced after the start of monetary tightening. Second, banks increasingly rely on quantity adjustments: the negative relationship between borrower risk and loan size strengthens significantly after July 2022. Thus, banks appear to substitute away from pricing-based risk differentiation toward volume-based rationing, in line with models in which asymmetric information or repayment fragility constrain the use of spreads as a screening tool.

We further document meaningful heterogeneity across institutions and markets. Banks with stronger capital positions exhibit larger adjustments in both pricing and quantities, behaving more cautiously in response to tightening—a pattern consistent with theories in which well-capitalized banks internalize risk more fully or adjust their portfolios more proactively. Conversely, in markets with strong bank competition, the ability to differentiate prices by risk weakens, consistent with evidence that competition can compress spreads and reduce the pass-through of borrower characteristics to loan terms (Buch et al., 2014; Andreeva and García-Posada, 2021). Together, these results highlight that the margin through which monetary policy operates depends not only on borrower risk but also on bank and market structure.

This paper contributes to several strands of research. First, we add to work on risk-based pricing and credit allocation in bank lending (Jiménez et al., 2012; Ioannidou et al., 2015; Andersen et al., 2024), documenting how non-linearities in risk pricing evolve during a major tightening cycle. Second, we contribute to the literature on the transmission of monetary policy through bank lending and risk-taking channels (Kashyap and Stein, 2000; Jiménez et al., 2014; Iosifidi and Kokas, 2015; Ippolito et al., 2018) by showing that monetary tightening can shift the primary margin of adjustment from pricing to quantities. Third, we relate to recent studies on selective credit allocation under tightening (Albuquerque and Mao, 2023), highlighting how banks reallocate credit across the risk distribution rather than applying uniform contraction. Finally, we speak to the literature on heterogeneous monetary transmission (Buch et al., 2014; Altavilla et al., 2020; Andreeva and García-Posada, 2021) by showing that bank capital and competitive structure meaningfully shape banks' adjustments to borrower risk.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 documents recent developments in lending rates and credit volumes. Section 5 outlines the empirical strategy. Section 6 presents the main results and heterogeneity analysis. Section 7 provides robustness checks. Section 8 concludes.

2 Literature review

Risk-based pricing refers to the practice of charging borrowers interest rates that reflect their credit risk. In principle, riskier borrowers pay higher rates (or may receive less credit) to compensate lenders for default risk (Gambacorta, 2008; Andersen et al., 2024). This mechanism is crucial for both bank solvency and the efficient allocation of credit: it ensures funds flow to productive uses while containing losses (Repullo, 2004). When banks properly price credit risk, this underpins the traditional bank lending channel of monetary policy – tighter policy raises borrowing costs and curtails credit, especially for high-risk firms (Jiménez et al., 2014). Effective risk-based pricing thus stabilizes the financial system and supports growth by allocating capital to borrowers capable of deploying it productively (Stiglitz and Weiss, 1981). Conversely, if risk is mispriced, credit can be misallocated toward weaker borrowers, sowing the seeds of future losses and inefficiencies in the economy.

Beyond borrower-specific risk, loan pricing also reflects macro-financial uncertainty, most notably uncertainty about inflation and the future path of policy rates. Such uncertainty affects the real value of contractual cash flows, raises default risk for interest-sensitive borrowers, and can weaken the pass-through of monetary policy to lending rates. Recent work shows that during tightening cycles, elevated uncertainty leads banks to demand higher risk premia or to reduce lending even when credit risk alone would not warrant it (Vansteenberghe, 2025).

Classic theories of credit markets show that banks might not continuously raise interest rates as borrower risk rises. Stiglitz and Weiss (1981) demonstrated that beyond a certain point, increasing the loan interest rate can backfire: it drives away safer borrowers and encourages remaining borrowers to take on more risk. As a result, banks may prefer to ration credit rather than charge extremely high rates to the riskiest borrowers. This implies a non-linear pricing relationship: beyond a certain risk threshold, loan rates stop increasing with risk. Instead of unlimited pricing for very risky firms, banks impose an implicit interest rate ceiling and either deny credit or offer only small loans. Bester (1985) and Crawford et al. (2018) provide further theoretical and empirical backing for this behaviour. Such credit rationing is a rational response to information asymmetry in lending markets. Empirical research and bank practice confirm this pattern: banks price for risk under normal ranges, but the risk-spread slope flattens out for the riskiest firms (Ioannidou et al., 2015). This suggests that both pricing and allocation decisions interact in shaping which firms gain access to credit.

While conventional theory posits that tighter monetary policy primarily operates by contracting the overall supply of credit (Bernanke and Gertler, 1995), a growing body of research highlights that the distribution of credit across firms is equally important for understanding real economic outcomes. Credit allocation determines which firms are able to invest, expand, or survive during periods of financial tightening, thereby shaping patterns of firm-level investment, business dynamism, and exit. In turn, these micro-level adjustments aggregate into broader consequences for productivity growth and the resilience of the economy (Gopinath et al., 2017; Ottonello and Winberry, 2020). This literature suggests that the transmission of monetary policy cannot be fully understood by examining aggregate credit volumes alone; attention must also be paid to how lending is reallocated across heterogeneous firms with different risk profiles and growth potentials.

In addition to this allocation perspective, recent work emphasizes that monetary policy conditions also shape how aggressively banks price risk, giving rise to a risk-taking channel of credit allocation. In low interest rate environments, banks face thin margins on safe assets and may search for yield by extending credit to riskier borrowers at relatively modest risk premiums (Bruno and Shin, 2015; Jiménez et al., 2014). Empirical evidence strongly supports this behaviour: Jiménez et al. (2014) find that when monetary policy is very accommodative, banks grant not only more loans, but disproportionately more credit to borrowers with weak credit histories. Ioannidou et al. (2015) confirm that exogenously lower rates lead to riskier lending at reduced spreads. These dynamics highlight that monetary conditions can distort risk-based pricing: prolonged low rates can lead to credit mispricing and excessive risk-taking. Although evergreening is more commonly associated with low interest rate environments, recent evidence from Albuquerque and Mao (2023) shows that banks may also engage in this practice during periods of monetary tightening, aiming to prevent defaults among highly indebted firms facing rising borrowing costs.

The degree of banking competition is another key determinant of risk-based pricing and credit allocation. In highly competitive markets, lenders may face pressure to keep interest rates low to retain or attract clients, potentially compressing risk premiums. Andersen et al. (2024) show that when competition intensifies, banks place less weight on borrower risk in pricing. A related mechanism operates through information dispersion: as competition increases, borrowers tend to maintain more banking relationships, and information becomes more widely spread across institutions. This reduces each bank's informational advantage, weakens screening incentives, and makes it harder to price risk accurately (Marquez, 2002; Dell'Ariccia and Marquez, 2004; Petersen and Rajan, 1995). Competition may therefore dilute risk pricing both by narrowing margins and by increasing adverse selection, as shown by Crawford et al. (2018) and Hellmann et al. (2000). Conversely, Repullo (2004) argues that banks with greater market power can better incorporate risk into loan terms, suggesting a non-monotonic relationship between competition and the sensitivity of credit conditions to borrower risk.

A stark breakdown of risk-based pricing may occur when banks are financially weak. Undercapitalized banks have strong incentives to evergreen loans to troubled borrowers to avoid recognizing losses. Peek and Rosengren (2005) and Caballero et al. (2008) show that such banks keep unviable firms afloat, distorting allocation and suppressing productivity. Acharya et al. (2019) document that after the ECB's support, weak European banks extended zombie credit rather than reallocating capital to healthier firms. Banerjee and Hofmann (2022) and Albuquerque and Mao (2023) find that zombie firms continued receiving concessional credit even during tightening. Stronger banks, by contrast, price risk more aggressively and are less inclined to support zombies (Gambacorta, 2008; Repullo, 2004). Thus, prudent risk-based pricing depends critically on bank capitalization, with undercapitalized institutions prone to systemic misallocation.

3 Data

This section describes the dataset used in the analysis, outlines the construction of key variables, and discusses the scope and limitations of the sample. Our empirical investigation relies on loan-level information from the Eurosystem's AnaCredit database, a harmonized euro-area micro dataset that provides detailed, loan-by-loan information on credit exposures of resident banks to legal entities. AnaCredit records any type of transaction that gives rise to credit risk for the reporting institution, making it a comprehensive source for studying bank–firm lending relationships.

Loan data are reported in AnaCredit whenever a bank's total exposure to a borrower equals or exceeds €25,000. The dataset, collected monthly since September 2018 under harmonized ECB statistical requirements, covers individual loans granted by around 3,000 credit institutions to nearly 5 million borrowers across the euro area. For the purposes of this paper, we use data from 2021 onward and extend the sample through the end of 2024.

