Drivers of rate dispersion in loan markets: information acquisition or search frictions?

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May 12, 2026
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ABSTRACT

An empirical regularity is the persistence of significant interest rate dispersion, even after controlling for firm characteristics and loan terms. We provide evidence that this unexplained dispersion reflects structural forces of the banking loan market, namely search frictions and banks' information acquisition. These drivers have opposite implications on pricing efficiency: dispersion arising from search frictions is pure mis-pricing, whereas dispersion induced by banks' screening reflects firms' fundamentals. Leveraging detailed micro-data on lending in France, spanning from 2006 to 2024, we characterize the time and cross sectional distribution of the unexplained dispersion in lending rates, and show evidence of bank screening: that rate residuals contain information about the future evolution of firms' creditworthiness, with considerable time and cross-section heterogeneity. We rationalize these findings with a tractable model that determines loan pricing as the outcome of the interaction of search frictions and bank screening under asymmetric information. The model delivers testable predictions on the dispersion of rates and on the predictive power of residuals depending on the strength of search frictions and the severity of asymmetric information. The model calibration suggest that the role of search frictions is predominant. Finally, we outline the implications for monetary policy and we use the model to interpret heterogeneous monetary policy pass-through using high-frequency monetary policy shocks.

*HEC Paris. This work has benefited from a State grant managed by the Agence Nationale de la Recherche under the Investissements d'Avenir programme with the reference ANR-18-EURE-0005 / EUR DATA EFM.

1 Introduction

Interest rates in credit markets exhibit substantial *interest rate fragmentation across firms and banks*. A substantial part of this dispersion is accounted for by macroeconomic conditions and fundamental factors, including bank-firm relationships, contract characteristics and observable credit risk - up to $80-85\%$ for the Euro Area (Altavilla et al. (2024)). However, an empirical regularity is the persistence of a significant unexplained component, a residual dispersion that survives after controlling for these observed fundamentals. This residual, as shown in a growing literature on rate dispersion and in this paper, should not be treated as noise, but rather reflects structural forces of the banking loan market.

One perspective is to focus on rate dispersion *across similar firms and loan products*. Amiti et al. (2026) use US large loan data to document that dispersion persists within bins of homogeneous firms and loan characteristics, originated in the same quarter. They entirely attribute this across-firms dispersion to search frictions. Similarly, Kozeniauskas (2024) argues that "idiosyncratic noise" arises from differing search abilities, preventing firms from securing the lowest available rates. In addition, in both papers the contribution of firms' default risk seems negligible, as the share of variance explained by default risk measures is fairly low. This finding is in contrast with a large literature on adverse selection, that suggests that the role of unobservables and banks' relationship lending matters for interest rates. For instance, Claessens et al. (2025) use internal bank ratings assigned by banks to show that private information component matters in determining lending rates.

More puzzling, using French loan-level data, we show that dispersion may persist not only across similar firms and products, but also within the same bank (*across firms, between banks*). To rationalize this finding, we reconcile the literature on dispersion and on private information by jointly considering search frictions and unobserved risk as determinants of the unexplained rate dispersion. Considering both drivers and understanding the nature of unexplained rate dispersion is crucial, as they have opposite implications on pricing efficiency and policy intervention. On the one hand, dispersion arising in an imperfectly competitive environment is generating mispricing across firms, with important consequences on firms' investment decisions and firm competition. In addition, monetary policy pass-through is impaired by banks' market power, and overall this provides a rationale for regulation and policy intervention. On the other hand, dispersion induced unobserved information on firms' true credit risk reflects the efficiency of the banking market in overcoming asymmetric information. Any policy intervention is at best unnecessary, and policy makers can be reassured about the full pass-through of monetary policy to rates. Moreover, the interaction between these forces has non-trivial implications for the transmission of monetary policy, as we will show in the paper. After showing evidence that both forces are at play, we will propose a framework to study their interaction and understand which is prevailing.

Firstly, leveraging detailed micro-data on lending in France, spanning from 2006 to 2024, we characterize the time and cross-sectional distribution of unexplained rate dispersion. Time-bank fixed effects and observable firm and loan characteristics account for 84% of total rate variation, which is consistent with the findings in Altavilla et al. (2024) for Euro area loans. The distribution of unexplained rate residuals over time shows significant dispersion and time variation, and it responds to monetary policy shocks - a thightening reduces total variance. Secondly, we show evidence that unexplained dispersion is not pure noise, but is related to measures of competition and unobserved information. Firms in more concentrated markets face higher interest rates, but also lower overall dispersion. This suggests that banks manage to squeeze rate offers towards higher rates. Moreover, we show that rates contain forward information about the future evolution of firms' creditworthiness. In particular, there is a positive and significant correlation between paying a relatively higher rate and being ex-post more likely to default. We exclude that this result is driven by a leverage effect - leverage increases, fundamentals deteriorate, leading to higher default probability. In fact, this effect is not stronger for larger loans. Also, we test the transmission of interest rate changes to firm-level risk, exploiting the interest rate structure of the contract, fixed versus floating. Consequently, these residuals contain banks' acquired information on firms' riskiness, orthogonal to observed characteristics, which feeds into the loan interest rate. Moreover, we show that in contexts where information matters the most, this correlation is stronger; using age as a proxy of the firms' track record in credit markets, we show that for younger firms this correlation is significantly larger than for relatively older firms.

We move to studying a tractable theoretical framework that determines loan pricing as the outcome of imperfect competition, modeled via search frictions, and asymmetric information with information acquisition by banks about observationally equivalent firms. The model features two symmetric banks and two firm types, differing in their risk (success probability); search frictions are modelled as in Burdett and Judd (1983). In addition, banks can acquire a symmetric signal on firms. We characterize the equilibrium dispersed rate distribution, showing that both frictions jointly contribute to observed dispersion. Search frictions deliver *within-type dispersion*. In a non-perfectly competitive environment, banks compete for borrowers, but search frictions prevent them from perfectly undercutting each other; consequently, even homogeneous face different rates as a mixed-strategy equilibrium arises. The information structure of the market affects banks' incentives to pool/separate borrowers, determining *between-type dispersion*; under perfect information, or when banks acquire a very precise signal, good types will pay on average lower rates than bad types, leading to a positive correlation between rates and default probability.

Second, we derive important implications on the welfare distribution. Under search frictions only, but perfect information, all firms match and maximum welfare is achieved; the stronger the search frictions, the larger the banks' share of total surplus. More interestingly, the information structure has dramatic implications on welfare losses and cross-subsidization. When adverse selection is severe, good types are either cross-subsidizing bad types in a pooling equilibrium, or are fully pushed out of the market, with consequent welfare losses; more information increases overall welfare and reduces the subsidy.

Finally, we derive implications on monetary policy transmission. As expected, limited competition generally weakens the pass-through of policy rates; in fact, as rates are already close to the maximum rate that firms are willing to accept, an increase in policy rates will only partially pass through to the rate distribution. Moreover, we show that this effect interacts with the information structure of the market. Via the cost of funds, monetary policy affects the total gains from trade for each type, but mostly for safer firms; consequently, under information asymmetry, higher rates move the equilibrium from a pooling to a separating one, with safe firms either heavily subsidizing riskier ones or being completely pushed out of the market. We derive and validate the model's predictions regarding monetary policy transmission. The model predicts that, following an increase in the policy rate, the funding cost for banks is higher, and total observed dispersion decreases. Using high-frequency monetary policy shocks, we find a reduction in the dispersion of interest rate residuals.

To get a sense of the relative magnitudes, we run a calibration exercise to recover the implied parameters of competition and signal precision from the unexplained rate distribution across Banque de France rating classes. We target 3 data moments: the total variance of rate residuals, decreasing in competition and increasing in signal precision; the correlation between rates and riskiness, increasing in both competition and signal precision; the maximum rate observed. The exercise suggests that the equilibrium is close to perfect information in ex-ante safer markets, with information decreasing as we move to ex-ante riskier rating classes. However, the relative contribution of competition to unexplained variance is predominant (0-5%), even under perfect information. This result hides substantial differences in surplus distribution across banks and types.

The remainder of the paper is organized as follows. Section 2 documents the literature. Section 3 and 4 presents the data and stylized facts. Section 5 outlines the theoretical framework. Section 6 details the estimation and quantitative results. Section 7 investigates the monetary policy implications.

2 Related Literature

Our focus is to explore the extent to which information acquisition and imperfect competition jointly determine loan prices. Both frictions have been widely explored in the banking literature in isolation. Seminal works on banking competition, such as Klein (1971), Monti (1972), establish how market power drives wedges between funding costs and lending rates. Parallel to this, the foundational literature on asymmetric information Stiglitz and Weiss (1981), Bester (1985) highlights how unobservable risk leads to credit rationing and screening. However, the literature specifically addressing loan pricing through the joint lens of these two forces is less developed.

Surely, the availability of data reporting granular loan terms is relatively recent. A growing body of work leverages this data to study loan pricing, though mostly focusing on observable characteristics. For instance, Claessens et al. (2025) use internal ratings assigned by banks to identify the private information component in pricing. Similarly, Altavilla et al. (2024) focus on understanding how observable firm and loan characteristics explain interest rate variations. While this literature mainly focuses on the *observed* determinants of interest rates, we focus on the *unexplained* component of rates to uncover the unobserved determinants.

Imperfect competition and rate dispersion. First, we relate to the literature identifying potential sources of interest rate dispersion. Search frictions contribute significantly to observed dispersion in loan markets, as documented in Puglisi (2023); Mazet-Sonilhac (2025), and similarly in other financial markets Degryse and Ongena (2009); Bech and Monnet (2015); Cebul et al. (2011). The literature has also identified switching costs as a crucial source of imperfect competition (e.g. Diamond (1971) Vives (2001), Drechsler et al. (2017)) which are typically associated with higher lending rates Allen and Gale (2004). Our findings are consistent with the trade-offs implied by switching costs: banks extract rents from locked-in firms (the "captive" borrowers) but must compete to attract new clients - consistent with this view, we find that the first contract between a bank and a firm typically carries a rate discount. However, it is important to note that existing quantification exercises in this literature often focus implicitly or explicitly on search frictions alone. We argue that ignoring the role of information acquisition may lead to a bias in the estimation of underlying parameters, potentially overestimating the contribution of search frictions to observed dispersion. Our contribution is to model both forces jointly and bring them together in the quantification exercise.

The interplay of information and market power. In disentangling imperfect competition and acquired information, we build upon the literature studying their interaction. Carletti et al. (2024) provide a comprehensive review of how informational advantage and market power coexist. A key mechanism here is the *hold-up problem* Rajan (1992); Cahn et al. (2024): when a bank acquires private information about a firm's high quality, it gains an informational monopoly. While the bank may lower the rate for this 'good" firm, the rate cut is smaller than implied by the lower risk because the bank knows competitors cannot distinguish this firm from a "bad" one. [See also: Ioannidou and Ongena (2010) on ratings; Amberg and Becker (2024) and Bonfim on bank closures; Berndt et al. (2018) on risk premia.]

We take this mechanism into account when interpreting our results. Specifically, the hold-up problem implies that banks are not incentivized to cut rates aggressively even for good signals, potentially compressing the left tail of the rate distribution. Conversely, for bad signals, banks have no incentive to offer discounts. We account for these asymmetric incentives in our framework.

Structural and theoretical contributions. Our paper is most closely related to recent works that jointly analyze these frictions. Crawford et al. (2018) propose a structural model of supply and demand to estimate the relative contribution of asymmetric information and imperfect competition to loan pricing. Like them, we deviate from a competitive framework and view rates as a screening tool. However, rather than a purely structural estimation, we propose a theoretical framework where banks can actively acquire information. This setup allows us to study the theoretical interaction of the two frictions and better replicate the specific shape of dispersion observed in the data.

Our work is also related to Mazet-Sonilhac (2025), who models search and information frictions to understand bank-firm matching. Furthermore, our theoretical setup shares features with Lester et al. (2019), who model search frictions and screening in asset markets via menus of prices and quantities. We adapt this logic to the lending market. Unlike their reliance on complex menus, we focus on a mix of screening via interest rates and active information acquisition, which we believe more accurately reflects the bank lending process.

Monetary policy transmission. Finally, we contribute to the understanding of monetary policy transmission. The literature has established that market structure affects transmission, either via the "deposit channel" in concentrated markets [e.g., Drechsler et al. (2017)] or via the "credit channel" where information asymmetries amplify shocks [e.g., Bernanke and Gertler (1995)]. More recently, Wang et al. (2022); Scharfstein and Sunderam (2016) have shown that market power dampens pass-through. We contribute to this debate by showing that the interaction of search frictions and weak information acquisition creates a specific rigidity in rates (pooling equilibria) that further impairs the transmission of policy shocks to the real economy.

3 Data

This paper draws mainly on three firm-level datasets provided by the Banque de France. It leverages in particular detailed loan issuance data at the loan level, which provide all loan terms and relevant firm characteristics which help to predict interest rates. This information is complemented with credit registry data and balance-sheet information on firms.

1. **Nouveaux Crédits (2006-2024)** *Source: Banque de France*

The *Nouveaux Crédits* is a quarterly survey in which banks report the universe of newly originated loan and credit lines contracts to businesses in the first month of each quarter. It includes all loan terms (rate, amount, maturity, loan purpose and type, fixed or variable rate, guarantees), for both new agreements and renegotiated contracts that specify interest rates for the first time or revise key financial terms. This dataset is matched to firm-level identifiers (anonymized SIREN) and enriched with information on firms' descriptives, accounting and credit information (main accounting variables like balance-sheet size, debt structure, short term due repayments, proportion of drawn and undrawn credit lines, revenues). It includes also the credit score assigned by Banque de France (outlined in the following section). This dataset allows us to estimate the expected interest rate by firm-loan category, offering insights into the pricing of credit, and particularly useful for studying the dispersion of interest rates, the role of firm risk, and the transmission of monetary policy. While we focus on term loans, we store information on additional products issued in the same month (bundles).

2. **Credit Registry (Service Central des Risques, SCR) (2006-2025)** *Source: Banque de France*

The *Service Central des Risques* (SCR) is a credit registry operated by the Banque de France, which collects monthly data on outstanding loans granted by credit institutions and investment firms to companies. The reporting threshold is set at €25,000 per lender-borrower pair, which is high enough to study bank relationships for medium and large firms, excluding micro entreprises. The SCR serves as a supervisory risk database, tracking exposures across the financial system. The dataset will be particularly useful to control for borrowing patterns, credit constraints, and long-term firm-bank relationships.

3. FIBEN (1989-2022) *Source: Banque de France*

The *Fichier Bancaire des Entreprises* (FIBEN) is the Banque de France's firm-level accounting database. It draws original data from the tax returns filed by French companies, and includes aggregates and ratios that are relevant for financial assessment purposes. It includes financial statements (balance sheet, income statement, and off-balance sheet items), which are submitted annually to the tax authorities. The included accounting information will be very useful to assess firms' financial health and computing ex-post performance of firms. While the Banque de France does not collect all forms or all variables, the database still provides rich firm-level financial data over long time periods.

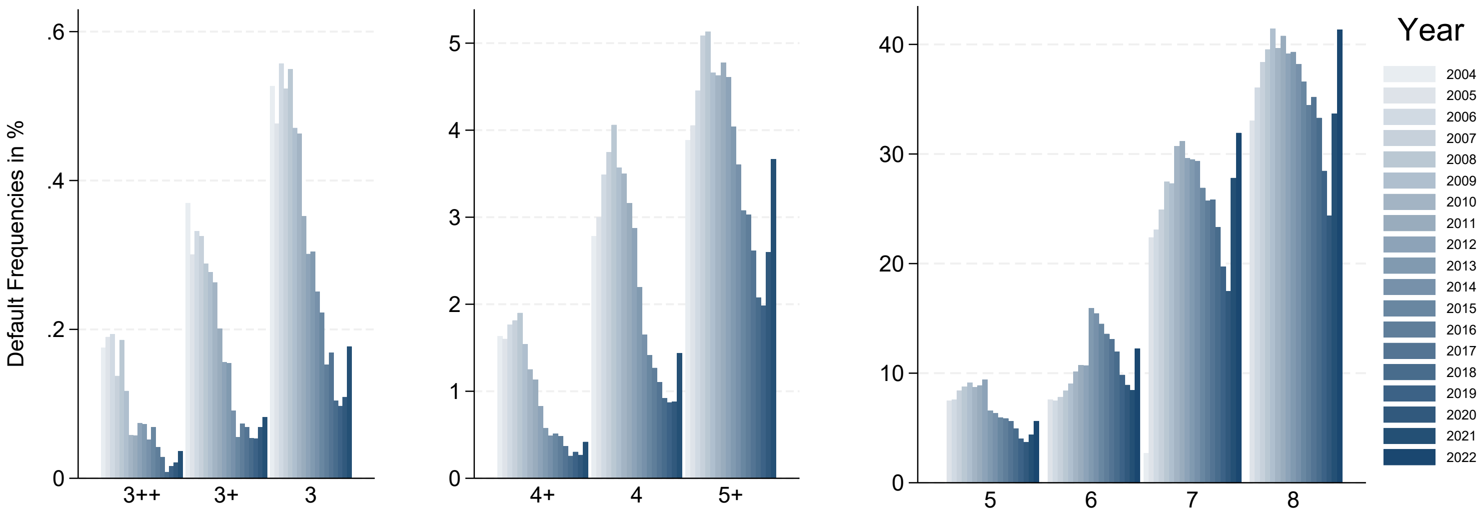
4. COTA (1989-2025) *Source: Banque de France*

This dataset contains the external rating provided by Banque de France to companies, with details on dates of revisions and relevant credit events. This rating is assigned by Banque de France annually on the basis of the latest balance-sheets and credit data available to firms beyond a sales threshold of 750K, increased in 2024 to 1250K. It is a forward-looking measure, as it gives an assessment of the firm's creditworthiness over a three-year period. Banque de France explicitly states to use the following information: the latest balance-sheet data available; data on default/delay events in payments (CIPE); sector-specific information; qualitative information, including interviews with firm managers on an annual basis, to assess the risks and difficulties the firm is facing. The rating entry is made of two component, summarizing firm size and creditworthiness; we will focus on the second one. As shown in Fig. A.1, the rating scale includes 12 rating categories, including two entries for liquidation (P) and a (0) when there is not enough information to assign a rating. A higher rating means higher default probability. This scale was reformed to a more granular one from January 2022; we will use the old scale and use Banque de France's conversion table for new categories.

From rating data to default frequencies.

Following Banque de France's approach to rating evaluations, we compute historical 3-year ahead default frequencies by rating class and year. For example, in year x we follow all firms with a rating equal to y on 01/01/x and compute the share of firms who defaulted on 31/12/x+2. The resulting default frequencies are reported in **??**. Since we are interested in the relative distance between types and transition to other rating classes, we fix default frequencies to one year (2021) and use it throughout the sample as representing the probability of default by rating class. In practice, this means that we only care about firms who change rating class over time, and we disregard the changes of PD frequencies within one class from one year to the other. We check for robustness that our analysis goes through also using default frequencies by year, which is explained by the fact that the default frequencies by class maintain the same order of magnitude over time.

Figure 1: **3-year ahead default frequencies, by rating class and year (2004-2022).**



4 Stylized facts

4.1 Dispersion

We document the dispersion in the loan market to show that **the law of one price does not hold in the lending market**. Using the loan level dataset (Nouveaux Credits), we estimate the expected interest rates for each loan on all observables, controlling for lender, firm and loan-level characteristics.

Cleaning and Sample. We start from all credit issued in the first month of each quarter, from 2006q1 to 2022q4. The original loan-level dataset has 4.6 million observations of which 1.8 unique firms. We restrict the sample to fixed-term loans to private companies and exclude credit lines/other types of credit with undefined maturity. We are left with 1.9 million observations and 0.9 million unique firms respectively. We report a descriptive table of the subsample effectively used for the regression, namely for which all relevant data entries are non missing.

Baseline Approach. We follow an approach that is vary similar to the one in Altavilla, Gürkaynak, Quaedvlieg (2024)[1], where they focus on interest rates spreads on unsecured loans in the euro area. As we cannot control for firm-level FE, because of the dataset being a subsample of issued loans, we will focus on firm's clusters, by including fixed effects of salient firm characteristics and also credit/accounting variables. For each firm-bank-time observation, we regress TEG (total effective rate) on firm characteristics, loan characteristics, and FE:

[1] Altavilla, Carlo and Gürkaynak, Refet S. and Quaedvlieg, Rogier, Macro and Micro of External Finance Premium and Monetary Policy Transmission (April, 2024). ECB Working Paper No. 2024/2934

Rating Scale	**N obs.**	**rate** (mean)	**rate** (s.d.)	**Quantity** (mean, K-Eur)	**Maturity** (mean, months)	**Var. Rate** (in %)	**Age** (mean, years)	**Loan/Assets** (mean, in %)	**Bank Debt/Assets** (mean, in %)
3++	7948	2.1	1.8	3754.5	59.0	35	39.0	5.4	19.6
3+	22681	2.2	1.8	2919.3	53.5	37	33.7	5.0	20.6
3	43073	2.3	1.8	2271.5	42.4	37	31.7	5.3	22.0
4+	71629	2.8	2.1	1092.2	34.8	39	28.1	6.2	23.0
4	112974	2.8	2.0	670.2	27.9	43	26.1	7.1	25.0
5+	106418	2.9	2.0	545.5	23.9	48	23.4	7.7	30.3
5	46510	3.5	2.2	781.8	17.9	51	23.1	8.3	31.0
6	13625	3.7	2.2	923.4	16.6	52	21.4	10.4	34.2
7	2657	4.2	2.3	134.7	14.8	62	19.7	8.6	32.7
8	1592	5.0	2.6	107.8	13.2	61	18.0	8.4	31.2
9	268	5.5	2.7	134.0	11.9	48	16.5	10.0	31.7
P (liquidation)	3716	5.0	2.0	114.5	3.4	26	21.8	5.7	33.4
0 (no rating)	24777	3.2	2.1	1895.8	45.0	40	16.1	12.4	27.2
Total	457868	2.9	2.1	1098.1	30.5	44	25.8	7.3	26.5

Table 1: Source: Banque de France (Nouveaux Credits, COTA, SCR, FIBEN) Descriptive table of the loan-level regression sample. Rate refers to total effective rate (including all fees).

$$\text{Rate}_{i,b,l,t} = \alpha + \beta \cdot \text{LoanChar}_{i,b,l,t} + \gamma \cdot \text{FirmChar}_{i,t} + \delta_{FE} + \varepsilon_{i,b,l,t} \tag{1}$$

where time t is quarter, b is bank, i is firm, l is loan; X includes loan size, risk weighting assigned by the bank, maturity, variable rate dummy, personal loan dummy, individual entrepreneur dummy, firm age and age squared, risk weighting, short term debts, turnover, collateral (% of assets, if available), available credit before limit, bank and non bank debt (potentially also past volatility from balancesheet data). Fixed effects include Quarter × Banks × Loan type × 2-digit Sector, which well captures the supply schedule for similar products for each bank; then we include region, size, rating, size, fixed effects, and whether the firm belongs to a group. The regression sample includes 458 thousand observations and 120 thousand firms.

Fig. 2 summarizes the share of variation explained by observables, while the regression table is reported in appendix Table B.1. The explained variation on observables is around 80%, with most of the variation explained by quarter (50%), lender (20%), and the remaining 10% explained by firms' key characteristics. These results resemble closely those by to Altavilla, Gürkaynak, Quaedvlieg (2024), who can control for firm FE directly and have a residual variation of around 12%; even if we can only control for firm's characteristics, it thus seems reasonable to think that having firm FEs would not drastically change the result. Consequently, the remaining variation is unexplained, and hints at the presence of some market frictions.

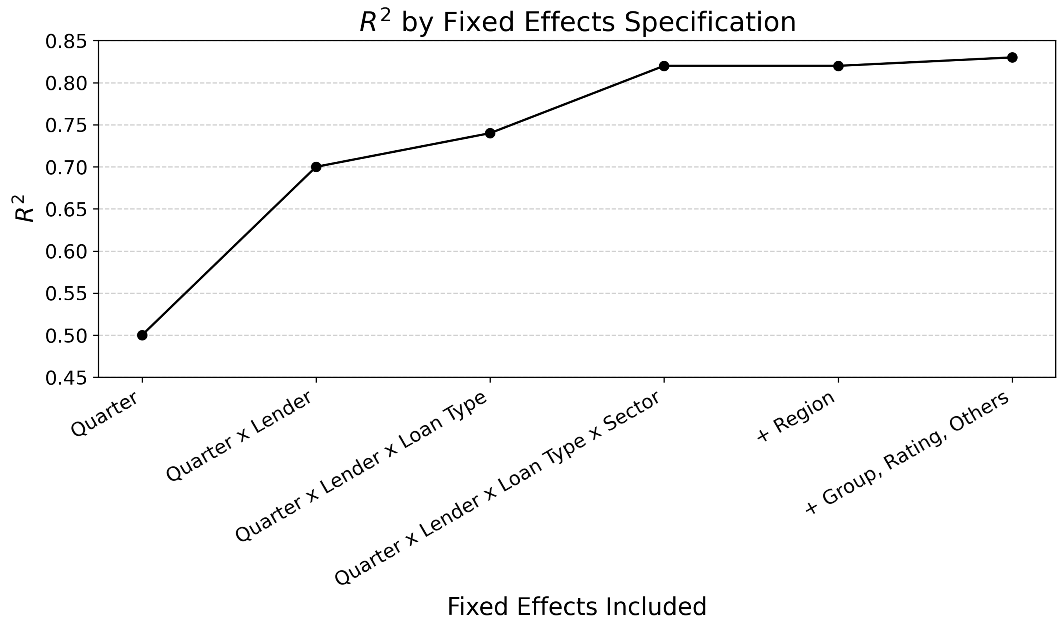


Figure 2: The figure shows the increase in R^2 of the baseline regression after gradually including fixed effects interactions and the other observables. Observables explain up to 83-84% of total rates variation.

4.1.1 Time and cross-sectional distribution of rate residuals

The residuals of the above regression represent the unexplained rate component with respect to the predicted rate. It is then possible to characterize their distribution, over time and across firm characteristics. The variance of unexplained rate residuals indicates substantial dispersion around the predicted rate, with firms one standard deviation above or below the mean facing a difference of 2 percentage points - a meaningful gap in the context of loan pricing and external financing in general (see Appendix B). In we report additional specifications, including a specification with firm fixed effects, varying dispersion by bank and alternative regression approaches.

4.2 Rate residuals and competition measures

We study the distribution of unexplained rate residuals in relation to standard measures of competition. We show that in more concentrated markets firms pay overall higher rates, but the distribution of rates is less dispersed.

Using credit registry data, we aggregate lending information across geographical areas and time. Specifically, we sum the amount of drawn credit for each firm at the bank-department-quarter level to assess the relative exposure of each bank in that market. As a robustness check, we verify that our results hold when including undrawn credit. Finally, we use each bank's total lending per department to compute a standard Herfindahl-Hirschman Index (HHI) of concentration. Fig. B.7

4.3 Rate residuals and unobserved information

In the following, we show that rate residuals are positively correlated with firms' realized riskiness, as implied by the evolution of firms' rating assigned by Banque de France and converted into a default probability measure (as explained in the Data section). We choose a measure of creditworthiness over others based on balance-sheet indicators or growth as utimately the bank cares about loan repayment. We will exclude that this correlation is purely driven by a leverage effect, and conclude that it is a measure of the unobservable information owned by the bank and embedded in rates.

4.3.1 Correlating ex-ante rate and ex-post change in default probability

Rate residuals might be the result of three factors; i) imperfect competition, which endow banks with some degree of market power ii) information that the lender acquires about the borrower, in addition to the public information observed in the registry iii) noise, from the above estimation procedure. In the first two cases, although for different reasons, rates will be correlated with ex-post firm outcomes. If the lender manages to extract a higher rent from a borrower, their leverage would increase with respect to other firms and their ex-post fundamentals will worsen; on the contrary, if the lender acquires information about the borrower, the rate should reflect beliefs about the true firm type. In both cases, a higher rate should be correlated with worse ex-post fundamentals.
We test for this correlation by including the changes probability of default of firm i P_i^{t+k} in our baseline rate regression.

$$\text{Rate}_{i,b,l,t} = \alpha + \beta \cdot \text{LoanChar}_{i,b,l,t} + \gamma \cdot \text{FirmChar}_{i,t} + \sum_{t+1}^{t+k} \beta_k \Delta P_i^{t+k} + \delta_b + \lambda_t + \varepsilon_{i,b,l,t} \tag{2}$$

where time t is quarter, b is bank, i is firm, l is loan. Standard errors are clustered at the lender-quarter level. An increase in P_i^{t+k} captures the transition to a worse rating class after k years from loan issuance. Since we control for information at time t, the coefficients β_k measure the correlation with unexplained changes in the borrower's default risk. We plot the β_k over the horizon $[t+1, t+h]$ in Fig. 3. We find a positive and significant correlation between the rate residuals and the future change in default probability, which is stronger in the first year after the loan issuance and then decreases over time. This suggests that rates contain forward-looking information about the borrower's creditworthiness that is not captured by observable characteristics at the time of loan issuance. The fact that the correlation is stronger in the first year may indicate that banks have better information about short-term risks or that the impact of unobserved factors diminishes over time.