Our analysis focuses exclusively on newly originated loans, rather than outstanding exposures. Restricting the sample to new lending is essential for identifying how borrower risk affects banks' contemporaneous lending decisions. Interest rates and loan amounts set at origination reflect the bank's up-to-date assessment of a firm's creditworthiness, funding conditions, and the broader market environment. By contrast, the terms on existing loans may be shaped by past conditions or contractual rigidities and therefore do not necessarily capture banks' current pricing of risk. Focusing on new lending thus allows us to observe how banks adjust the pricing and allocation of credit in real time, and it also eliminates concerns that distressed or defaulted legacy exposures may mechanically bias the results.

To measure borrower risk, we rely on the probability of default (PD) reported by banks that use the Internal Ratings-Based (IRB) approach for regulatory capital purposes. These PDs offer a consistent and forward-looking assessment of firm-specific creditworthiness, reflecting banks' internal evaluation of the likelihood that a borrower defaults within a one-year horizon. As such, they provide a natural metric for examining how banks incorporate firm risk into lending prices and quantities. PDs are time-varying, as banks typically revise them annually under the IRB framework.

A key advantage of using the PD as a risk measure is that it reflects banks' internal assessments of a firm's default probability, providing an intentional, ex-ante measure of risk-taking by banks. Moreover, banks typically have access to more extensive information than is observable to a researcher, as they gather additional insights through relationships with firms. Whether banks utilize this information for more accurate risk assessment is another matter. Banks may have an incentive to under-report risk to alleviate the pressure of loan-loss provisions on capital, particularly during economic downturns when they face an increased number of loan defaults (Huizinga and Laeven, 2012; Brezigar-Masten et al., 2015). This is a potential threat to internal validity, as the PD may be subject to measurement error — a limitation that applies equally to alternative risk metrics.

An important limitation is that PD data are available only for banks adopting the IRB regulatory approach. Consequently, our sample covers 53% of new loan contracts and 61% of the total loan volume. IRB banks tend to be larger, more sophisticated institutions with distinct business models and funding structures compared to non-IRB banks. As a result, the estimation sample is not a random subset of AnaCredit, which may constrain the external validity of the findings. This caveat should be kept in mind when interpreting the results. It is also worth noting that PDs are designed for regulatory purposes and capture credit risk on a through-the-cycle basis. They therefore vary less over time than point-in-time measures used for loan-loss provisioning, but should nonetheless provide a reliable relative ranking of firms' underlying riskiness.

We apply a set of data-cleaning procedures to mitigate the influence of outliers on our results. First, we drop observations with implausible lending rates, excluding any loans with interest rates below zero or above 20%. Second, to ensure a meaningful distribution of borrower risk, we remove cases where the PD is below 0.03%[1], which is the regulatory floor for IRB estimates, or above 10%, a range that captures the vast majority of firms while eliminating extreme outliers. These filters help ensure that our estimated relationships are not driven by mechanical data artefacts or atypical observations. After all cleaning steps, we are left with over 10 million loan-level observations, covering 552 banks and 1.6 million firms.

Table 1 presents summary statistics for the main variables used in the analysis. The average probability of default is around 2%, consistent with the predominance of relatively sound borrowers in the new lending segment. The mean lending rate is close to 4%, while the average lending spread, defined as the difference between the lending rate and the relevant reference rate[2], is approximately 2.2 percentage points, suggesting that banks apply non-negligible risk and margin premia on top of benchmark funding costs. Loan amounts average around €134,000, which is notably above the 75th percentile, indicating the presence of a small number of very large loans in the sample.

Table 1: Summary statistics of main variables

	Mean	p25	p50	p75	SD	N
Probability of default (%)	1.972	0.745	1.320	2.442	1.760	10,278,725
Lending rate (%)	3.993	1.901	3.996	5.793	2.323	10,278,725
Lending spread (pp)	2.183	1.390	2.256	2.745	1.659	10,278,725
Lending amount (EUR 1000)	133.975	4.301	21.211	45.000	2791.118	10,277,828

Note: The table reports summary statistics of the main variables. Lending spread is defined as the difference between the lending rate and the relevant reference rate. Lending amount refers to outstanding nominal amount. The unit of observation is the individual loan. The sample comprises new loans issued by euro area IRB banks to non-financial corporations between January 2021 and December 2024. p25, p50, and p75 refer to the 25th, 50th (median), and 75th percentiles of the distribution, respectively, and SD denotes the standard deviation.
Source: AnaCredit, own calculations.

4 Evolution of lending rates and amounts

This section examines the evolution of lending rates and loan volumes across borrower risk profiles over the period 2021 to 2024. We classify firms as either higher or lower risk depending on whether their PD is above or below the sample median, calculated over the full 2021–2024

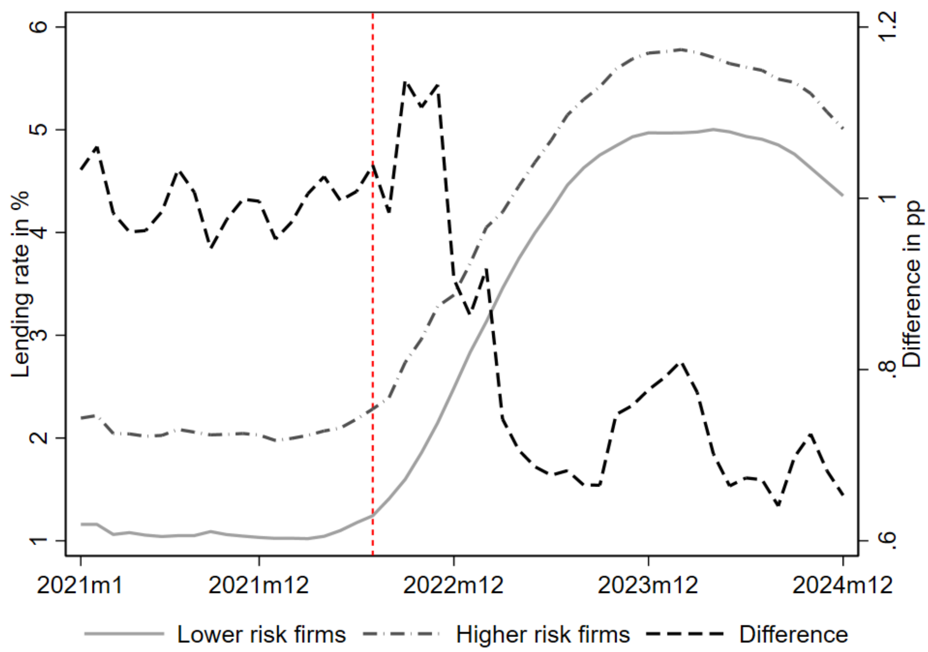
[1]Under the Basel III finalisation package, implemented in the EU through CRR3, the regulatory PD floor for non-defaulted corporate exposures will increase from 0.03% to 0.05%. This change applies only after the reform's phase-in period and does not affect the 2021–2024 sample used in this paper.

[2]For variable- and mixed-rate loans, we use the spread reported in AnaCredit. For fixed-rate loans, we compute the spread as the difference between the contractual loan rate and the overnight index swap (OIS) rate of matching maturity.

period. This classification is fixed over time to ensure consistency. We then examine how average lending rates and the distribution of new loan volumes evolved across the two risk groups, with particular attention to changes following the ECB's initial policy rate increase in July 2022.

Figure 1 presents the average lending rates by borrower risk category. Lending rates increased for both groups over the sample period, in line with monetary policy tightening. Rates for higher-risk borrowers were consistently above those for lower-risk borrowers, reflecting compensation for higher expected default. However, beyond the level effect, the dynamics of the risk premium over time are particularly noteworthy. In the immediate months following the ECB's first policy hike in July 2022, the spread between rates for high- and low-risk borrowers widened modestly, peaking at roughly 1.1 percentage point. This could reflect an initial effort by banks to maintain or even reinforce pricing discipline under tightening conditions. Yet, this trend reversed over the subsequent months, with the premium gradually compressing by approximately 40 basis points. By the end of the observation period, the risk premium was significantly narrower than at the onset of monetary tightening.

Figure 1: Lending rate evolution by borrower risk profile



Source: AnaCredit, own calculations. The figure presents the (weighted average) lending rates for higher- and lower-risk firms, as well as the spread between them. Firms are classified as higher or lower risk based on whether their PD is above or below the median. The sample includes new loans issued by euro area IRB banks to non-financial corporations between January 2021 and December 2024.