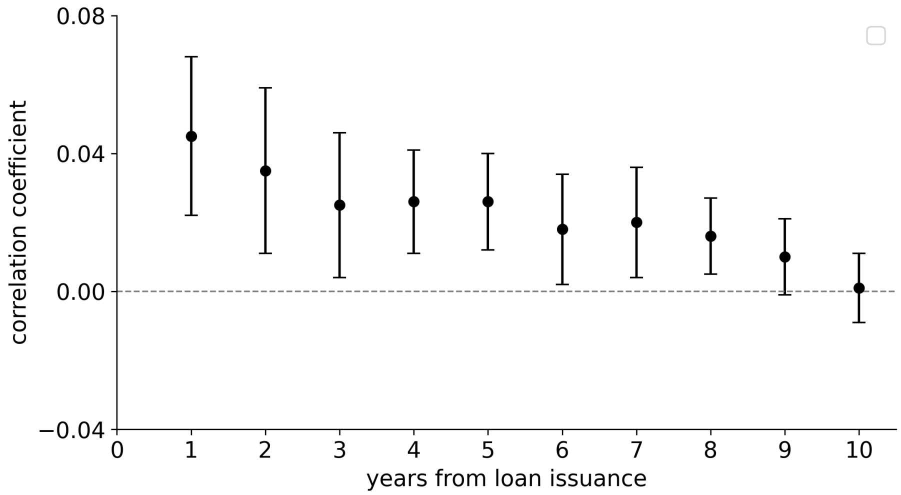


Figure 3: Correlation between rate residual and unexpected changes in default probability, by year. Balanced sample.

Excluding the leverage effect. We adopt two approaches to show that the observed correlation between rate residuals and unexpected changes in riskiness is not driven by a leverage effect - higher rates induce higher ex-post riskiness through the worsening of firm's fundamentals. Instead, it identifies banks' additional information with respect to the econometrician - banks recognize riskier types within the same rating class and offer a higher rate. A more comprehensive treatment of this analysis is provided in the Appendix B.6.

Firstly, we analyse this correlation in the cross-section. We show that, contrarily to what a leverage effect would imply, this correlation is not significantly stronger for worse rating classes, where firms are closer to the default threshold and should be more sensitive to higher rates. Then, we expect the leverage effect to be stronger if the firm is paying a rate premium over a large proportion of its liabilities. However, we compare the correlation coefficients for quantiles of loans over assets and find no significant difference. We repeat the same exercise with the share of bank debt, in case the residual was informative of the rates on other loans, and results are robust. Finally, we show that these correlations are stronger in contexts when information is more valuable, namely when banks may put more effort in acquiring additional information or screening applications. We then use firms' age to distinguish firms for which we expect the unobserved creditworthiness component contained in rates to be very large and dispersed (proxy for risk/growth prospects Haltiwanger, Jarmin,Miranda, 2013) and as a proxy of the length in the credit market (Cloyne, Ferreira, Froemel, Surico, 2023). As expected, we find that the correlation for younger firms (below the 20% percentile of age in our sample) is significantly larger than for older ones (above 80% percentile).

Secondly we directly test the transmission of interest rate changes to firm-level risk in a quasi experimental setting. We exploit the different rate structure offered to firms (floating vs fixed rate) to test the impact of a rise in reference rates on firms' riskiness. We find no significant impact of increased debt-servicing costs on subsequent rating worsening, suggesting that an increase in servicing costs inducing an increase in leverage cannot alone induce a worsening firm-level risk. Interestingly, while the rate increase does not induce a worse ex-post outcome, the loan interest rate remains a significant predictor of ex-post riskiness. As the intensity of the effect depends on the individual exposure to variable rate, we further add an interaction term of the reference rate increase with the loan-to-assets and total bank debt-to-assets ratios; the result is unchanged. To further mitigate the issue of self-selection of firms into fixed or floating rate contracts, we repeat the exercise on loans originated at the end of the ZLB period, when firms did not expect a rate hike (end 2021), with same results.

5 Model

We introduce a model of loan pricing in which imperfect competition and asymmetric information are jointly at play. The framework draws from the general market setting proposed by Lester et al. (2019). We adapt it to the bank loan market, however we deviate from the assumption of menu contracts, for which we find little evidence in our sample[2]. Instead, we assume that banks set interest rates based on simmetric signals they receive on firms, thus focusing purely on interest rates setting and fixing quantity. We further introduce an interest rate "leverage effect", which will introduce firm-specific bank costs of lending, and the possibility for banks to acquire signals on firms. In the next sections, we will calibrate this framework to provide an estimate of the relative importance of screening and search in our framework, and then test the monetary policy implications of the model.

5.1 Environment

We examine the interactions between two homogeneous and risk-neutral banks banks and a continuum of firms. Firm sample banks' offers to take one loan of fixed quantity 1 at an interest rate r to undertake a project. Projects are risky, characterized by a success probability p, which for generalization could be endogenous to the interest rate on the loan r - a higher interest rate linearly decreases the ex-post success probability. This captures the idea that higher interest rates may lead to higher default probabilities, as they increase leverage and thus reduce the net return of the project. Formally, we assume that the success probability is a decreasing function of the interest rate:

$$p = p(r), \quad \text{with} \quad \frac{\partial p}{\partial r} < 0. \tag{3}$$

Consequently, the bank's effective cost of lending, denoted by c, becomes a function of the interest rate charged. As the rate rises, the default risk increases, implying:

$$c_i = c_i(r), \quad \text{with} \quad \frac{\partial c}{\partial r} > 0. \tag{4}$$

[2] we find that, conditional on all observable characteristics in our sample, there is a negative relationship between rates and quantity

5.1.1 Gains from trade.

Banks. The opportunity cost of bank capital is set by the central bank's policy rate, r^{CB}. Due to *limited liability*, firms only repay the loan if the project is successful. Therefore, the competitive break-even rate for banks, c, is defined by the condition that the expected repayment equals the opportunity cost of capital:

$$c = \frac{r^{CB}}{p(c)} \tag{5}$$

Firms. There is a continuum of risk-neutral firms of measure 1 per bank. We assume that firms have a reservation rate R, which for simplicity represent the value of the project if successful[3]. The expected return for a firm facing an interest rate r is:

$$\Pi_{firm} = p(r)(R - r) \quad \text{if} \quad r \leq R, \quad \text{and} \quad \varepsilon > 0 \quad \text{otherwise} \tag{6}$$

In other words, firms will only accept a loan if the interest rate is below their reservation rate. We also assume that firms are affected by monetary policy rates exclusively through bank lending.

5.1.2 Market Frictions

The model departs from the standard competitive framework by introducing two distinct types of frictions: imperfect competition via search frictions and asymmetric information regarding firm types.

Search Frictions. We introduce search frictions as in the dispersed equilibrium framework of Burdett and Judd (1983), which generates imperfect competition between banks and rate dispersion not related to credit risk. Specifically, we assume that a fraction π of firms are "shoppers", meaning they sample offers from both banks and accept the lowest one, while the remaining fraction $1 - \pi$ are "captive", meaning they only sample one offer and accept it if it is below their reservation rate. Banks know the aggregate proportion π, but the specific number of offers a firm has sampled is private information to the firm. For expositional convenience, we assume that π is constant across firm types, although this assumption can be relaxed. This structure leads to a mixed-strategy equilibrium in interest rates.

Asymmetric Information. The population of firms is divided into two types, *Good* (share μ_g) and *Bad* (share μ_b), where $\mu_b + \mu_g = 1$, differing in riskiness, as the probability of success is lower for bad firms: $p_b(r) < p_g(r)$. Consequently, for banks the cost of lending to a bad firm is strictly higher than lending to a good firm at a given interest rate r: $c_g(r) < c_b(r)$. In the following, we also assume that the reservation rate of good firms is lower than that of bad firms: $\bar{r}^g < \bar{r}^b$. This assumption is not crucial to solve the model, but it will be important to deliver the positive correlation between the firm's type and the interest rate paid. The bank cannot directly observe the

[3] it may also represent the minimum rate available in the non-bank market

type of a firm, but it knows the population shares and the type-specific cost functions and reservation rates. This structure leads to a separating or partially pooling equilibrium in interest rates, depending on the severity of the adverse selection problem. Finally, we look at the case in which $c_g(r) < c_b(r) < \bar{r}^g < \bar{r}^b$.

5.1.3 Information Acquisition

Let $\theta \in \{g, b\}$ denote the firm's true type, with population shares μ_g and $\mu_b = 1 - \mu_g$. Each bank can acquire a binary signal $s \in \{g, b\}$ at cost C_s per firm. The signal is informative but imperfect:

$$\Pr(s = \theta \mid \theta) = q_\theta > 0.5, \quad \forall \theta \in \{g, b\}$$

where q_g is the probability of correctly identifying a good type, and q_b is the probability of correctly identifying a bad type.

The fraction of firms receiving each signal is:

$$\sigma_g \equiv \Pr(s = g) = q_g \mu_g + (1 - q_b)\mu_b$$
$$\sigma_b \equiv \Pr(s = b) = q_b \mu_b + (1 - q_g)\mu_g$$

By construction, $\sigma_g + \sigma_b = 1$.

Bayesian updating. Upon observing signal $s_i \in \{g, b\}$, the bank updates its prior belief μ_g to a posterior belief about facing a good type:

$$\alpha^{s_g} \equiv \Pr(\theta = g \mid s = g) = \frac{q_g \mu_g}{q_g \mu_g + (1 - q_b)\mu_b}$$
$$\alpha^{s_b} \equiv \Pr(\theta = g \mid s = b) = \frac{(1 - q_g)\mu_g}{(1 - q_g)\mu_g + q_b \mu_b}$$

Note that $\alpha^{s_g} > \mu_g > \alpha^{s_b}$: a good signal increases the belief that the firm is good, while a bad signal decreases it. The complementary probabilities of facing a bad type are:

$$1 - \alpha^{s_g} = \frac{(1 - q_b)\mu_b}{q_g \mu_g + (1 - q_b)\mu_b}, \quad 1 - \alpha^{s_b} = \frac{q_b \mu_b}{(1 - q_g)\mu_g + q_b \mu_b}$$

5.2 Equilibrium Analysis

We start by examining the equilibrium properties of the model in the extreme cases of perfect information (or perfect signal) or no information (or no signal). The equilibrium will feature dispersed rate distributions: *within types* for any value of $\pi \in (0, 1)$, excluding extreme cases of monopoly and perfect competition; *between types*, depending on the underlying hypothesis on the information structure.

5.3 Equilibrium under perfect information (or perfect signal)

The bank perfectly recognizes the type when it meets a firm. Basically, this is equivalent to solving two type-specific maximization problems.

Profit maximization. Banks' expected profits are as follows:

$$Profits^i(r) = \begin{cases} \mu_i[(1-\pi) + \pi(1 - F(r))](r - c_i) & \text{if } r \leq \bar{r} \\ 0 & \text{otherwise} \end{cases}$$

That is, the bank trades-off higher profits and lower acceptance probability: every firm i is met with probability μ_i; the bank gets $(r - c_i)$ if the firm accepts; the firm accepts with probability 1 if it is captive, and if it observes a higher offer from the other bank when it is a shopper, with probability $(1 - F(r))$. $F(r)$ is the equilibrium rate distribution.

Limit cases of monopoly/competition $\pi = \mathbf{0}, \mathbf{1}$. It is useful to examine the extreme cases of monopoly and perfect competition to build the intuition for the general case. In general, when banks operate under monopoly or perfect competition, the distribution is degenerate. The bank offers to each type the reservation rate $\bar{r}^i$ under monopoly, as all firms will always sample only one offer and accept it for as long as it is not higher than the reservation rate; and the competitive rate c_i under perfect competition, as all firms will visit both banks and get two rate quotes.

Imperfect competition $\pi \in (0, 1)$ Under imperfect competition, a dispersed rate equilibrium arises, as in Burdett and Judd (1983). Intuitively, take any rate between the cost and the reservation rate. This rate could not be the pure-strategy equilibrium, as deviations are profitable: each bank would be tempted to either lower the offered rate, and win all the shoppers; or raise the interest rate, and get more profits from captive firms. The problem of the bank is to offer a distribution of rates such that 1) it makes equal profits in expectation and 2) it maximizes possible profits. We find $\mathbf{F^i(r)}$ such that:

$$\mu_i(1-\pi)(\bar{r}^i - c_i) = \mu_i[1 - \pi + \pi(1 - F^i(r))](r - c_i)$$

where I am assuming that, although the cost will be convex in r, the slope of c(r) at $\bar{r}^i$ is lower than 1. This implies that the highest rate coincides with the reservation rate, for each type. The bank makes maximum profits from captive firms at the reservation rate; then, for all other rates on the support, it makes equal profits in expectation.

Proposition 5.1. *For $\pi \in (0, 1)$ and under perfect information (or perfect signal), there exists a unique symmetric mixed-strategy equilibrium. For each firm type i, banks randomize their rate offers according to the cumulative* *distribution function $F^i(r)$ on the support $[\underline{r}^i, \bar{r}^i]$:*

$$F^i(r) = \begin{cases} 0 & \textit{if } r < \underline{r}^i \\ 1 - \frac{1-\pi}{\pi}\left[\frac{\bar{r}^i - r}{r - c_i(r)}\right] & \textit{if } \underline{r}^i \leq r \leq \bar{r}^i \\ 1 & \textit{if } r > \bar{r}^i \end{cases}$$

where the upper bound $\bar{r}^i$ is the reservation rate, and the lower bound $\underline{r}^i$ is implicitly defined by $F(\underline{r_i}) = 0$.

Finally, the observed rate distribution across types is the mixture of the distributions, weighted by each type's population share.

$$F^i(r) = \begin{cases} 0, & \text{if } r < \underline{r^g} \\ \mu_g F^g(r) + \mu_b F^b(r), & \text{if } \underline{r^g} < r \leq \bar{r}^b \\ 1, & \text{if } r > \bar{r}^b \end{cases}$$

Densities f(r).:

$$f^i(r) = \frac{\partial F^i(r)}{\partial r} \qquad\qquad f(r) = \mu_g f^g(r) + \mu_b f^b(r)$$

Given a specific functional form for the cost function, we can solve for the dispersion (simply the variance of the total distribution) and the correlation between observed rates and default probabilities to match the empirical findings. We will solve and simulate a version of the model in the next section.

5.4 Equilibrium under no information (or uninformative signal)

The bank operates under information asymmetry, namely it cannot distinguish the firm type upon meeting. We may still assume that the bank knows the population composition and the type-specific costs and reservation rates. Consequently, it faces a type-specific demand on two separate intervals: if $r < \bar{r}^g$, both types would accept an offer (pooling), while if $\bar{r}^g < r < \bar{r}^b$ the bank knows that only bad types would accept. The equilibrium will feature a pooling or separating region depending on the severity of the adverse selection problem; mild adverse selection would incentivize pooling, while in the severe adverse selection case banks are more likely to reduce or avoid pooling and offer only high rates.

Limit cases of monopoly/competition $\pi = 0, 1$. We begin by analyzing the equilibrium in the extreme cases of monopoly and perfect competition to build the intuition for the general case.

Monopoly $\pi = 0$. The bank makes profits

$$\Pi = \begin{cases} (r - c^{avg}(r)) & \text{if } \underline{\underline{r}} < r \leq \bar{r}^g \\ \mu_b(r - c_b(r)) & \text{if } \bar{r}^g < r \leq \bar{r}^b \end{cases}$$

where $c^{avg}(r) = \mu_g c_g(r) + \mu_b c_b(r)$ is the weighted average of the type-specific costs. The bank compares the maximum profit it can extract in each region:

$$\max\{(\bar{r^g} - c_{avg}(r^g)), \mu_b(\bar{r^b} - c_b(\bar{r^b}))\}$$

We assume that marginal costs increase sufficiently slowly ($c'(r) < 1$) such that profits are increasing in rates within each interval[4]. Consequently, the optimal strategy must be a corner solution: the bank compares the maximum profit from pooling (at $\bar{r}^g$) against the maximum profit from screening (at $\bar{r}^b$).

Lemma 5.1. ***Define*** ϕ***:***

$$\boxed{\phi \equiv (\bar{r}^g - c^{avg}(\bar{r}^g)) - \mu_b(\bar{r}^b - c_b(\bar{r}^b))}$$

Under monopoly ($\pi = 0$), $c'(r) < 1$ and with an uninformative signal, the unique equilibrium is $\bar{r^g}$ if $\phi > 0$, and $\bar{r^b}$ if $\phi \leq 0$.

Under monopoly, the unique profit-maximizing interest rate depends on the sign of ϕ. **We can interpret ϕ and an indicator of the strength of asymmetric information.** If $\phi \leq 0$, adverse selection is severe, and banks extract more profits from trading with bad types only. If $\phi > 0$ adverse selection is mild, and banks extract more profits from pooling good and bad types.

Perfect competition $\pi = 1$ In this case, the bank makes zero profits, offering the competitive rate in the population.

Lemma 5.2. *Under perfect competition ($\pi = 1$) and asymmetric information, the unique equilibrium is a pooling contract at the competitive rate $r^c = c^{avg}$, implicitly defined by the break-even condition given average costs. Given the assumption $c^b < \bar{r}^g$, this rate is strictly below the reservation rate of both types and is accepted by the entire population.*

When $\pi = 1$, firms always compare offers. Bertrand competition drives the interest rate down to the break-even point. Since the competitive rate satisfies $r^c < \bar{r}^g$ by assumption, both types participate, and the bank faces the average cost of the population. The equilibrium profit is therefore $\Pi = (\mu_b + \mu_g)(r^c - c^{avg}(r^c)) = 0$.

[4]if $c'(r)$ was increasing over the rate interval, there may be a point where the cost is higher than the benefit, and an internal solution would be optimal ($r* < \bar{r^g}$ or $r* < \bar{r^b}$)

General case: Imperfect Competition. Bank profits depend on the interval.

$$\Pi = \begin{cases} [1-\pi+\pi(1-F(r))](r-c^{avg}(r)) & \text{if } r \leq \bar{r}^g \\ \mu_b[1-\pi+\pi(1-F(r))](r-c_b(r)) & \text{if } \bar{r}^g < r \leq \bar{r}^b \end{cases}$$

where $c^{avg}(r) = \mu_g c_g(r) + \mu_b c_b(r)$. As in the perfect information case, the bank trades-off profits and acceptance probability. However, the bank knows that both firms would accept a rate in the pooling region, while a rate on the separating region would be accepted by bad types and rejected by good type, that would exit the market. As in the perfect information case with one type, the equilibrium CDF will be derived as the isoprofit function given profits at the maximum rate charged. However, now the maximum rate depends on the severity of adverse selection, as captured by the value of ϕ.

5.4.1 Severe adverse selection: $\phi \leq 0$

Banks surely trade with bad types, and possibly offer some rates in the pooling region. When trading with captive firms, the bank makes more profits from trading with bad types than pooling. Therefore, the maximum rate observed in the market is $\bar{r}^b$. The bank offers a distribution of rates on the separating region to extract profits from bad types, and may also offer some rates in the pooling region to extract profits from good types, such that:

$$\begin{aligned} &[1-\pi+\pi(1-F^a(r))](r-c^{avg}(r)) = \mu_b(1-\pi)(\bar{r}^b - c_b(\bar{r^b})) && \text{if } r \leq \bar{r}^g \\ &\mu_b[1-\pi+\pi(1-F^a(\bar{r^g})-F^b(r))](r-c_b(r)) = \mu_b(1-\pi)(\bar{r}^b - c_b(\bar{r}^b)) && \text{if } \bar{r}^g < r \leq \bar{r}^b \end{aligned}$$

Proposition 5.2. *For $\pi \in (0,1)$, $\phi \leq 0$, $c'(r) < 1$ and with an uninformative signal, there exists a unique symmetric mixed-strategy equilibrium. Banks randomize their rate offers according to the cumulative distribution function $F(r)$ on the support $[\underline{r}^a, \bar{r}^b]$:*

$$F(r) = \begin{cases} 0 & \text{if } r < \underline{r}^a \\ F^a(r) & \text{if } \underline{r}^a \leq r \leq \bar{r}^g \\ F^a(\bar{r}^g) + F^b(r) & \text{if } \bar{r}^g < r \leq \bar{r}^b \\ 1 & \text{if } r > \bar{r}^b \end{cases}$$

where the equal profit condition on each interval gives $F^a(r), F^b(r)$:

$$\begin{aligned} F^a(r) &= \min\left\{1 - \frac{1-\pi}{\pi}\left[\frac{\mu_b(\bar{r}^b - c_b(\bar{r}^b))}{(r-c^{avg}(r))} - 1\right], 0\right\} \\ F^b(r) &= 1 - F^a(\bar{r^g}) - \frac{1-\pi}{\pi}\left[\frac{(\bar{r}^b - c_b(\bar{r}^b))}{(r-c_b(r))} - 1\right] \end{aligned}$$

and the lower bounds $\underline{r}^a$ and $\underline{r}^b$ are implicitly defined by $F^a(\underline{r}^a) = 0$ and $F^b(\underline{r}^b) = 0$.

$$\underline{r}^a = c^{avg}(\underline{r}^a) + \mu_b(1-\pi)(\bar{r}^b - c_b(\bar{r}^b))$$
$$\underline{r}^b = c_b(\underline{r}^b) + \frac{\bar{r}^g - c^{avg}(\bar{r}^g)}{\mu_b}$$

This form ensures that the combined function on the two intervals cumulates to 1: by construction, $F^a(\bar{r^g}) + F^b(\bar{r^b}) = 1$. Our equilibrium differs from Burdett and Judd (1983) in accounting for demand heterogeneity, preserving the mixed-strategy equilibrium result. On the existence of a pooling region, we find that it depends on the severity of adverse selection, as captured by ϕ.

Lemma 5.3. *The pooling region exists when adverse selection is relatively mild* $-\frac{\pi}{1-\pi}(\bar{r}^g - c^{avg}) < \phi \leq 0$, *while for values of* ϕ *below this threshold the equilibrium is fully separating.*

We find the threshold from $F^a(\bar{r}^g) > 0$. Intuitively, when adverse selection is severe, the bank prefers to offer only separating contracts, as the profits from pooling are too low. When adverse selection is mild, the bank offers some pooling contracts to extract profits from good types, while still offering some separating contracts to extract profits from bad types.

5.4.2 Weak Adverse Selection: $\phi > 0$

Banks trade with both types (Pooling Equilibrium). Banks make more profits from pooling both firms at the reservation rate of good types when meeting captive firms. Consequently, the maximum rate observed in the market is $\bar{r^g}$, trades will only happen in the pooling region and all firms will receive credit. The CDF of rates is found by setting the equal profit condition on the pooling region:

$$[1-\pi+\pi(1-F^a(r))](r - c^{avg}(r)) = (1-\pi)(\bar{r^g} - c_{avg}(\bar{r^g}))$$

Proposition 5.3. *For* $\pi \in (0,1)$, $\phi > 0$, $c'(r) < 1$ *and with an uninformative signal, there exists a unique symmetric mixed-strategy equilibrium. Banks randomize their rate offers according to the cumulative distribution function* $F(r)$ *on the support* $[\underline{r}, \bar{r}^g]$:

$$F(r) = \begin{cases} 0 & \text{if } r < \underline{r} \\ 1 - \frac{1-\pi}{\pi}\left[\frac{(\bar{r}^g - r)}{(r - c^{avg}(r))}\right] & \text{if } \underline{r} \leq r \leq \bar{r}^g \\ 1 & \text{if } r > \bar{r}^g \end{cases}$$

Where the upper bound $\bar{r}^g$ *is the reservation rate of the good type, and the lower bound* $\underline{r}$ *is implicitly defined by* $F(\underline{r}) = 0$.

With mild adverse selection, the equilibrium is closest to the Burdett and Judd (1983) dispersed price equilibrium, as banks offer only pooling contracts.

5.5 Equilibrium under informative signal

We now examine the scenario where banks can acquire an imperfect signal about each firm's type for a fixed cost C_s. This allows us to analyze the endogenous information acquisition decision and characterize the equilibrium as signal precision varies from uninformative to perfect.

Signal-Specific Equilibria. Conditional on acquiring the signal, banks face σ_g firms with good signals and σ_b firms with bad signals. For each group, the bank solves a rate-setting problem analogous to the no-information case, but with updated beliefs about the shares of types in the population receiving signal s_i. The sign of ϕ^{s_i} determines whether the equilibrium is pooling or separating. For each signal s_i, define:

$$\phi^{s_i} \equiv (\bar{r}^g - c^{avg,s_i}(\bar{r}^g)) - (1-\alpha^{s_i})\left(\bar{r}^b - c_b(\bar{r}^b)\right)$$

As before, the equilibrium is full pooling if $\phi^{s_i} > 0$, mixed if $-\frac{\pi}{1-\pi}(\bar{r}^g - c^{avg,s_i}(\bar{r}^g)) \leq \phi^{s_i} \leq 0$, fully separating if $\phi^{s_i} \leq -\frac{\pi}{1-\pi}(\bar{r}^g - c^{avg,s_i}(\bar{r}^g))$

Bank profits. For firms with signal s_i, bank profits are:

$$\Pi^{s_i}(r) = \begin{cases} [1-\pi+\pi(1-F^{s_i}(r))]\,(r - c^{avg,s_i}(r)) & \text{if } r \in [\underline{r}^{s_i}, \bar{r}^g] \\ (1-\alpha^{s_i})\,[1-\pi+\pi(1-F^{s_i}(r))]\,(r - c_b(r)) & \text{if } r \in (\bar{r}^g, \bar{r}^b] \end{cases}$$

The first region corresponds to rates that both types (weighted by α^{s_i}) would accept; the second region contains only bad types. After observing signal s_i, the bank's expected pooling cost of lending at rate r is $c^{avg,s_i}(r) \equiv \alpha^{s_i} c_g(r) + (1-\alpha^{s_i})c_b(r)$, where $c_\theta(r) = r_{CB}/p_\theta(r)$ as before.

Proposition 5.4 (Signal Specific Equilibrium)**.** *For $\pi \in (0,1)$ and under signal acquisition, there exists a unique symmetric mixed-strategy equilibrium. Conditional on receiving signal s_i, banks randomize their rate offers according to the cumulative distribution function $F^{s_i}(r)$ that takes the same functional form as in the no-information case, with population share μ_b replaced by $(1-\alpha^{s_i})$ and average cost $c^{avg}(r)$ replaced by $c^{avg,s_i}(r)$. The aggregate distribution is the mixture of signal-specific distributions weighted by the shares of the population receiving the signal σ_i.*

Explicitly, the signal-specific distributions are as follows, depending on the sign of ϕ^{s_i}:

Case 1: Pooling equilibrium ($\phi^{s_i} > 0$)

$$F^{s_i}(r) = \begin{cases} 0 & \text{if } r < \underline{r}^{s_i} \\ 1 - \dfrac{1-\pi}{\pi}\left[\dfrac{\bar{r}^g - r}{r - c^{avg,s_i}(r)}\right] & \text{if } \underline{r}^{s_i} \leq r \leq \bar{r}^g \\ 1 & \text{if } r > \bar{r}^g \end{cases}$$

where $\underline{r}^{s_i}$ solves $F^{s_i}(\underline{r}^{s_i}) = 0$.

Case 2: Hybrid/Separating equilibrium ($\phi^{\mathbf{s_i}} \leq \mathbf{0}$)

$$F^{s_i}(r) = \begin{cases} 0 & \text{if } r < \underline{r}^{s_i,a} \\ F^{s_i,a}(r) & \text{if } \underline{r}^{s_i,a} \leq r \leq \bar{r}^g \\ F^{s_i,a}(\bar{r}^g) + F^{s_i,b}(r) & \text{if } \bar{r}^g < r \leq \bar{r}^b \\ 1 & \text{if } r > \bar{r}^b \end{cases}$$

where the equal-profit condition on each interval gives:

$$F^{s_i,a}(r) = \min\left\{1 - \frac{1-\pi}{\pi}\left[\frac{(1-\alpha^{s_i})(\bar{r}^b - c_b(\bar{r}^b))}{r - c^{avg,s_i}(r)} - 1\right], 0\right\}$$

$$F^{s_i,b}(r) = 1 - F^{s_i,a}(\bar{r}^g) - \frac{1-\pi}{\pi}\left[\frac{\bar{r}^b - c_b(\bar{r}^b)}{r - c_b(r)} - 1\right]$$

and the lower bounds $\underline{r}^{s_i,a}$, $\underline{r}^{s_i,b}$ are implicitly defined by $F^{s_i,a}(\underline{r}^{s_i,a}) = 0$ and $F^{s_i,b}(\underline{r}^{s_i,b}) = 0$.

Aggregate Rate Distribution. The distribution of rates across the entire population is the mixture of signal-specific distributions weighted by population fractions:

$$F(r) = \sigma_g F^{s_g}(r) + \sigma_b F^{s_b}(r)$$

The corresponding density is:

$$f(r) = \sigma_g f^{s_g}(r) + \sigma_b f^{s_b}(r)$$

where $f^{s_i}(r) = \frac{dF^{s_i}}{dr}$.

Convergence to Perfect Information

As signal precision approaches perfection ($q_g, q_b \to 1$), posterior beliefs converge to certainty:

$$\alpha^{s_g} = \frac{q_g\mu_g}{q_g\mu_g + (1-q_b)\mu_b} \to \frac{1\cdot\mu_g}{1\cdot\mu_g + 0\cdot\mu_b} = 1$$

$$\alpha^{s_b} = \frac{(1-q_g)\mu_g}{(1-q_g)\mu_g + q_b\mu_b} \to \frac{0\cdot\mu_g}{0\cdot\mu_g + 1\cdot\mu_b} = 0$$

where, as a reminder, α^{s_i} denotes the probability of being a good type given s_i. This implies:

- **Good signal group:** $c^{avg,s_g}(r) \to c_g(r)$, so

  $$\phi^{s_g} \to \bar{r}^g - c_g(\bar{r}^g) > 0$$

  The CDF $F^{s_g}(r)$ converges to $F_g(r)$, the good-type distribution under perfect information.

- **Bad signal group:** $c^{avg,s_b}(r) \to c_b(r)$, so

  $$\phi^{s_b} \to (\bar{r}^g - c_b(\bar{r}^g)) - \left(\bar{r}^b - c_b(\bar{r}^b)\right) \le 0$$

  The CDF $F^{s_b}(r)$ converges to $F_b(r)$, the bad-type distribution under perfect information.

Furthermore, $\sigma_g \to \mu_g$ and $\sigma_b \to \mu_b$, so the aggregate distribution converges to:

$$F(r) \to \mu_g F_g(r) + \mu_b F_b(r)$$

which is the perfect-information equilibrium from Section 5.4.