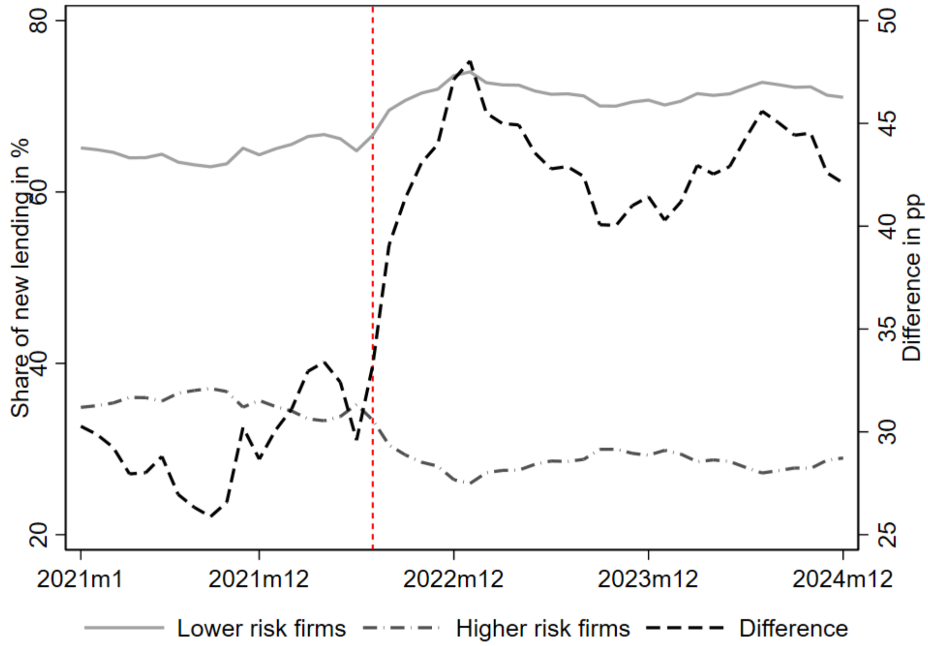
This declining differential suggests that the pass-through of rising policy rates to lending rates may have been more subdued for higher-risk borrowers than for their lower-risk peers. Several mechanisms could explain this evolution. First, banks may have deliberately limited rate increases for financially weaker firms in order to reduce the likelihood of default or preserve long-term client relationships. Second, the composition of borrowers receiving loans might have shifted within the risk groups themselves, with banks granting credit to relatively stronger firms within the high-risk category, leading to lower average rates. Third, competitive pressures or reputational concerns could have constrained how aggressively banks repriced risk. The declining risk premium over time, while not sufficient on its own to draw conclusions about credit supply behaviour, nonetheless signals a potentially asymmetric transmission of monetary policy across the firm risk distribution.

Figure 2 shows how credit volumes were distributed across the two borrower risk categories. Throughout the sample period, lower-risk firms—those with below-median PDs—consistently received a significantly larger share of new lending, averaging around 70%. Following the ECB's first policy rate hike in July 2022, this gap widened further, with the difference in lending shares between lower- and higher-risk firms increasing by more than 10 percentage points. This shift indicates a notable reallocation of credit toward less risky firms, which coincided with the tightening of monetary conditions. While this pattern is observational, it is consistent with the notion that, in more restrictive financial environments, lending becomes increasingly concentrated in segments of the market perceived as safer.

Several mechanisms may underlie this shift. On the demand side, lower-risk firms likely remained more resilient to higher borrowing costs, maintaining their access to credit and investment plans, while higher-risk firms may have reduced their demand due to affordability constraints or weaker economic outlooks. On the supply side, the rising cost of funds may have prompted banks to reassess the profitability of extending credit to marginally riskier borrowers, opting instead to channel lending toward safer exposures. This behaviour echoes findings in the literature documenting how banks rebalance their loan portfolios toward higher-quality borrowers during tightening cycles (Jiménez et al., 2012; Dell'Ariccia et al., 2017).

This reallocation of credit—alongside the muted rise in lending rates for riskier borrowers—raises important questions about how banks manage risk under tightening conditions. While lower risk premia could suggest leniency toward vulnerable firms, the simultaneous shift in volumes toward safer borrowers complicates this interpretation. Economic theory provides

Figure 2: Lending amount evolution by borrower risk profile



Source: AnaCredit, own calculations. The figure shows the share of new lending allocated to higher- and lower-risk firms, along with the difference between them. Firms are classified as higher or lower risk based on whether their PD is above or below the median. The sample covers new loans issued by euro area IRB banks to non-financial corporations between January 2021 and December 2024.

a framework for understanding such behaviour. As Stiglitz and Weiss (1981) argue, beyond a certain threshold, increasing interest rates can become self-defeating: they may discourage creditworthy firms from borrowing while attracting riskier ones, ultimately worsening the risk composition of the loan portfolio. In such contexts, banks may prefer to cap interest rates and instead adjust the quantity of lending—resorting to credit rationing rather than continuous price adjustments. This has been observed empirically in banking behaviour, for instance by Burgstaller and Scharler (2010), who document such selective rationing dynamics. In the empirical analysis that follows, we test whether the evolution of rates and volumes is consistent with this mechanism—namely, whether banks respond to borrower risk by flattening the pricing curve and shifting adjustments to the extensive margin of credit allocation.

5 Methodology

To systematically assess the dynamics observed in lending rates and credit volumes, we now turn to a formal empirical framework. While the descriptive patterns in the previous section suggest a differentiated response of credit conditions across borrower risk profiles—particularly following the onset of monetary tightening—these patterns alone cannot isolate the role of borrower risk or identify the drivers of observed changes. Our empirical strategy addresses this by quantifying the relationship between a firm's estimated PD and loan outcomes, in terms of both pricing (loan spreads) and quantities (loan amounts). Specifically, we pursue three objectives. First, we establish a causal relation between firm riskiness and lending spreads and amounts. Second, we examine how this sensitivity varies with loan, firm, and bank characteristics, allowing for heterogeneity across lending features. Third, we test whether the strength of this relationship changed following the ECB's initial policy rate hike in July 2022. The analysis is based on the following baseline regression specification:

$$Y_{ibft} = \beta PD_{bft} + X_{ibft}^{Loan} + X_{mt}^{Market} + \delta_{bt} + \sigma_{ILST} + \epsilon_{ibft} \quad (1)$$

We use indices i for loans, b for banks, f for firms, t for time (month), and m for markets (defined geographically). The dependent variable Y_{ibft} represents either the lending spread or the log of the loan amount. The coefficient β captures the degree to which loan pricing and allocation responds to changes in borrower risk, thereby indicating the strength of risk-based behaviour.

To isolate the effect of PD on loan spreads and amounts from other potential confounding influences, we include a set of controls addressing five potential sources of bias.

First, firm-level characteristics can influence both a firm's assessed PD and the terms under which credit is granted, making it essential to account for these potential confounding factors. A firm's financial health, asset structure, and operational environment shape its perceived risk and, simultaneously, affect its bargaining position when negotiating loan conditions. For instance, firms with more tangible assets may be better able to pledge collateral, thereby securing more favorable loan terms. Likewise, larger or more profitable firms may enjoy greater bargaining power, leading to lower spreads or more generous credit conditions. Furthermore, differences in loan demand across firms—driven by investment opportunities, financing needs, or expectations about the economic outlook—can also affect the observed allocation of credit and pricing outcomes.

These factors are often difficult to observe directly in the data and may be correlated with the firm's PD, potentially biasing the estimated effect of risk on loan pricing or amounts. To mitigate this concern, we introduce a rich set of fixed effects that absorb unobserved heterogeneity in firm characteristics. Specifically, we include industry-location-size-time fixed effects, denoted by σ_{ILST}, following the approach of Degryse et al. (2019).[3] This design allows us to compare firms operating within the same industry, region, size category, and time period, thereby isolating variation in loan outcomes attributable to differences in PD rather than broader macroeconomic or structural firm factors. An additional advantage of this approach, relative to the firm–time fixed effects estimator of Khwaja and Mian (2008), is that it also includes firms borrowing from a single bank. This feature is particularly important for studying new lending, where only a small fraction of firms obtain loans from multiple banks at the same time, and thus helps preserve sample size and representativeness.