Information Acquisition Decision

Proposition 5.5 (Signal Acquisition)**.** *Both banks acquire the signal if and only if the expected profit gain exceeds the cost:*

$$\mathbb{E}[\Pi^{signal}] - \mathbb{E}[\Pi^{no\ signal}] \ge C_s$$

where:

$$\mathbb{E}[\Pi^{signal}] = \sigma_g \cdot \Pi^{s_g} + \sigma_b \cdot \Pi^{s_b}$$

$$\mathbb{E}[\Pi^{no\ signal}] = \begin{cases} (1-\pi)(\bar{r}^g - c^{avg}(\bar{r}^g)) & \text{if } \phi > 0 \\ \mu_b(1-\pi)(\bar{r}^b - c_b(\bar{r}^b)) & \text{if } \phi \le 0 \end{cases}$$

Comparative statics. The profit gain from acquiring information is larger when:

1. **Signal precision is high:** Higher q_θ increases separation between α^{s_g} and α^{s_b}
2. **Population heterogeneity:** Larger $|\mu_g - \mu_b|$ amplifies the value of distinguishing types
3. **Cost differences:** Larger $|c_g - c_b|$ increases the benefit of risk-based pricing
4. **Market power:** Lower π (less competition) increases profit margins, making information more valuable

In the limit of perfect competition ($\pi \to 1$), banks earn zero profits under both information regimes, so they will not pay any positive cost $C_s > 0$ to acquire information. This highlights the interaction between market structure and information acquisition incentives.

5.6 Welfare Implications

Total surplus. The population of firms aggregated for both banks is $2(1-\pi)+\pi$. Under perfect information or perfect signal, total surplus is realized as all firms are matched $TS^{q=1} = (2(1-\pi)+\pi)(\mu_b(\bar{r}^b - c_b) + \mu_g(\bar{r}^g - c_g))$. Under no information, total surplus depends on the severity of adverse selection: under partial or fully separating equilibrium, the share of good firms that is offered a rate beyond their reservation rate refuses and exits the market, thus the gains from trade remain unrealized.

Bank's and firms' share of total surplus. Under perfect information, the bank gets a share of realised surplus per trade exactly equal to $1-\pi$, while firms get the remaining π share. Under asymmetric information, banks profits are lower: in pooling, the bank looses $(1-\pi)(\bar{r^b} - \bar{r^g})$ from each bad type with respect to the perfect information case; in separating, the banks do not get the share of surplus from good firms that exit the market. In addition, under asymmetric information and pooling there is cross-subsidization between types: good types pay a share of the surplus equal to $(1-\pi)\mu_b(c_b - c_g)$. Asymmetric information constrains banks from achieving the profit levels under perfect information. When adverse selection is mild $\phi > 0$, the bank cannot fully extract surplus from bad firms due to pooling at lower interest rates. Conversely, when adverse selection is severe $\phi \leq 0$, the bank incurs losses as high-quality firms exit the market and low-quality firms are partially pooled at subsidized rates. Both cross-subsidization and exit are costs of asymmetric information that good firms are paying, and information reduces both costs. The following table illustrates the expected gains from trade for each bank:

PROFITS		Perfect Info	Imperfect Info	No Info
Max surplus	$\phi > 0$	✓	✓	✓
	$\phi \leq 0$	✓	X	XX
Banks' profit loss	$\phi > 0$	–	↑	↑↑
	$\phi \leq 0$	–	↑	↑↑
Cross-subsidy	$\phi > 0$	–	↑	↑
	$\phi \leq 0$	–	↑ or –	↑ or –

Table 2: Banks' profits under perfect and no information.

6 Calibration

The next step is to give a quantitative assessment of the relative contribution of search and information to explained variance, along with the welfare trade-offs. Because the structural parameters, π for competition and q for the signal precision, are inherently latent, we employ a calibration exercise to recover these values by matching the model to specific moments of the residual distribution across Banque de France rating classes. For each rating class, we calibrate three parameters: the search friction intensity π, the signal precision q, and the reservation rate for good types $\bar{r}_g$. The central bank funding cost r_{CB} is fixed at 1, consistent with the average policy rate over the sample period. Four additional parameters are calibrated directly from the data: $\mu_b, p_g, p_b, \bar{r}_b$. We can observe the evolution of firms into good and bad rating classes; we can then denote as good/bad the firms that transition to better/worse rating classes, and derive the population share of bad types μ_b and the average success probabilities p_g and p_b in each population (computed as one minus the three-year-ahead default frequencies from Banque de France historical data), and the upper bound $\bar{r}_b$ (set at the maximum observed rate in each rating class). For each rating class, we rescale all residuals by the average rate over the period.

6.1 Calibration Strategy

The calibration proceeds in two stages. First, we conduct a grid search over the parameter space, evaluating 20^3 combinations of parameter values within economically plausible bounds: $\pi \in [0.05, 0.95]$, $q \in [0.5, 1.0]$, and $\bar{r}_g \in [0.5\,\bar{r}_{\text{mean}}, 0.98\bar{r}_b]$, where $\bar{r}_{\text{mean}}$ is the class mean rate. For each combination, we compute the model-implied moments—mean rate, variance, and correlation with subsequent default probability changes—using the equilibrium distribution derived in Section 5. We keep the combination that minimizes the objective function, which is the weighted sum of squared percentage errors of targeted moments. Second, we refine the best grid point using local optimization (L-BFGS-B algorithm) to minimize the weighted sum of squared percentage deviations between model and data moments.

The objective function to minimize is the sum of squared proportional errors across the three moments[5]:

$$Q(\theta) = \left(\frac{m_{\text{mean}}^{\text{model}} - m_{\text{mean}}^{\text{data}}}{m_{\text{mean}}^{\text{data}}}\right)^2 + \left(\frac{m_{\text{var}}^{\text{model}} - m_{\text{var}}^{\text{data}}}{m_{\text{var}}^{\text{data}}}\right)^2 + \left(\frac{m_{\text{corr}}^{\text{model}} - m_{\text{corr}}^{\text{data}}}{m_{\text{corr}}^{\text{data}}}\right)^2 \tag{7}$$

With three moments and three free parameters (r_{CB} fixed), the system is exactly identified. However, we impose additional structure through the equilibrium restrictions: the parameters must generate a feasible equilibrium (costs below reservation rates), and the distribution must satisfy the mixed-strategy conditions. These restrictions provide implicit identifying moment conditions beyond the three explicit moments we match.

6.2 Counterfactual Analysis

To decompose the relative contributions of search frictions and information acquisition, we compute counterfactual equilibria holding recovered parameters $(\hat{\pi}, \hat{\bar{r}}_g)$ and calibrated parameters $\mu_b, p_g, p_b, \bar{r}_b, r_{CB}$ fixed while varying the signal precision q. In particular, we compare the percentage increase in variance given the calibrated parameters against the counterfactual with $q = 0.5$ (no information) isolates the role of search frictions:

$$\text{Information Contribution} = \frac{\text{Var}(\hat{q}) - \text{Var}(q = 0.5)}{\text{Var}(q = 0.5)} \times 100\% \tag{8}$$

6.3 Calibration Results

Table 3 presents the calibrated parameters for each rating class; Table 4 reports the corresponding model fit. The correlation moment is matched closely across all classes. Mean and variance are less precisely matched, possibly reflecting unmodeled sources of dispersion.

Table 3: Search Frictions and Information by Rating Class

Rating	$\hat{\pi}$	$\hat{q}$	$\hat{\bar{r}}_g$	Info Contr. (%)	Obj. Value $Q(\theta)$
3+	0.813	0.990	2.499	5.96	0.60
3	0.805	0.996	2.731	5.07	0.53
4+	0.788	0.993	3.434	4.48	0.36
4	0.789	1.000	3.605	4.53	0.42
5+	0.787	0.984	3.955	1.56	0.40
5	0.767	0.853	4.812	0.08	0.25
6	0.763	0.553	5.242	0.00	0.22
7	0.746	0.553	7.076	0.00	0.12

Notes: $\hat{\pi}$ is the search-friction parameter, $\hat{q}$ the signal precision, $\hat{\bar{r}}_g$ the reservation rate of good borrowers, and "Information Contribution" measures the percentage increase in rate dispersion attributable to screening relative to the no-information benchmark.

[5] proportional errors are used to ensure that moments of different scales are weighted comparably in the estimation.

Table 4: Model Fit: Observed vs. Model-Implied Moments

	Mean		Variance		Correlation	
Rating	Data	Model	Data	Model	Data	Model
3+	1.67	1.59	0.400	0.090	0.025	0.025
3	1.83	1.70	0.440	0.119	0.033	0.033
4+	2.40	2.04	0.550	0.231	0.032	0.032
4	2.37	2.12	0.730	0.264	0.048	0.047
5+	2.57	2.27	0.860	0.326	0.040	0.040
5	3.36	2.71	0.980	0.527	0.017	0.017
6	3.63	2.92	1.130	0.652	0.000	0.000
7	4.79	3.88	1.840	1.306	0.000	0.000

Notes: All moments computed on residual rates within each rating class. Correlation is between the residual rate and the three-year-ahead default indicator.

The calibration results reveal three key findings. First, search frictions are relatively low across all rating classes, with $\hat{\pi}$ estimated between $[0.74, 0.81]$, increasing over ex-ante safety. This suggests that the French corporate lending market is relatively competitive, with most firms sampling multiple lenders—consistent with the high concentration of bank relationships documented in Section 4.1, where on average 60% of firms across classes maintain at least two active banking relationships.

Second, screening intensity exhibits heterogeneity across the credit quality distribution. Good borrowers (ratings 3+ through 5+) face near-perfect screening ($\hat{q} \geq 0.98$), while poor borrowers (ratings 6 and 7) face essentially no screening ($\hat{q} \approx 0.55$).

Third, despite high screening intensity implied by the data moments for good ratings, information contributes minimally to observed rate dispersion. The information contribution to variance never exceeds 5%, indicating that search frictions account for most of unexplained dispersion even in segments with near-perfect screening. This partly reflects the mild severity of the adverse selection problem within each rating class, for example, the relative low distance of default probabilities between types mechanically limit between-type variance.

6.4 TBA: example of welfare loss/surplus share of banks/firms, cross-subsidy between good and bad types, etc.

in progress

7 Monetary policy implications

This section examines the implications of the model for monetary policy transmission via the bank lending channel. Specifically, we analyze how market power and information asymmetries affect the pass-through of policy rate changes to lending rates.

7.1 Model predictions

The model yields key implications on monetary policy transmission.

1. Low competition impairs monetary policy transmission As expected, less competition impairs the pass-through of a rate increase. When competition is low, banks possess market power; they set rates well beyond marginal cost and close to borrowers' reservation rates. In this environment, banks would only partially pass-through a policy rate hike, to preserve both their market share and their profit margins. In sum, following a rate hike, we expect the average rate to be stickier in a setting where the market is both non-competitive and we should expect lower rate dispersion around the average.

2. The information structure interacts with competition. Bank's screening ability and its role in loan pricing is a critical determinant of policy rates transmission. When banks fail to screen, the pass-through is strengthened/weakened, depending on actual payoffs.

3. Monetary policy affects gains from trade in the market. Higher rates reduce gains from trade in the market. This in turn increases the severity of adverse selection. Thus an increase in policy rates in a market with little screening may determine the transition from a pooling to a screening strategy by banks, with the exit of firms with lower expected returns.

7.2 Empirical evidence: Rate dispersion responds to monetary policy

We test the model implications by examining the response of the distribution of interest rate residuals (i.e. the unexplained term) from the baseline regression to monetary policy. We compute high-frequency monetary policy shocks for the euro area, following the methodology of Altavilla et al. (2019). These shocks are identified using changes in asset prices (OIS) around ECB monetary policy announcements, capturing the unexpected component of policy decisions. The identifying assumption is that monetary policy, which is endogenous to asset price changes, would not respond at such a high frequency to changes in asset prices; in fact, the short window around the announcement ensures to capture the market surprise. The used shock series is reported in Fig. B.8 in Appendix.

First, we expect a monetary policy shock to reduce the variance and skewness of the observed rate distribution. We regress the variance and skewness of loan residuals on the shocks. The results indicate that both dispersion (variance) and asymmetry (skewness) of loan rate residuals respond systematically to monetary policy surprises, suggesting that policy changes influence not only the average cost of borrowing, but also the degree of heterogeneity across firms. The specification is carried out in both levels and changes. In levels:[6]

$$Y_{lender,t} = \beta_0 + \beta_1 \cdot \text{MPshock}_t + \beta_2 Y_{lender,t-1} + \text{FE}_{lender} + \varepsilon$$

[6] β_1 measures the effect of MP on the level of dispersion of premia , controlling for its lag. Assumes that there is inertia in the dispersion of rates over time.

And in first differences:[7]

$$\Delta Y_{lender,t} = \gamma_0 + \gamma_1 \cdot \text{MPshock}_t + \text{FE}_{lender} + \epsilon$$

	Dispersion		ΔDispersion		Skewness		ΔSkewness	
L1.rate shock	-0.0096***	-0.0085***	-0.0071**	-0.0049	-0.0135***	-0.0099*	0.0012	0.0053
	(0.000)	(0.003)	(0.028)	(0.175)	(0.010)	(0.093)	(0.860)	(0.490)
L2.rate shock		0.0001		0.0069**		-0.0227***		-0.0024
		(0.979)		(0.041)		(0.000)		(0.732)
L3.rate shock		-0.0017		-0.0007		-0.0208***		-0.0099
		(0.568)		(0.851)		(0.000)		(0.196)
L1.SD / L1.Skew	0.2813***	0.2799***			0.1294***	0.1171***		
	(0.000)	(0.000)			(0.000)	(0.000)		
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	7,189	7,077	7,189	7,077	7,189	7,077	7,189	7,077
R^2	0.40	0.41	0.01	0.01	0.23	0.24	0.00	0.00

p-values in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Data: Nouveaux Credits, BdF, 2006q1-2024q2, quarterly shocks. The table shows the effect of a monetary policy rate shock on the standard deviation and skewness of the residuals' distribution.

Table 5 show that a monetary tightening has a downward effect on the variance of the distribution of the unexplained component of interest rates, both in levels and changes, and a negative effect on the level of the skewness. This is consistent with what is expected in the theoretical framework. Further analysis on the response in different markets with varying competition/screening levels would further clarify the strength of the pass-through with respect to the competitive and perfect screening benchmark.

8 Conclusion

In this paper, we explore the extent to which information acquisition and imperfect competition jointly determine loan prices. We empirically document interest rate dispersion and use it to derive important relationships in the data, showing that rates contain forward information about the future evolution of firms' creditworthiness. Specifically, there is a positive and significant correlation between paying a relatively higher rate and being ex-post more likely to default.

[7] γ_1 measures the effect of MP on the change of dispersion of premia. No need to worry about trend.

To shed light on these dynamics, we propose a framework where loan pricing is the outcome of imperfect competition and asymmetric information. Our theoretical analysis yields two main results: first, imperfect competition delivers within-type dispersion; second, the information structure determines between-type dispersion when banks acquire additional information.