Second, bank-level characteristics play an important role in shaping credit pricing and allocation decisions, particularly in response to borrower risk. A bank's financial condition influences not only its willingness to lend but also the terms it is able to offer. For example, while well-capitalized banks may have greater capacity to absorb potential losses, several studies suggest they tend to behave more conservatively, displaying lower tolerance for riskier borrowers (Gambacorta and Mistrulli (2004)). Similarly, differences in funding structures—such as reliance on wholesale markets versus retail deposits—can affect sensitivity to changes in monetary policy and the cost of extending credit. Banks with more stable and cheaper sources of funding may be better positioned to insulate lending margins and avoid sharp increases in borrowing costs for clients.

To account for this variation, we include a full set of bank-time fixed effects, denoted by δ_{bt}. These controls absorb all time-varying bank-level heterogeneity, capturing shifts in financial conditions, regulatory responses, business models, or funding environments that may influence lending behaviour. By identifying within-bank variation at each point in time, we ensure that our estimates of the effect of borrower risk on credit terms are not confounded by concurrent changes in the financial position or strategic orientation of the bank. This approach follows the empirical literature on credit supply, which emphasizes the need to control for dynamic bank heterogeneity (e.g., Jiménez et al. (2012); Buch et al. (2015)).

Third, market structure and the intensity of competition in the local credit market can

[3] Industry is defined at the NACE 2-digit level, capturing variation across 89 distinct business activities. Location is specified using the NUTS-3 classification, which includes over 1,000 regional units across the euro area, reflecting geographic differences in economic conditions, banking competition, and local credit markets. Firm size is measured using deciles of total assets, allowing us to distinguish between micro, small, medium-sized, and large firms. Time is defined at the monthly frequency, controlling for common shocks or trends such as monetary policy changes or seasonal lending patterns.

significantly influence how banks price risk. In highly competitive environments, financial institutions may be pressured to reduce lending margins or offer more favorable terms to retain or attract borrowers, which could compress the risk premium and weaken the observed relationship between borrower PD and loan spreads. This is particularly relevant when banks compete for higher-yield segments, potentially leading to underpricing of credit risk—an outcome documented in the banking literature on competition and risk-taking behaviour (e.g., Keeley, 1990; Martínez-Miera and Repullo, 2010).

To capture this dimension, we include in our specification the logarithm of the number of active banks in each market (X_{mt}^{Market}), where markets are defined at the NUTS-3 regional level. This variable serves as a proxy for the degree of local credit market competitiveness, reflecting how crowded a market is with lending institutions. A larger number of banks operating within a given region implies more intense competition, which may shape pricing strategies even when controlling for borrower risk. By accounting for this variation, we aim to isolate the effect of borrower PD on lending conditions from distortions introduced by regional competitive dynamics.

Fourth, loan-specific characteristics can directly shape both the pricing and the allocation of credit, as they capture contractual terms that influence a loan's risk profile and profitability from the bank's perspective. Banks typically manage credit risk not solely through adjustments in interest rates, but also by tailoring non-price terms such as the collateral requirements, loan maturity, and repayment structure. For instance, loans with higher loan-to-value (LTV) ratios expose banks to greater loss-given-default, potentially prompting higher pricing or more restrictive lending practices. Similarly, loans with longer maturities may carry elevated credit and interest rate risk, especially in uncertain economic environments, which can influence the decision to grant credit or the premium charged.

To capture these important dimensions of credit contracts, the vector X_{ibft}^{Loan} includes a set of key loan-level controls. Specifically, we account for the LTV ratio, which proxies for the amount of security backing the loan; the maturity of the loan, measured in months; and an indicator for whether the loan carries a fixed or variable interest rate, which affects the transmission of monetary policy and borrower exposure to rate fluctuations. Additionally, when modeling the lending spread as the dependent variable, we include the log of the loan amount to capture potential scale effects—larger loans may benefit from economies of scale in monitoring or negotiation, leading to more favorable pricing.

While these loan-level characteristics capture important contractual dimensions, it is important to note that they may themselves be jointly determined with the key outcomes of interest. Variables such as the LTV ratio, maturity, interest-rate type, and loan size are often negotiated simultaneously with the lending spread and may therefore reflect both borrower fundamentals and bank policies. In this sense, they can be considered "bad controls" (Angrist and Pischke, 2009), as conditioning on them may absorb variation that is itself influenced by borrower risk (PD) or by other unobserved factors shaping the contracting process. Including such variables may consequently attenuate or distort the estimated effect of PD. To account for these concerns, the results section presents specifications both with and without loan-level controls, allowing an assessment on how conditioning on jointly determined contract terms affects the estimated relationship between PD and credit conditions.

Lastly, macroeconomic conditions can play a critical role in shaping both the behaviour of banks and the financial condition of borrowers. Factors such as economic growth, inflation, and monetary policy influence the overall lending environment and can simultaneously affect banks' willingness to extend credit and firms' ability to repay loans. For example, in periods of economic expansion, improved borrower cash flows and investor confidence may lead to more favorable lending terms, while downturns tend to heighten credit risk and prompt banks to tighten lending standards. Although we do not include explicit macroeconomic control variables in our baseline specification—such as GDP growth, inflation, or policy interest rates—we account for broader macroeconomic influences indirectly. This is achieved through the inclusion of time-varying fixed effects at both the bank level (δ_{bt}) and the industry-location-size segment level (σ_{ILST}), which absorb aggregate and region-specific economic fluctuations that could otherwise bias the estimation of risk-pricing relationships.

6 Results

We now turn to the empirical results, which examine how lending spreads and credit volumes vary with borrower risk, and how these relationships evolved during the recent period of monetary tightening. The first step of our analysis is to establish a relationship between borrower risk—measured by the probability of default—and two key credit terms: the loan spread and the (log) amount of newly issued credit (Tables 2 and 3). In both cases, we progressively introduce controls for loan characteristics, firm-specific heterogeneity, and bank-time effects to ensure the estimated PD coefficient reflects a genuine risk-pricing or allocation mechanism. We then take the fully specified model and investigate how the strength of risk sensitivity varies across loan, firm, and bank characteristics (Tables 4 and 5), and assess whether these patterns changed following the ECB's initial policy rate hike in July 2022 (Tables 6 and 7).

The spread regressions are reported in Table 2. Column (1) starts with a simple specification regressing the loan spread on borrower PD. The coefficient is positive and statistically significant, suggesting that riskier firms are charged higher interest rate spreads. In subsequent columns, we progressively add controls: bank-time fixed effects (column 2), ILST fixed effects for firm characteristics (column 3), loan-level terms like maturity, rate type, and collateral (column 4), and finally local banking competition via the log number of lenders in each market (column 5). These controls substantially tighten the identification of the PD coefficient, yet the estimate remains stable—0.091 in the fully specified model compared to 0.130 in the naïve specification without controls.

Table 2: Impact of firm default probability on bank lending spreads

	(1)	(2)	(3)	(4)	(5)
Probability of default	0.130	0.105	0.095	0.091	0.091
	[0.000]	*[0.000]*	*[0.000]*	*[0.000]*	*[0.000]*
Bank-time fixed effects		✓	✓	✓	✓
Firm controls (ILST FE)			✓	✓	✓
Loan-specific factors				✓	✓
Competition					✓
Number of observations	10.3m	10.3m	10.3m	9.6m	9.6m
R-square	0.020	0.593	0.670	0.696	0.696

Note: The table reports the estimated effects of firm riskiness—measured by banks' probability of default (PD) assessments—on lending spreads. Lending spread is defined as the difference between the lending rate and the reference rate. The unit of observation is the individual loan. The sample comprises new loans issued by euro area IRB banks to non-financial corporations (NFCs) between January 2021 and December 2024. Competition is measured with the logarithm of the number of banks active in each NUTS3 market. Loan-specific factors are maturity, collateral and interest rate fixation. ILST FE denotes industry-location-size-time fixed effects. Standard errors are clustered at bank level. Square brackets contain p-values.
Source: AnaCredit, own estimates.

The positive and robust relationship between borrower PD and loan spreads confirms that banks actively incorporate risk assessments into their pricing decisions, even after accounting for a comprehensive set of potential confounding factors. A one percentage point increase in PD leads to a rise of about 9 basis points in the lending spread. While this marginal effect may appear modest, it remains economically meaningful when viewed in terms of the distribution of the data. A one–standard-deviation increase in PD (0.018) implies an increase in spreads of roughly 16 basis points, which corresponds to about 10% of the standard deviation of lending spreads (0.017).

Two factors likely contribute to this relatively muted sensitivity. First, as noted earlier, PDs under the IRB approach are designed as through-the-cycle measures, making them relatively inert to short-term fluctuations in firm fundamentals. Regulatory PDs may not fully reflect the internal risk assessments that banks use when setting loan prices. If regulatory PDs diverge from banks' proprietary measures of expected loss or borrower quality, the estimated sensitivity of spreads to PDs may understate the true role of risk-based pricing. Second, much of the sample period (2021–2024) coincides with a generally favorable macro-financial environment, characterized by ample liquidity, and a strong post-pandemic rebound. These conditions may have reduced banks' incentives to sharply differentiate pricing across risk categories, thereby dampening the estimated pass-through from borrower risk to loan spreads.

Turning to the volume regressions reported in Table 3, we investigate how borrower risk, proxied by PD, relates to the size of newly extended loans. In contrast to the spread regressions, the initial bivariate specification in column (1) yields a counterintuitive result: the coefficient on PD is positive and statistically significant, implying that higher-risk firms receive larger loan amounts. However, this naive correlation likely reflects severe omitted variable bias, as it does not account for systematic differences in firm characteristics, bank behaviour, or market conditions that jointly influence PD and loan size.

As we sequentially introduce controls across columns (2) through (5), the coefficient on PD becomes increasingly negative and ultimately stabilizes at –3.657 in the fully specified model. A one–percentage-point increase in PD lowers loan amounts by about 3.7%, and a one-standard-deviation increase in PD corresponds to a decline of roughly 3% of the standard deviation of log loan amount. This suggests that borrower risk indeed negatively affects credit volumes. Importantly, this pattern reinforces the role of PD not just as a pricing variable, but also as a determinant of credit allocation decisions. While spreads respond moderately to borrower risk, the extensive margin, i.e how much credit is granted, appears more sensitive. This may reflect banks' aversion to concentrated exposure to high-risk borrowers, especially in an environment of rising policy rates and increased macroeconomic uncertainty. By limiting loan size rather than

Table 3: Impact of firm default probability on lending amounts

	(1)	(2)	(3)	(4)	(5)
Probability of default	2.109	-5.917	-4.489	-3.656	-3.657
	[0.000]	*[0.001]*	*[0.000]*	*[0.000]*	*[0.000]*
Bank-time fixed effects		✓	✓	✓	✓
Firm controls (ILST FE)			✓	✓	✓
Loan-specific factors				✓	✓
Competition					✓
Number of observations	10.3m	10.3m	10.3m	9.6m	9.6m
R-square	0.001	0.366	0.515	0.551	0.551

Note: The table reports the estimated effects of firm riskiness—measured by banks' probability of default (PD) assessments—on the volume of new loans. Lending amount is expressed in logs. The unit of observation is the individual loan. The sample comprises new loans issued by euro area IRB banks to non-financial corporations (NFCs) between January 2021 and December 2024. Competition is measured with the logarithm of the number of banks active in each NUTS3 market. Loan-specific factors are maturity, collateral and interest rate fixation. ILST FE denotes industry-location-size-time fixed effects. Standard errors are clustered at bank level. Square brackets contain p-values.
Source: AnaCredit, own estimates.

charging prohibitively high rates, banks may aim to mitigate potential losses.

6.1 Heterogeneity in risk sensitivity across banks, firms, and loans

Building on the baseline relationship between borrower risk and credit terms, we next explore how this sensitivity varies across key contextual factors. Tables 4 and 5 report regressions that interact borrower PD with binary indicators for whether specific characteristics (denoted as *Factor* in the tables) exceed their sample medians.[4] We consider five dimensions: market competition (number of banks in a NUTS-3 region), bank size, firm size (both proxied by total assets), bank capitalization (leverage ratio)[5], and borrower risk itself. For the latter, we interact PD with a high-risk dummy equal to one if a borrower's PD is above the median, allowing us to test for non-linearities in the relationship, specifically, whether the marginal effect of risk on pricing and loan volumes intensifies for already-risky firms. These interactions provide insight into whether the responsiveness of spreads and amounts to risk is amplified or dampened in different lending environments or institutional settings.

We begin by examining the role of market competition in shaping banks' sensitivity to bor-

[4]The median split is a simple and ad hoc threshold, used only to provide an easily interpretable indication of whether the PD–spread (or PD–amount) relationship differs across the distribution of the variable of interest. It should not be interpreted as identifying the structural form or precise location of any underlying non-linearity.

[5]We use the leverage ratio instead of regulatory capital ratios because COREP reports, which contain risk-weighted capital measures, are not available to us for euro-area banks. The leverage ratio should therefore be viewed as an approximation of banks' capitalization rather than a regulatory capital metric.

rower risk. The results in Table 4 suggest that in more competitive credit markets, banks exhibit a lower sensitivity of spreads to borrower risk. In other words, the spread differential between high- and low-risk borrowers is smaller in markets where banks face greater competitive pressure. This finding is consistent with the traditional view that competition can erode banks' ability to price discriminate based on borrower risk, leading to a compression of risk premia (Keeley (1990); Petersen and Rajan (1995)). When competition intensifies, banks may be reluctant to raise rates too aggressively for riskier borrowers out of concern that they will lose market share, thereby softening the relationship between risk and price.

Table 4: Heterogeneous impact of firm default probability on lending spreads

Interaction factor:	Competition	Bank size	Firm size	Capitalization	PD
Probability of default (PD)	0.096	0.055	0.107	0.080	0.256
	[0.000]	*[0.000]*	*[0.000]*	*[0.000]*	*[0.000]*
PD $\times$ I(Factor)	-0.012	0.070	-0.018	0.068	-0.185
	[0.031]	*[0.000]*	*[0.201]*	*[0.021]*	*[0.000]*
I(Factor)	0.000		0.001		0.002
	[0.060]		*[0.004]*		*[0.000]*
Number of observations	9.6m	7.1m	8.4m	8.9m	9.6m
R-square	0.697	0.656	0.693	0.720	0.697

Note: The table reports estimates of the heterogeneous impact of the probability of default (PD) on lending spreads. I(Factor) is a dummy variable that is equal to one if the value of specific factor (competition, bank size, firm size, bank capitalization or PD) is above median. Bank and firm size are measured by total assets, while bank capitalization is proxied by the leverage ratio, defined as the ratio of capital to total assets. All specifications include the full set of control variables, as in column (5) of Table 2. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, IBSI, own estimates.

The interaction between market competition and PD in the lending amount regressions (Table 5) is small and statistically insignificant, indicating that competitive intensity does not influence the allocation of credit across borrower risk categories. One possible interpretation is that credit volumes are shaped more by internal bank constraints, such as risk limits, capital buffers, and portfolio considerations, than by external market pressures.

Turning to bank size, the results indicate that it plays a significant role in shaping both the pricing and allocation of credit in response to borrower risk. Specifically, the interaction terms show that larger banks exhibit a stronger sensitivity to PD: they tend to charge higher spreads per additional point of borrower default probability and also extend smaller loan amounts to riskier firms. This pattern suggests that larger banks are more conservative in their credit risk management practices. Several factors may contribute to this behaviour. Larger institutions often face tighter regulatory scrutiny and have more formalized risk assessment frameworks, which can lead to more disciplined risk-based pricing and allocation. Additionally, they may have greater capacity to absorb high-quality loan demand, allowing them to be more selective when facing borrowers with elevated risk. These findings align with earlier studies suggesting that large banks tend to apply stricter credit standards and maintain more robust risk mitigation strategies (Berger and Udell (1995); Kashyap and Stein (2000)).

Table 5: Heterogeneous impact of firm default probability on lending amounts

Interaction factor:	Competition	Bank size	Firm size	Capitalization	PD
Probability of default (PD)	-3.400	-1.752	-2.964	-3.701	-7.339
	[0.000]	*[0.031]*	*[0.001]*	*[0.000]*	*[0.215]*
PD × I(Factor)	-0.568	-3.522	-2.668	0.044	4.235
	[0.209]	*[0.001]*	*[0.092]*	*[0.977]*	*[0.453]*
I(Factor)	-0.051		0.702		-0.062
	[0.036]		*[0.000]*		*[0.258]*
Number of observations	9.6m	7.1m	8.5m	8.9m	9.6m
R-square	0.551	0.607	0.561	0.551	0.551

Note: The table reports estimates of the heterogeneous impact of the probability of default (PD) on lending amounts, expressed in logs. I(Factor) is a dummy variable that is equal to one if the value of specific factor (competition, bank size, firm size, bank capitalization or PD) is above median. Bank and firm size are measured by total assets, while bank capitalization is proxied by the leverage ratio, defined as the ratio of capital to total assets. All specifications include the full set of control variables, as in column (5) of Table 3. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, IBSI, own estimates.