The model yields key implications on monetary policy transmission. As expected, limited competition generally weakens the pass-through of policy rates. Furthermore, the interaction of search frictions and weak information acquisition creates a specific rigidity in rates that further impairs the transmission of policy shocks. Using high-frequency monetary policy shocks, we find a reduction in the dispersion of interest rate residuals, consistent with the model predicts that total observed dispersion decreases following an increase in the policy rate.

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A Additional tables and figures

LA COTE DE CRÉDIT
(capacité de l'entreprise à honorer ses engagements financiers à 3 ans)

3++	Excellente
3+	Très forte
3	Forte
4+	Assez forte
4	Correcte
5+	Assez faible
5	Faible
6	Très faible
7	Appelant une attention spécifique présence d'au moins un incident de paiement significatif
8	Menacée
9	Compromise
P	Procédure collective redressement ou liquidation judiciaire
0	Pas de documentation comptable analysée et absence d'informations défavorables

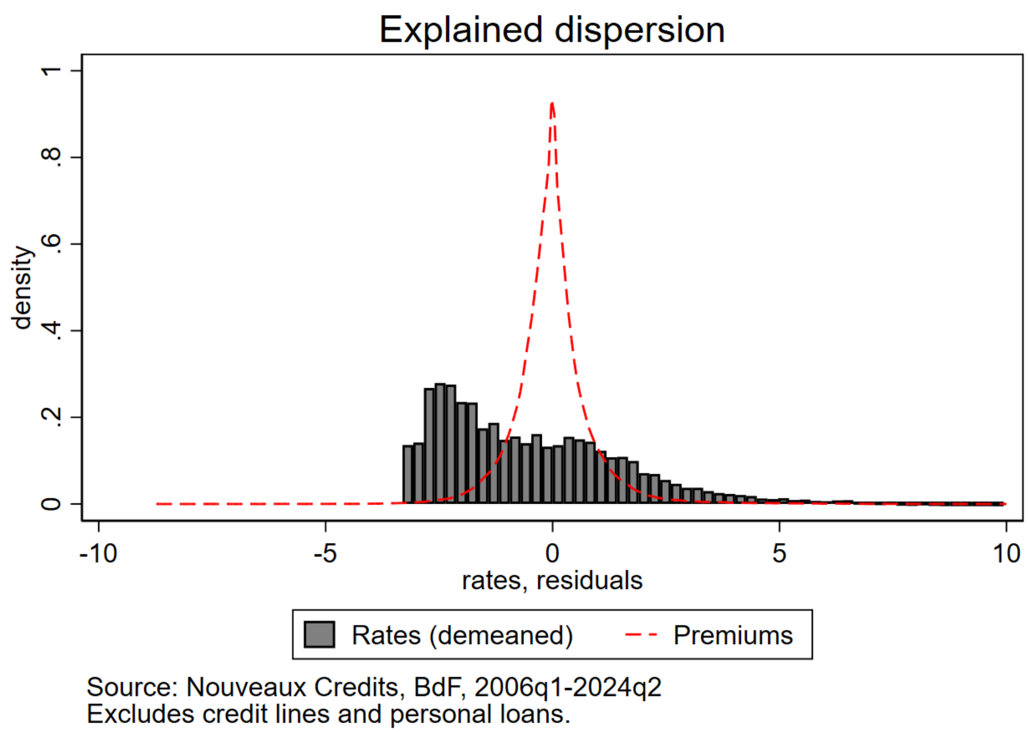
Figure A.1: Source: Banque de France. Credit rating scale until 2022.

B Additional facts on rate dispersion

Table B.1: Data: Nouveaux Credits (BdF), 2006q1-2024q2. Excludes credit lines and personal loans. All credit and balance-sheet variables are expressed in terms of reported assets.

	Total effective rate					
log.Loan quantity (K-Eur)	-0.2219***	-0.1535***	-0.1537***	-0.1436***	-0.1467***	-0.0989**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity (months)	-0.0005*	0.0022***	0.0032***	0.0021*	0.0022***	0.0020***
	(0.073)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)
Age	-0.0141***	-0.0095***	-0.0084***	-0.0074***	-0.0073***	-0.0038***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	0.0001***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young firm 0-3y (dummy)	-0.0577***	-0.0404	-0.0424	-0.0190	-0.0161	-0.0669**
	(0.001)	(0.297)	(0.285)	(0.528)	(0.575)	(0.012)
New bank-firm relationship (dummy)	0.1988***	0.0183	0.0145	-0.0171	-0.0179	-0.0403**
	(0.000)	(0.639)	(0.715)	(0.293)	(0.285)	(0.025)
Variable rate (dummy)	0.4528***	0.4905***	0.1665*	0.1184	0.1167	0.1434
	(0.000)	(0.000)	(0.051)	(0.196)	(0.196)	(0.119)
Personal loan (dummy)	-0.2999**	-0.0612	0.0400	-0.0066	-0.0043	0.0603
	(0.035)	(0.674)	(0.620)	(0.943)	(0.962)	(0.447)
Individual entrepreneur (dummy)	0.5724***	0.5680***	0.5333***	0.4320***	0.4195***	0.2404***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Loan over assets	0.1613**	0.0983*	0.0986*	0.1057*	0.1039*	0.0474*
	(0.021)	(0.064)	(0.080)	(0.079)	(0.076)	(0.086)
Pledged guarantees	0.8325***	0.1146	-0.0204	-0.2563**	-0.2360**	-0.1759*
	(0.003)	(0.132)	(0.709)	(0.016)	(0.011)	(0.025)
Revenues	-0.0444***	-0.0165	-0.0114	0.0034	0.0050	-0.0073
	(0.000)	(0.367)	(0.367)	(0.592)	(0.449)	(0.180)
Bank Debt	0.1594***	0.1219**	0.1158**	0.1097***	0.1218***	-0.0001
	(0.000)	(0.008)	(0.014)	(0.001)	(0.001)	(0.994)
Non-Bank Debt	-0.0395	-0.0583	-0.0455	-0.0055	-0.0009	-0.0167
	(0.401)	(0.630)	(0.723)	(0.945)	(0.991)	(0.742)
Mobilised credit	-0.0117*	-0.0021	0.0013	0.0000	0.0003	0.0025
	(0.023)	(0.471)	(0.700)	(0.991)	(0.927)	(0.300)
Short Term Debt	0.0009	-0.0024	-0.0009	0.0190	0.0190	-0.0125
	(0.967)	(0.871)	(0.951)	(0.159)	(0.159)	(0.283)
Undrawn credit lines (K-Eur)	-0.0109	-0.0058	-0.0044	-0.0070	-0.0071	-0.0025
	(0.967)	(0.871)	(0.951)	(0.159)	(0.159)	(0.283)
Quarter FE	✓					
Lender × Quarter FE		✓				
Lender × Quarter × Loan Type FE			✓			
Lender × Quarter × Loan Type × 2digit Sector FE				✓	✓	✓
Region FE					✓	✓
Group indicator, Rating FE						✓
Observations	457,868	457,868	457,868	457,868	457,868	457,868
R^2	0.55	0.72	0.76	0.82	0.82	0.83

p-values in parentheses
* p< 0.10, ** p< 0.05, *** p< 0.01



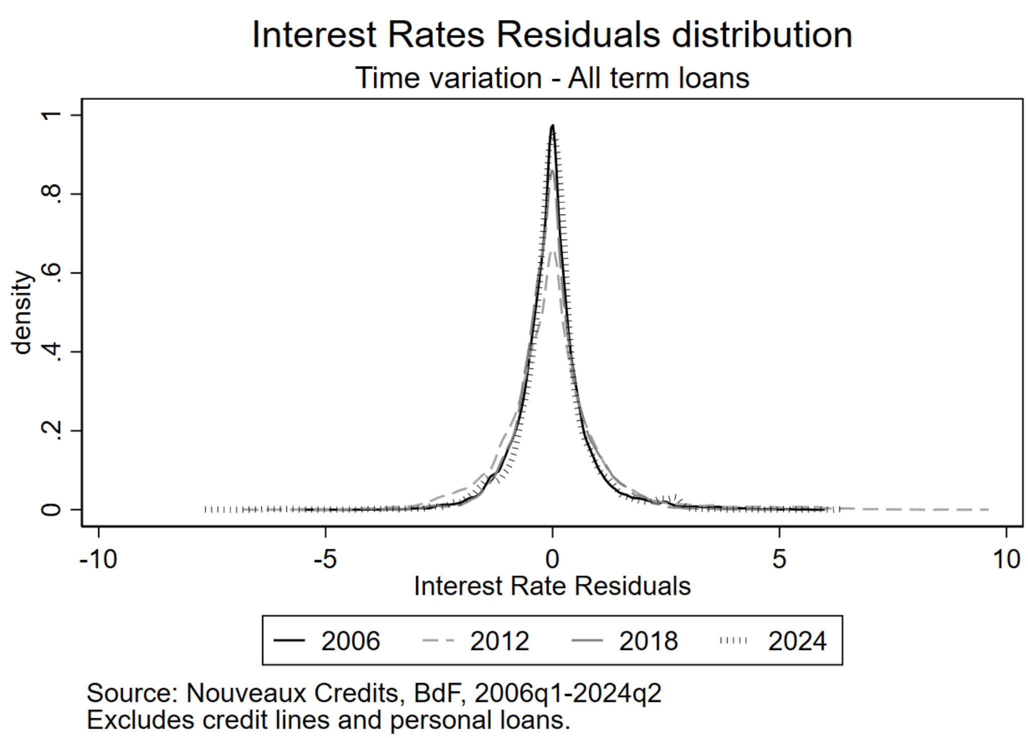
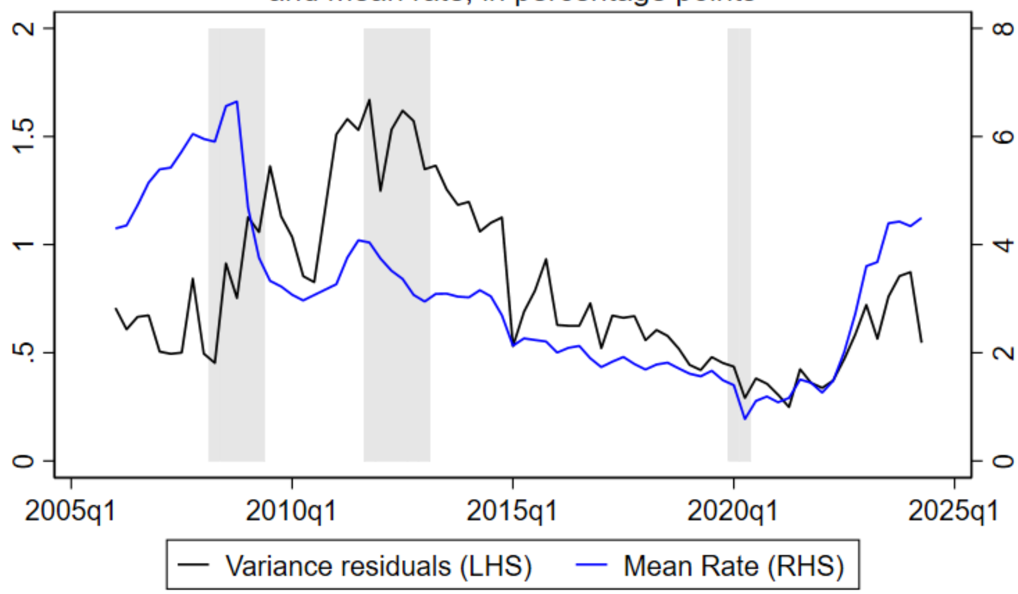


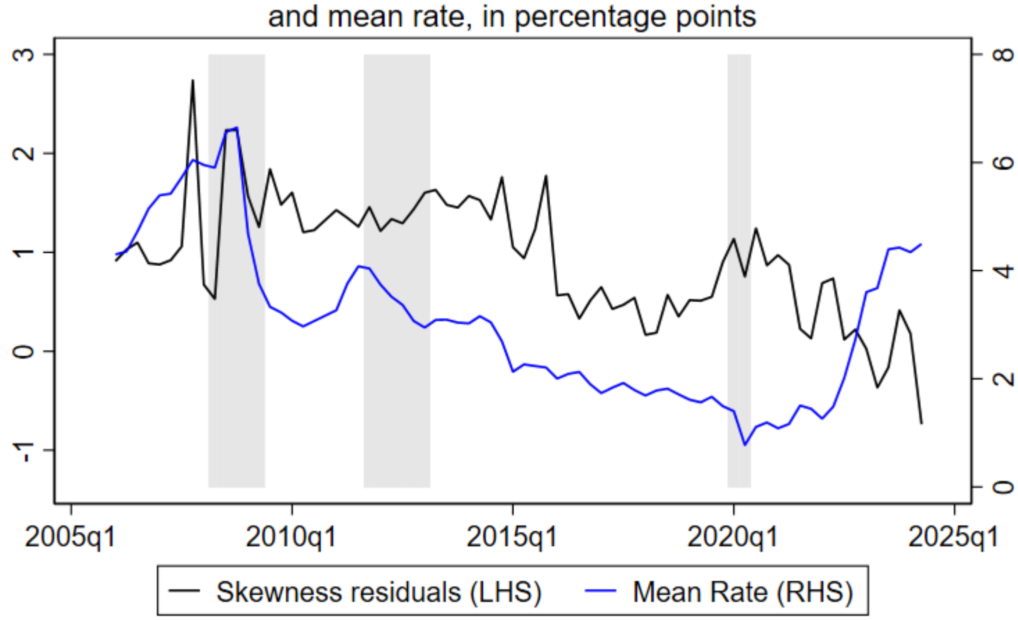
Figure B.2: Regression outcome. Top: residuals versus actual rates, all sample. Bottom: residuals distribution for selected years.