Firm size appears to influence the way banks adjust credit conditions in response to borrower risk, particularly via credit amounts. The results in Table 5 indicate that for larger firms the negative relationship between PD and loan amounts is more pronounced. In other words, when risk increases, banks scale back loan volumes more sharply for larger firms than for smaller ones. This heightened sensitivity on the credit allocation side is not mirrored in the pricing response, where the interaction between firm size and PD in the spread regressions is economically small and statistically insignificant (Table 4).

The higher sensitivity of credit amounts to borrower risk among larger firms suggests that banks may be particularly cautious when extending sizable exposures to riskier clients. Even though such firms are typically better known to banks and may benefit from more transparent financials or longstanding relationships, their potential default could imply greater losses due to the sheer scale of the lending. As a result, banks might prefer to curtail loan amounts rather than adjusting prices, thereby managing their portfolio risk more discreetly.

The absence of a significant pricing response for larger firms may also reflect market dynamics—larger borrowers often have more bargaining power and better access to alternative funding sources, which could limit the banks' ability to increase spreads even when credit risk rises. Instead, banks may opt to reduce exposure via smaller loan volumes. This finding echoes earlier research suggesting that banks use loan quantities more flexibly than prices when managing risk in lending to large firms (Boot (2000); Jiménez et al. (2012)).

Banks with stronger capitalization, in terms of their leverage ratio, appear to exhibit greater risk sensitivity in their pricing behaviour. In particular, the interaction between PD and bank capitalization in Table 4 shows that banks with higher leverage ratio charge higher spreads for each percentage point increase in borrower PD, compared to their less capitalized peers. This finding suggests a more conservative pricing stance, potentially reflecting a lower risk tolerance or a stricter internal risk rules among well-capitalized institutions, consistent with empirical studies like Gambacorta and Mistrulli (2004) and Jiménez et al. (2012).

However, the corresponding interaction in Table 5 indicates that this heightened caution does not extend to the quantity of credit allocated: the coefficient is close to zero and statistically insignificant. This implies that while banks with higher leverage ratio are more deliberate in pricing risk, they do not necessarily restrict loan amounts more aggressively in response to borrower PD. One possible interpretation is that capital buffers allow banks to maintain credit flows to riskier borrowers while using price as the primary margin of adjustment. That is, stronger banks may tolerate risk exposure in volume terms, provided they are sufficiently compensated via higher spreads.

Finally, we explore whether the sensitivity of credit terms to borrower risk is non-linear by interacting PD with a high-risk dummy, which is equal to one if a firm's PD exceeds the sample median. The results indicate a clear asymmetry in pricing behaviour. For lower-risk firms (below-median PD), spreads increase by about 26 basis points for each percentage point rise in PD. In contrast, for higher-risk firms, the sensitivity drops to just 7 basis points (last column in Table 4) . This implies that beyond a certain risk threshold, banks refrain from raising interest rates proportionally with risk—possibly to avoid pushing already vulnerable firms into distress or to preserve existing exposures.[6]

Such behaviour is consistent with theories of credit rationing (Stiglitz and Weiss, 1981), which suggest that lenders may prefer to restrict access to credit rather than continue raising interest

[6] A potential alternative explanation could be the presence of legal interest-rate ceilings. However, such caps are generally uncommon for loans to firms, as business lending is treated as a commercial activity where pricing is determined by market forces. Where interest-rate ceilings do exist, they typically apply to households, especially in consumer credit, because individuals are considered more vulnerable and face greater information asymmetries.

rates, particularly when higher rates might attract riskier borrowers. An alternative explanation is that banks tend to offer relatively more favorable pricing to riskier firms, as the sensitivity of spreads to PD diminishes sharply in the upper half of the risk distribution. Supporting this interpretation, we find that the relationship between PD and loan amounts also weakens for high-PD borrowers, although the interaction is not statistically significant. Altogether, the results suggest that risk-based pricing is stronger among safer borrowers, while responses flatten at the riskier end of the spectrum.

6.2 Risk sensitivity before and after monetary tightening

While the baseline and cross-sectional patterns provide a static view of risk sensitivity, we next explore how these dynamics evolved over time, particularly during the monetary policy tightening initiated by the ECB in July 2022. To do so, we re-estimate our fully specified model, allowing the coefficient on borrower PD to differ before and after the onset of the tightening cycle. This approach enables us to assess whether the transmission of borrower risk into loan terms intensified or weakened as financial conditions tightened. We also examine whether this shift in risk sensitivity differs across bank, firm, and market characteristics by re-estimating the heterogeneity interactions separately for the post-tightening period.

The baseline results reported in Tables 6 and 7 provide the first indication of how risk sensitivity evolved following the onset of monetary tightening in July 2022. Specifically, we find no statistically significant change in the sensitivity of lending spreads to borrower PD after the start of the tightening cycle. This suggests that, on average, banks did not systematically adjust their pricing behaviour in response to increased policy rates, at least not in terms of how sharply they differentiate interest rates across risk profiles. In contrast, the results for loan volumes point to a modest shift in credit allocation. The coefficient on PD becomes more negative in the post-tightening period, indicating that banks may have become slightly more restrictive in extending credit to riskier borrowers. Although the difference is only marginally significant at the 10% level, this pattern suggests that monetary tightening may have led to greater caution on the extensive margin—i.e., through limiting the volume of credit rather than altering the pricing terms.

Turning to the heterogeneity in risk sensitivity after the onset of monetary tightening, the most notable change emerges for high-risk firms. Specifically, we observe a significant decline in

Table 6: Heterogeneous impact of firm PD on lending spreads during monetary tightening

Interaction factor:	Baseline	Competition	Bank size	Firm size	Capitalization	PD
Probability of default (PD)	0.092	0.091	0.055	0.107	0.079	0.200
	[0.000]	*[0.000]*	*[0.000]*	*[0.000]*	*[0.000]*	*[0.001]*
PD × I(After)	-0.002	0.010	0.001	-0.001	0.001	0.090
	[0.830]	*[0.329]*	*[0.973]*	*[0.981]*	*[0.900]*	*[0.018]*
PD × I(Factor)		0.003	0.824	-0.008	0.062	-0.128
		[0.780]	*[0.001]*	*[0.666]*	*[0.044]*	*[0.028]*
PD × I(After) × I(Factor)		-0.027	-0.020	-0.017	0.012	-0.091
		[0.027]	*[0.242]*	*[0.219]*	*[0.088]*	*[0.015]*
I(Factor)		0.003		-0.002		0.002
		[0.140]		*[0.008]*		*[0.006]*
I(Factor) × I(After)		0.000		0.004		0.001
		[0.815]		*[0.417]*		*[0.322]*
Number of observations	9.6m	9.6m	7.1m	8.5m	8.9m	9.6m
R-square	0.697	0.697	0.656	0.693	0.712	0.697

Note: The table reports estimates of the heterogeneous impact of the probability of default (PD) on lending spreads during the monetary tightening. I(After) equals 1 for loans issued from July 2022 onward, coinciding with the ECB's initiation of policy rate hikes. I(Factor) is a dummy variable that is equal to one if the value of specific factor (competition, bank size, firm size, bank capitalization or PD) is above median. Bank and firm size are measured by total assets, while bank capitalization is proxied by the leverage ratio, defined as the ratio of capital to total assets. All specifications include the full set of control variables, as in column (5) of Table 2. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, IBSI, own estimates.

the sensitivity of lending spreads to borrower PD for firms above the median risk threshold. This decline builds on the earlier finding of non-linearity in risk pricing, where the pass-through of risk to spreads was already weaker for riskier borrowers and indicates that this pattern became even more pronounced after July 2022. In other words, banks became increasingly reluctant to raise interest rates for riskier borrowers as monetary policy tightened. One possible interpretation is that lenders were concerned about exacerbating financial fragility among already vulnerable firms. Rather than fully transmitting higher policy rates to these borrowers, banks may have opted to moderate pricing adjustments in an effort to avoid defaults or maintain long-term relationships. This behaviour resonates with the findings of Albuquerque and Mao (2023), who show that banks may offer more favorable conditions to financially weak firms in order to delay or avoid the recognition of losses on distressed exposures.

The loan allocation patterns, however, do not corroborate this interpretation. The results for loan amounts show the opposite shift: after the ECB began raising interest rates, banks became more restrictive in their credit allocation to riskier firms. The negative relationship between PD and loan amounts intensified, suggesting that banks reduced the size of loans extended to high-risk firms more sharply than before. This pattern is indicative of heightened caution in lending decisions, especially on the extensive margin. It suggests that while pricing may have softened for vulnerable borrowers—possibly to avoid signaling distress or preserving existing relationships—actual credit exposure was reduced more decisively.

The joint evidence from spreads and volumes thus points to a dynamic form of credit adjustment during the tightening cycle. Initially, banks responded to rising policy rates by raising lending spreads across the board.[7] However, as policy rates continued to rise, the scope for further rate increases for risky firms appeared to narrow, likely due to growing concerns over adverse selection and repayment capacity. Instead of continuing to reprice risk, banks shifted toward more selective lending, reducing credit volumes to higher-risk borrowers. This shift is consistent with the theory of credit rationing by Stiglitz and Weiss (1981), which posits that lenders may prefer to restrict loan quantities rather than raise rates when higher pricing would disproportionately attract riskier borrowers. The observed adjustment also aligns with previous studies on monetary transmission through bank lending behaviour (Kashyap and Stein, 2000; Dell'Ariccia et al., 2017).

Table 7: Heterogeneous impact of firm PD on lending amounts during monetary tightening

Interaction factor:	Baseline	Competition	Bank size	Firm size	Capitalization	PD
Probability of default (PD)	-3.032	-3.235	-1.078	-2.750	-3.060	-12.503
	[0.000]	*[0.000]*	*[0.146]*	*[0.000]*	*[0.000]*	*[0.010]*
PD × I(After)	-1.084	-0.298	-1.228	-0.328	-1.106	8.243
	[0.094]	*[0.613]*	*[0.121]*	*[0.733]*	*[0.084]*	*[0.411]*
PD × I(Factor)		0.416	-4.191	-1.902	1.067	10.036
		[0.502]	*[0.001]*	*[0.310]*	*[0.521]*	*[0.034]*
PD × I(After) × I(Factor)		-1.729	1.120	-1.479	-1.807	-9.404
		[0.052]	*[0.242]*	*[0.550]*	*[0.067]*	*[0.035]*
I(Factor)		-0.078		0.707		-0.105
		[0.144]		*[0.000]*		*[0.070]*
I(Factor) × I(After)		0.044		-0.003		0.073
		[0.390]		*[0.959]*		*[0.281]*
Number of observations	9.6m	9.6m	7.1m	8.5m	8.9m	9.6m
R-square	0.551	0.551	0.607	0.561	0.552	0.551

Note: The table reports estimates of the heterogeneous impact of the probability of default (PD) on lending amounts during the monetary tightening. I(After) equals 1 for loans issued from July 2022 onward, coinciding with the ECB's initiation of policy rate hikes. I(Factor) is a dummy variable that is equal to one if the value of specific factor (competition, bank size, firm size, bank capitalization or PD) is above median. Bank and firm size are measured by total assets, while bank capitalization is proxied by the leverage ratio, defined as the ratio of capital to total assets. All specifications include the full set of control variables, as in column (5) of Table 3. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, IBSI, own estimates.

Another noteworthy pattern concerns the role of bank capitalization in moderating risk

[7] Actually, as shown in Figure 1, banks initially increased lending rates more sharply for riskier firms following

sensitivity after the onset of monetary tightening. We find that banks with higher leverage ratio became more risk-sensitive after July 2022, in terms of both pricing and credit allocation. This suggests that stronger capital buffers enabled these banks to act more prudently in the face of heightened uncertainty, by more sharply differentiating credit terms based on borrower risk. Well-capitalized institutions may have had greater balance sheet flexibility to enforce stricter lending standards, thus intensifying their selective behaviour.

We also observe that the impact of local market competition on risk-based pricing became more pronounced after the ECB began raising policy rates. While competitive dynamics did not appear to significantly alter credit volumes, they increasingly shaped how banks priced risk. In particular, banks operating in more competitive markets exhibited weaker differentiation in lending spreads across borrower risk profiles during the tightening cycle. This pattern suggests that in high-competition environments, banks may have been constrained in their ability to fully pass on risk premiums to borrowers, either due to fear of losing clients or because competitors were willing to price more aggressively. This effect becomes evident only after the onset of monetary tightening, potentially because higher nominal rates expanded the pricing space, giving banks more room to undercut competitors without reducing absolute returns. In essence, while monetary tightening typically encourages more conservative lending behaviour, the extent to which banks could implement this approach was partly constrained by the intensity of competitive pressures in their local markets.

7 Robustness tests

In this section, we assess the robustness of our baseline findings on the sensitivity of lending spreads and credit volumes to borrower risk. We subject our empirical strategy to a series of validation exercises designed to verify that the documented patterns are not driven by model specification, measurement choices, or timing assumptions. First, we implement the identification approach of Khwaja and Mian (2008), which exploits within–firm-bank variation to further isolate the causal component of risk sensitivity. Second, we re-estimate all specifications using lagged rather than contemporaneous borrower PDs to mitigate concerns about simultaneity between loan terms and risk assessments. Third, we replace our baseline competition proxy, the number of active lenders in a NUTS-3 market, with a Herfindahl–Hirschman Index to ensure

the onset of monetary tightening.

that our results do not depend on the specific measure of market structure. Fourth, we test the robustness of our results on the change in risk sensitivity during monetary tightening by assuming that the tightening cycle began in January 2022 rather than July 2022. Finally, we report estimates using bank–time clustered standard errors to address potential concerns about within-bank serial correlation in risk-pricing behaviour. We discuss each robustness exercise in turn below.

Table 8 reports the key coefficients from specifications that replace ILST fixed effects with firm–time fixed effects in the spirit of Khwaja and Mian (2008), estimated on the subset of firms borrowing from more than one bank in a given period. By absorbing firm–time heterogeneity, these regressions further purge borrower-specific demand shocks and isolate bank-side supply responses. The baseline PD coefficient for lending spreads remains positive and statistically significant (0.046, $p < 0.01$), and the corresponding coefficient for lending amounts remains negative and marginally significant (–1.200, $p \approx 0.05$). The non-linear patterns with respect to borrower risk and the changes during the monetary tightening period are also qualitatively preserved, although some interaction terms become less precisely estimated, reflecting the smaller sample (3.4 million observations versus 9.6 million when using ILST FE). Overall, the results in Table 8 confirm that our main conclusions on risk-based pricing and credit allocation are robust to using a Khwaja–Mian–type identification strategy, even though the associated firm–time fixed effects estimator trades off external validity for tighter internal identification.

To address potential endogeneity, we re-estimate the baseline specifications using lagged PD (t–1) instead of the contemporaneous value. The rationale is straightforward: loan terms agreed today, such as spreads and amounts, could themselves influence a firm's assessed risk in the same period, creating a mechanical correlation between PD and loan conditions. Using lagged PD helps break this contemporaneous link. As reported in Table 9, the results remain fully consistent with our baseline findings. The estimated effects of PD on both lending spreads and loan amounts retain their expected signs and remain statistically highly significant, although their magnitudes are somewhat smaller when using lagged information. Overall, this robustness check reinforces that our main results are not driven by reverse causality.

We also examine whether our results regarding the role of competition depend on how local market structure is measured. We replace the log number of active banks in a NUTS-3 region with a Herfindahl–Hirschman Index (HHI) constructed from banks' credit exposures to NFCs.

Table 8: Key estimates using Khwaja and Mian (2008) methodology

	Lending spread			Lending amount		
	Baseline	Non-lin.	Tightening	Baseline	Non-lin.	Tightening
Probability of default (PD)	0.046	0.059	0.053	-1.200	-2.181	-5.992
	[0.000]	*[0.115]*	*[0.100]*	*[0.051]*	*[0.423]*	*[0.065]*
PD × I(After)			0.018			6.061
			[0.760]			*[0.206]*
PD × I(PD)		-0.017	0.002		0.538	5.327
		[0.078]	*[0.998]*		*[0.818]*	*[0.234]*
PD × I(After) × I(PD)			-0.035			-7.502
			[0.089]			*[0.040]*
I(PD)		0.004	0.006		0.030	-0.047
		[0.349]	*[0.144]*		*[0.552*	*[0.240]*
I(PD) × I(After)			-0.001			0.114
			[0.651]			*[0.189]*
Number of observations	3.4m	3.4m	3.4m	3.4m	3.4m	3.4m
R-square	0.914	0.914	0.914	0.783	0.783	0.783

Note: The table reports key estimates of lending spreads and loan amounts using the Khwaja and Mian (2008) approach, including the baseline specification, non-linearities with respect to PD, and changes during the monetary tightening period. I(After) equals 1 for loans issued from July 2022 onward. I(PD) is a dummy equal to 1 when the probability of default is above the median. All specifications include the full set of control variables from column (5) of Table 2. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, own estimates.