Variance of Interest rates premia
and mean rate, in percentage points



Source: Nouveaux Credits, BdF, 2006q1-2024q2. All term loans.
Recession dates for France from AFSE: 2008q2-2009q2, 2011q4-2013q1, 2020q1-2020q2

Skewness of Interest rates premia
and mean rate, in percentage points



Source: Nouveaux Credits, BdF, 2006q1-2024q2. All term loans.
Recession dates for France from AFSE: 2008q2-2009q2, 2011q4-2013q1, 2020q1-2020q2

B.1 Additional specification 1: Firm fixed effects

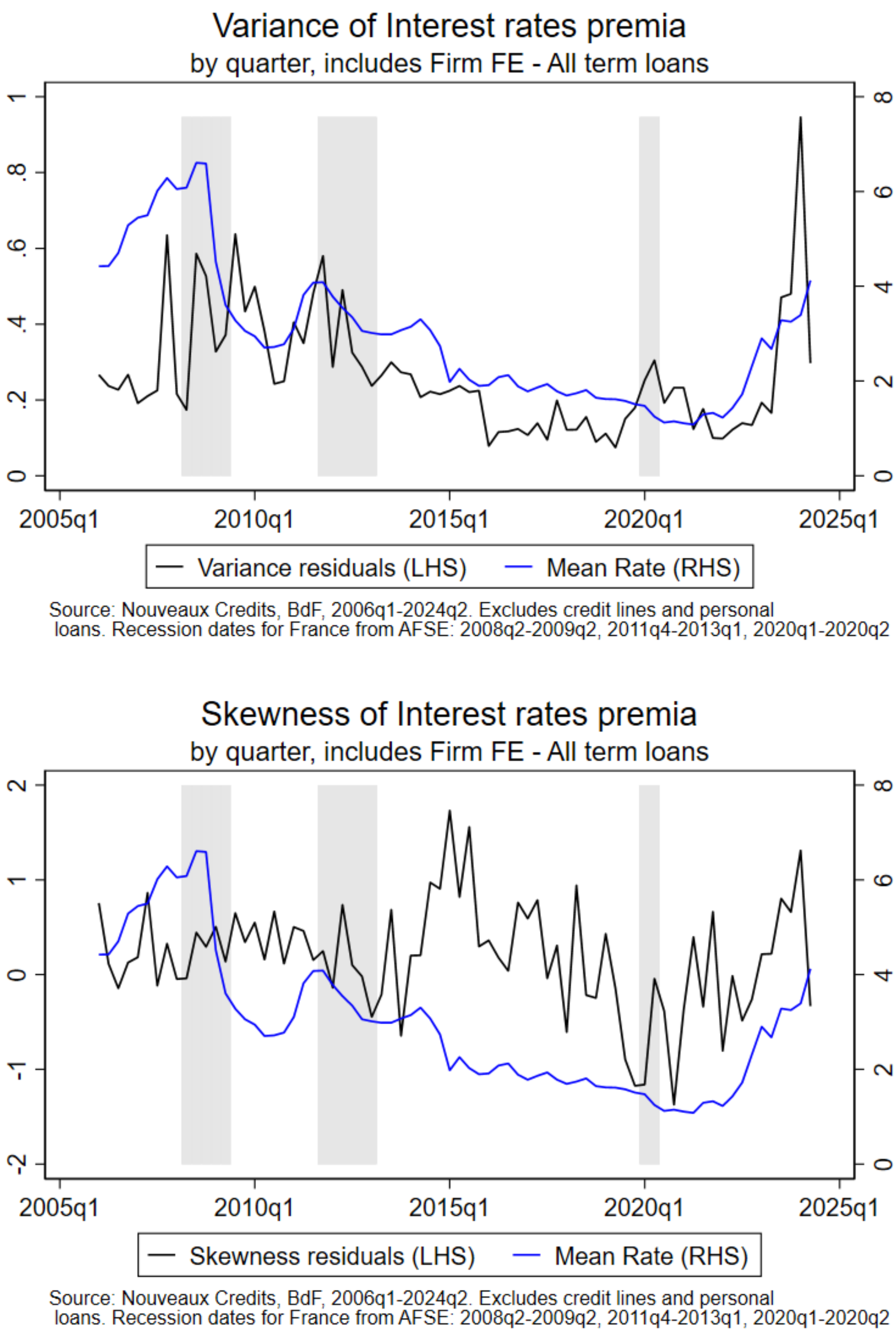
	Total effective rate					
Loan quantity (K-Eur)	-0.0000***	-0.0000***	-0.0000	-0.0000	-0.0000**	-0.0000
	(0.000)	(0.006)	(0.486)	(0.143)	(0.044)	(0.117)
Maturity (months)	-0.0016***	0.0013***	0.0015***	0.0015***	0.0014***	0.0014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variable rate (dummy)	0.2381***	0.1357***	0.2176***	0.2368***	0.2113***	0.1995***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan over assets	0.0524***	-0.0068**	-0.0076***	-0.0070**	-0.0069**	-0.0074***
	(0.000)	(0.025)	(0.009)	(0.012)	(0.012)	(0.007)
Quarter FE	✓					
Firm × Quarter FE		✓	✓	✓	✓	
Lender FE			✓			
Lender × Quarter FE				✓	✓	
Firm × Lender × Quarter FE						✓
Loan Type FE					✓	✓
Observations	590,621	197,343	197,328	196,048	196,042	156,211
R^2	0.51	0.92	0.93	0.94	0.94	0.94

p-values in parentheses

* p< 0.10, ** p< 0.05, *** p< 0.01

Table B.2: "Data: Nouveaux Credits (BdF), 2006q1-2024q2""Excludes credit lines and personal loans. All credit and"" balancesheet variables are expressed in terms of reported assets."

Figure B.3: variance and skewness of residuals from firm FE specification



B.2 Additional specification 2: truncated regression approach

One possible concern is that it is not possible to observe rates below 0. Regression approaches assuming normality may be downward biased, predicting negative rates even when they are impossible to observe. Two approaches can help address this issue. Firstly, one can verify to what extent the OLS is predicting negative values. It seems that most of the variation being absorbed by fixed effect, this is a minor concern, as 0.4% of predictions fall slightly below zero. Secondly, the same analysis can be repeated using Tobit regression, which accounts for this lower bound; this approach is more limited towards the inclusion of many interactions of fixed effects, thus it forces a more parsimonious approach. In any case, the resulting distribution of residuals does not seem very affected.

B.3 Rate dispersion and bank heterogeneity

One question that naturally arises is: is this dispersion hiding heterogeneity across banks? The answer is yes. There is consistent heterogeneity between banks in the explained variation, as shown below by repeating the above estimation of rates by bank, and collecting the R^2.

$$\text{Rate}_{i,b,t} = \alpha + \beta \cdot \text{LoanChar}_{i,b,t} + \gamma \cdot \text{FirmChar}_{i,t} + \lambda_t + \varepsilon_{i,b,t} \tag{9}$$

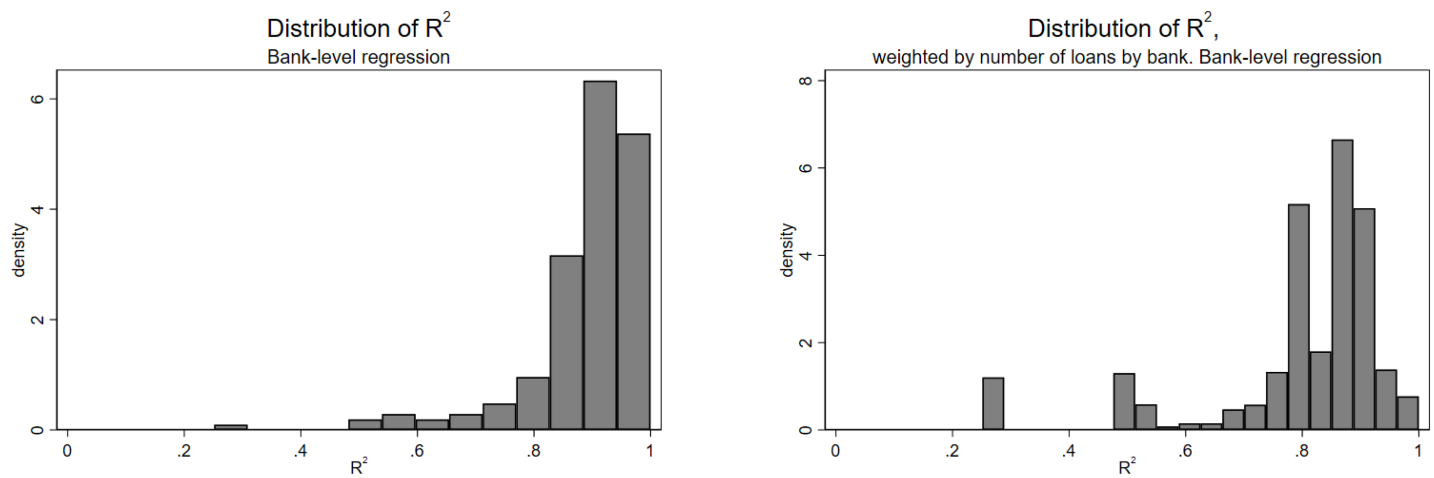


Figure B.4: The right image reports the distribution of R^2 weighted by the number of loans issued.

In the following section the credit rating of firms will be used as a source of public information available to banks and to study the evolution of firm's outcome in terms of their default probability/outcome. Consequently, it is interesting at this stage to report to which extent banks use these ratings. Firstly, the same estimation is repeated by including only the rating as explanatory variable, along with time and loan type FE and by lender, and collect the R^2.

$$\text{Rate}_{i,b,t} = \alpha + \beta \cdot \text{Firm Rating}_{i,b,t} + \lambda_t + \varepsilon_{i,b,t} \tag{10}$$

where the only fixed effects kept are by loan type and quarter.

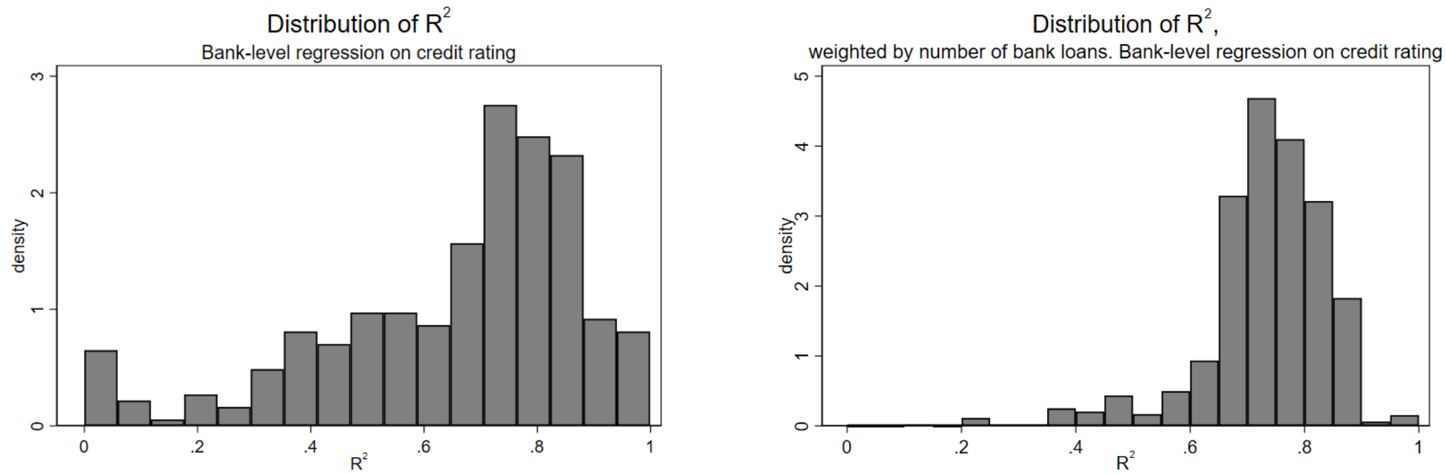


Figure B.5: The right image reports the distribution of R^2 weighted by the number of loans issued.

Secondly, one can look at how much of the variation is explained when including the public rating, in particular by collecting the increment in the R^2.

$$\begin{aligned} \text{Rate}_{i,b,t} &= \alpha + \lambda_t + \varepsilon_{1,i,b,t} && \rightarrow \text{Get } R_1^2 \\ \text{Rate}_{i,b,t} &= \alpha + \beta \cdot \text{Firm Rating}_{i,b,t} + \lambda_t + \varepsilon_{2,i,b,t} && \rightarrow \text{Get } R_2^2 \\ \Delta R^2 &= R_2^2 - R_1^2 \end{aligned}$$

where the only fixed effects kept are by loan type and quarter.

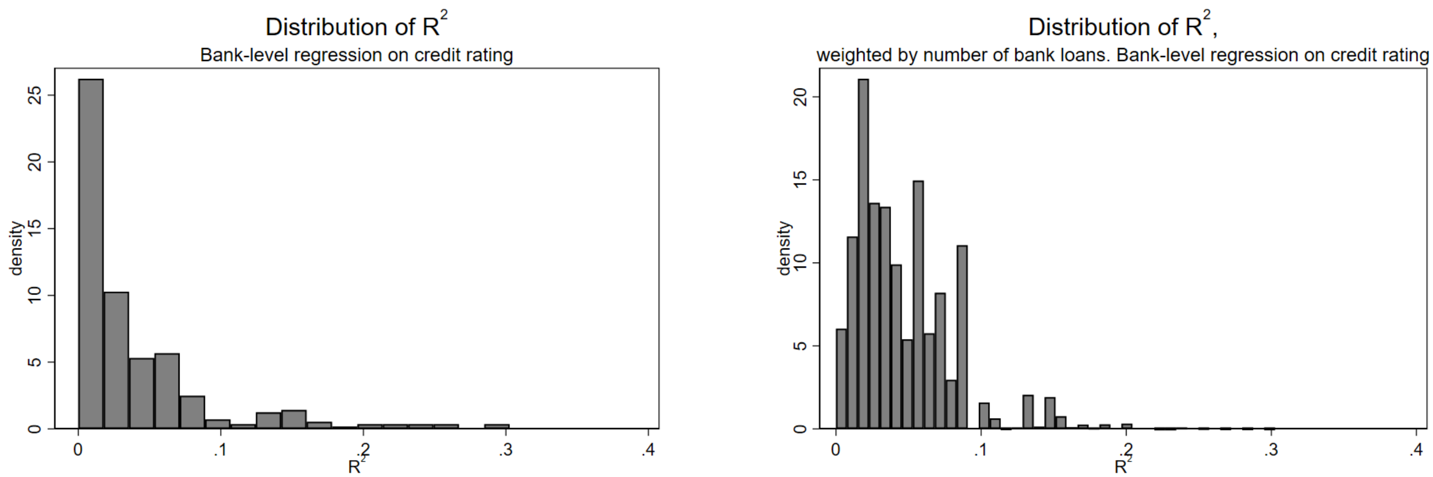


Figure B.6: The right image reports the distribution of R^2 weighted by the number of loans issued.