Unlike the simple count of banks, which assigns equal weight to all institutions, the HHI places greater weight on large banks and could therefore provides a more informative measure of market concentration. As shown in Table 9, the results using the HHI closely mirror those obtained with the baseline measure. The interaction term indicates that the sensitivity of lending spreads to borrower PD is weaker in more competitive markets, consistent with our main findings. Because a higher HHI corresponds to a less competitive environment, the estimated coefficient naturally flips sign relative to the baseline specification using the number of banks, but the underlying interpretation is unchanged. For loan amounts, the interaction remains statistically insignificant, again matching the baseline pattern. Overall, the robustness check confirms that our conclusions about competition shaping banks' risk-pricing behaviour are not driven by the particular competition metric employed.

Next, to account for the possibility that banks reacted to anticipated monetary tightening before the ECB's first policy rate hike in July 2022, we construct an alternative dummy that sets I(After) = 1 beginning in January 2022, when forward-looking market rates, such as the 12-month Euribor, had already started to rise in response to mounting inflation pressures. This adjustment allows us to test whether our baseline results are sensitive to the precise timing of the

Table 9: Results with lagged PD and HHI competition measure

	Lending spreads		Lending amounts	
	Lagged PD	HHI	Lagged PD	HHI
Probability of default (PD)	0.020	0.081	-0.808	-3.252
	[0.000]	*[0.000]*	*[0.001]*	*[0.000]*
PD × I(HHI)		0.015		-0.642
		[0.064]		*[0.411]*
I(HHI)		-0.001		-0.007
		[0.018]		*[0.276]*
Number of observations	7.9m	6.6m	7.9m	9.6m
R-square	0.740	0.697	0.534	0.551

Note: The table reports results from two robustness checks: (1) replacing contemporaneous PD with its lagged value, and (2) using the Herfindahl–Hirschman Index (HHI) as the competition measure instead of the log number of banks. I(HHI) equals 1 when the HHI is above its median. All specifications include the full set of control variables from column (5) of Table 2. Standard errors are clustered at the bank level. Square brackets report p-values.
Source: AnaCredit, own estimates.

tightening cycle. As reported in Table 10, the estimated effects of borrower PD on both lending spreads and loan amounts remain highly consistent with the original July-based specification. The baseline coefficients preserve their signs, magnitudes, and statistical significance, and the qualitative patterns in the non-linear interactions similarly carry over. While a few interaction terms shift slightly in size, the overall conclusions regarding how banks' risk sensitivity evolved during tightening are unaffected. This robustness check therefore confirms that the main findings do not depend on the specific dating of the monetary policy regime change.

Finally, following the guidance of Cameron et al. (2011), we re-estimate our baseline regressions using standard errors that are two-way clustered at the bank and month levels. This adjustment simultaneously accounts for serial correlation within banks over time and common shocks affecting all banks within a given month. The results remain virtually unchanged. In both the spread and amount specifications, the coefficients on borrower PD continue to be highly statistically significant, with p-values below 0.1 percent. This confirms that our inference is not sensitive to the choice of clustering scheme and that the main patterns identified in the paper are robust to more demanding assumptions about the structure of the error terms.

8 Conclusion

This paper examines how banks adjust credit terms in response to borrower risk during periods of monetary tightening—an important channel through which policy is transmitted to the real

Table 10: Results with monetary tightening starting in January 2022

	Lending spreads		**Lending amounts**	
	Baseline	Non-linearity	Baseline	Non-linearity
Probability of default (PD)	0.094	0.181	-3.079	-13.012
	[0.000]	*[0.005]*	*[0.000]*	*[0.023]*
PD × I(After)	-0.004	0.097	-0.805	7.410
	[0.682]	*[0.026]*	*[0.297]*	*[0.0.455]*
PD × I(PD)		-0.106		10.668
		[0.084]		*[0.068]*
PD × I(After) × I(PD)		-0.103		-8.484
		[0.015]		*[0.088]*
I(PD)		0.002		-0.119
		[0.019]		*[0.029]*
I(PD) × I(After)		0.001		0.078
		[0.203]		*[0.297]*
Number of observations	9.6m	9.6m	9.6m	9.6m
R-square	0.697	0.697	0.551	0.697

Note: The table reports estimates of the heterogeneous impact of the PD on lending spreads and amounts during the monetary tightening - starting in January 2022. I(After) equals 1 for loans issued from January 2022 onward, and I(PD) equals 1 for firms with above-median PD. All specifications include the controls from column (5) of Table 2. Standard errors are clustered at the bank level, and p-values are shown in square brackets.
Source: AnaCredit, own estimates.

economy. Motivated by concerns that aggregate lending responses may mask important distributional shifts, we focused on whether and how banks differentiate loan pricing and amounts across firms with varying default risk. The findings provide a nuanced answer: while banks consistently adjust spreads and volumes based on borrower PD, the sensitivity varies significantly with firm risk levels, bank characteristics, and competitive pressures, and evolves with the policy cycle. This highlights that the transmission of monetary policy is not uniform, but shaped by heterogeneous institutional and market conditions.

We find evidence that banks systematically differentiate credit terms based on borrower risk. Lending spreads increase with higher PDs, while loan volumes decline. These patterns are broadly in line with standard theories of risk-based pricing and credit rationing. The relatively modest sensitivity of lending spreads and amounts to changes in PDs likely reflect the through-the-cycle nature of PDs, which evolve slowly with firm conditions, as well as the supportive macroeconomic environment during much of the sample period.

Importantly, these average effects mask substantial heterogeneity across institutional and market dimensions. Larger and better-capitalized banks exhibit stronger risk sensitivity, pointing to more conservative lending behaviour among institutions with greater financial buffers.

On the other hand, competitive market environments tend to weaken the link between risk and lending spreads, consistent with theories predicting that competition can undermine prudent pricing. Notably, this effect of competition is limited to pricing and does not extend to loan amounts, indicating that banks remain cautious in risk allocation even in highly contested markets.

In addition to institutional heterogeneity, we uncover strong non-linearities in how banks respond to borrower risk. For firms with low to moderate PDs, spreads rise strongly with increases in risk. However, for already-risky borrowers (those above the median PD), the marginal pricing response is much flatter. This suggests that, beyond a certain threshold, banks may cease to differentiate rates, possibly due to concerns about adverse selection, repayment capacity, or regulatory avoidance. Such behaviour is consistent with the credit rationing theory.

The monetary tightening cycle introduced an additional layer of variation in bank behaviour. The most prominent shift occurs among high-risk firms, for whom the sensitivity of lending spreads to borrower risk declines significantly—extending earlier evidence of non-linear pricing. This suggests banks became increasingly hesitant to raise rates for vulnerable borrowers, possibly also to avoid triggering defaults or realizing losses. However, this softer pricing was not matched by more generous credit allocation: on the contrary, banks reduced loan volumes more sharply for riskier firms after tightening, signalling heightened caution in loan allocation. These diverging responses in price and quantity reflect a form of credit rationing, where banks curb risk exposure through stricter allocation rather than continued repricing. This pattern was particularly pronounced among well-capitalized banks, which appear to have exercised greater risk discrimination under tightening.

Taken together, our findings carry several important policy implications. First, during monetary tightening, the composition of new lending shifts toward firms with lower measured risk. This may support financial stability but could also lead to unintended constraints for vulnerable borrowers, especially small or high-risk firms with limited access to alternative financing. Second, the muted pricing response for riskier borrowers underscores the limits of rate-based transmission and suggests that quantity effects may dominate in tight financial conditions. Third, heterogeneity in bank behaviour—driven by capitalization, size, and market contestability—implies that monetary policy may have uneven effects across regions and borrower segments.

These findings also carry broader macroeconomic implications. As banks respond to monetary tightening by reallocating credit away from riskier firms, particularly through reductions in loan volumes, there may be downstream effects on firm survival, investment, and employment, especially for smaller or financially constrained enterprises. If credit reallocation is too abrupt or indiscriminate, it could amplify economic heterogeneity or lead to inefficient firm exits, with adverse effects on productivity dynamics. Conversely, a shift towards more prudent lending may improve long-run resource allocation by containing excessive risk-taking.

Future research could build on these findings by linking firm-level borrowing patterns to real economic outcomes such as investment activity, employment growth and incidence of default. Understanding how changes in credit pricing and allocation, particularly under monetary tightening, translate into firms' operational and financial decisions would provide a more comprehensive view of the transmission mechanism. For instance, if reduced credit access for higher-risk firms leads to cutbacks in investment or workforce reductions, the aggregate impact of tightening could be amplified. Conversely, if reallocation towards more creditworthy firms improves overall credit efficiency without adverse real effects, the policy trade-offs may be less severe.

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