B.4 Residuals and market competition

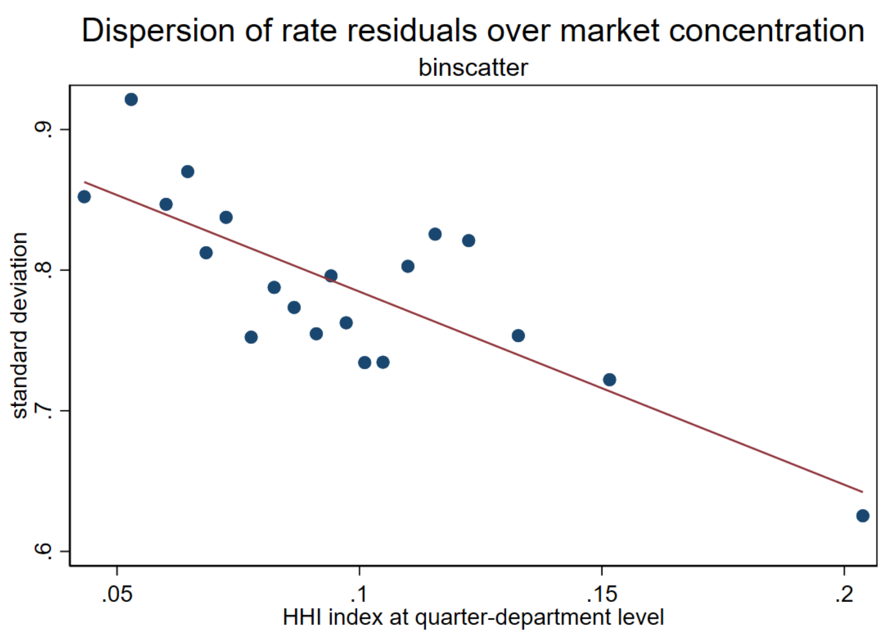
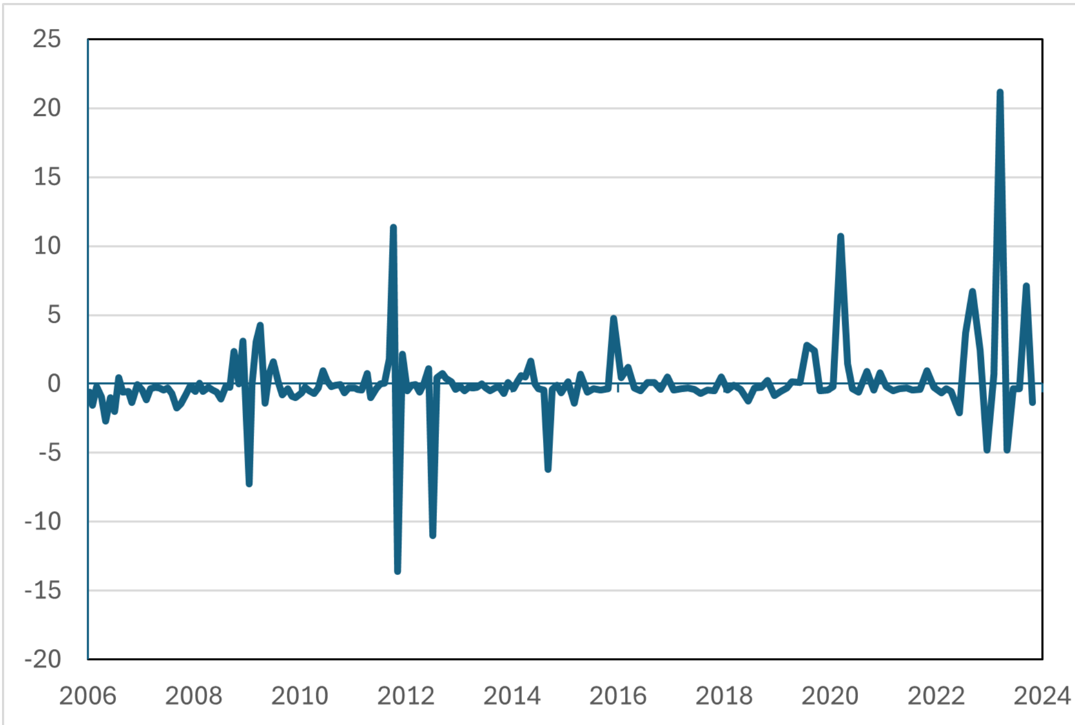


Figure B.7: Unexplained rate residuals' dispersion over HHI by department-quarter.

B.5 Monetary policy implications

Figure B.8: Interest rate shock factor estimated from changes in short term OIS rates in a narrow window after the ECB press release.



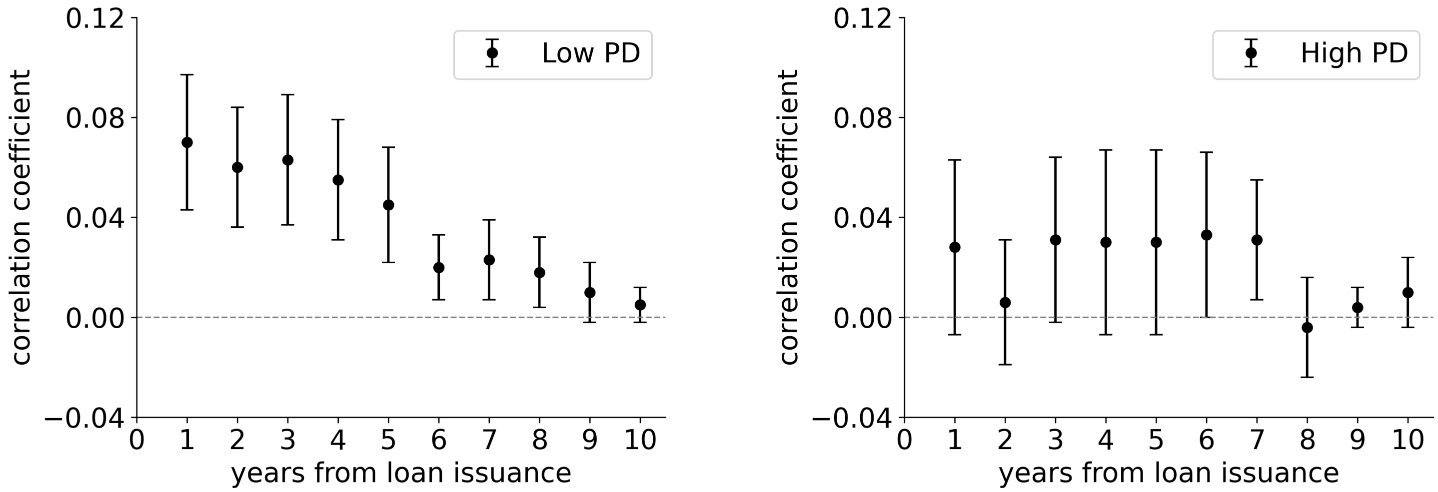
B.6 Excluding the mechanical effect of higher rates on default probability

We adopt two approaches to show that the observed correlation between rate residuals and unexpected changes in riskiness is not driven by a leverage effect - higher rates induce higher ex-post riskiness through the worsening of firm's fundamentals. Instead, it identifies banks' additional information with respect to the econometrician - banks recognize riskier types within the same rating class and offer a higher rate. A more comprehensive treatment of this analysis is provided in the appendix.

Approach 1: analyzing the correlation in the cross section.

We study how the correlation varies across different rating classes and firm characteristics to test if the correlation we observa can be potentially driven by a mechanical effect of rates on firm fundamentals. One first hypothesis is that the leverage effect should be stronger for firms that are already closer to the default threshold, namely in worse rating classes. We find the opposite, namely a stronger effect in ex-ante safer classes, while it becomes non significant for worse ratings (Fig. B.9).

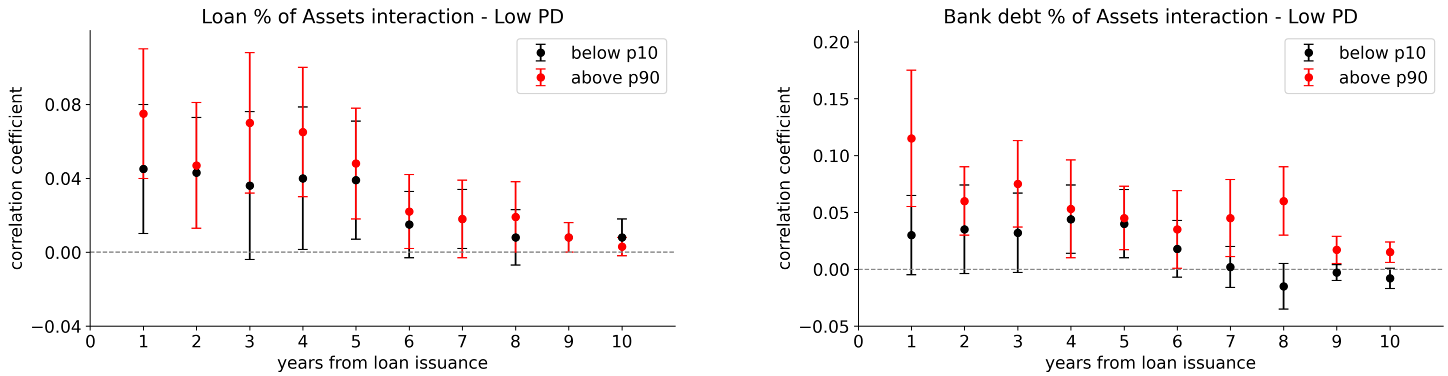
Figure B.9: Correlation computed separately for firms with ex ante good rating (default probability $< 0.62\%$) vs bad (default probability $> 3.45\%$).



The second hypothesis is that, if the deterioration in firm fundamentals was solely the result of receiving a worse rate offer ex-ante, the effect should be stronger when the loan represents a larger share of the firm's balance sheet. We test whether loan size relative to the firm's balance sheet explains the correlation between higher ex-ante rates and higher ex-post default. Empirically, we compare firms with a relatively large share of loan over asset (above 90^{th} percentile) and firms with a relatively low share (below 10^{th} percentile). In practice, we add an interaction term between the realized ex-post default probability and a dummy variable to distinguish between groups. As shown in Fig. B.10, in classes where there was an overall strong and significant correlation, the coefficients are not statistically different between groups of firms with large vs small loans. In other words, the size of the loan relative to the firm's balance sheet does not systematically explain the observed correlation. This is consistent with the assumption that rates contain banks' additional information about firm risk beyond what is captured by public information. For robustness, we repeat the same exercise with the size of total bank loans over total assets (Fig. B.10), to include the possibility that the observed rate on a single loan reflects the ones on all bank loans.

Finally, we want to test that the correlation between rates and the evolution of default probability is stronger in contexts when information is more valuable; in this case, we expect the information component to play a stronger role. Relying on the literature, we use firms' age to distinguish firms for which we expect the unobserved creditworthiness component contained in rates to be very large and dispersed (proxy for risk/growth prospects Haltiwanger, Jarmin,Miranda, 2013); length in the credit market Cloyne, Ferreira, Froemel, Surico, 2023). Older firms are, in general, the survivors, with a good overall credit quality; for young firms, instead, ex-post outcomes might be way more uncertain and dispersed, and banks may put more effort in screening among the to acquire more information on their actual riskiness. We expect the correlation between rates and ex-post outcome to be much stronger for relatively young firms in our sample (below 10^{th} age percentile) than relatively old firms (above

Figure B.10: Interactions of ex-post default probability and loan-size over assets (left) and bank debt over assets (right)



The figure compares the correlation coefficients of residual rates and unexpectedchanges in ex-post default probability across percentiles of i) loan-size over assets (left) and ii) size of bank debt over assets (right) for firms with ex-ante low default probability $< 0.62\%$.

90^{th} age percentile). As shown in Fig. B.11, this is indeed what we find.

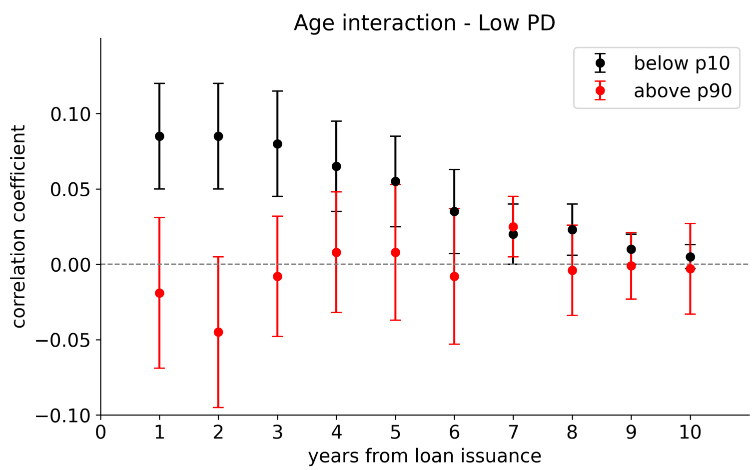


Figure B.11: The figure shows the correlation coefficients of the interactions of ex-post default probability and age (below 10^{th} vs above 90^{th} age percentile). Sample of firms with ex-ante low default probability $< 0.62\%$.

Approach 2: exploiting the difference between fixed and floating rate loans.

We proceed with an exercise to test the transmission of interest rate changes to firm-level risk. We exploit the difference caused by the floating and fixed rate loans on firm's liability, to test whether firms borrowing variable rate loans are more likely to downgrade when reference rates increase. The argument is that the reference rate increases are exogenous to individual firms as they are determined by aggregate monetary policy. The interest rate structure has been used to evaluate the effects of monetary policy on firms' liabilities and outcomes; for example, Gürkaynak et al. (2022) use stock market equity prices to show that investors price-in policy rate changes more when firms have a higher share of floating rate liabilities; Core et al. (2025) also exploit the difference between floating and fixed rate loans to show that the effect of a monetary policy tightening on inflation is weakened if firms facing higher borrowing costs adjust prices. Here, we use a similar strategy to test to which extent interest rates can affect firm's riskiness.

We evaluate the impact of an increase in reference rates following loan origination on firms' creditworthiness after 3 years, using again rating classes transitions and historical default frequencies to approximate the relative increase in default risk. We estimate several specification, including variable rate dummies, yearly increases in reference rates and their interactions with the share of the loan over assets. Unfortunately, we cannot perfectly observe the share of variable rate loans for each firm, so we use the share of variable rate loans in the sample as a proxy. We also use monetary policy shocks as instruments. The baseline specification is the following:

$$\Delta PD_{f,t+3} = \sum_{k=0}^{3} \beta_{1,k} \Delta RefRate_{t+k} + \sum_{k=0}^{3} \beta_{2,k} (\Delta RefRate_{t+k} \times \text{Share Loan}_t) + \gamma_{b,t,p,s} + \epsilon_{f,t} \tag{11}$$

We estimate this specification across sub-samples of loans with maturities exceeding one and two years, to avoid results driven by refinancing. We find no significant impact of increased debt-servicing costs on rating worsening, suggesting that, at least in our sample, an increase in rates inducing an increase in leverage cannot alone induce a worsening firm-level risk. Interestingly, while the rate increase does not induce a worse ex-post outcome, the loan interest rate remains a significant predictor of ex-post riskiness.

However, the validity of our estimates rests on the assumptions that firms do not sort into contract types based on private information or rate expectations (*self-selection*). We mitigates this concern showing that the contract choice is predominantly determined by supply-side lender preferences rather than firm-specific unobservables. Focusing on firms with a rating at the time of the loan, we estimate a linear probability model of the form:

$$Floating_{loan} = \beta X^{observables} + \delta_{q,b,t,s} + \varepsilon_{loan} \tag{12}$$

where $Floating_{loan}$ is a dummy for variable-rate loans and $\delta_{t,b,p,s}$ is the fixed effects interaction term for month, bank, loan purpose and firm sector. Following a variance decomposition approach, we gradually saturate the model with fixed effects. As shown in Table reftab:variance, the lender-quarter dimension alone accounts for approximately 60% of the variation, with the full specification explaining up to 91% of the total variance. This suggests that the contract choice is predominantly driven by supply-side and sectoral factors rather than idiosyncratic firm risk; in fact, banks may prefer to offer floating rate contracts if a variable rate schedule is applied to their own liabilities (see Kirti (2020)).

Table B.3: Variance Decomposition of Variable Rate Choice

Fixed Effects Included	**Adjusted** R^2
Quarter	0.04
+ Lender	0.63
+ Loan Type	0.86
+ Firm Sector	0.91

We also check the balance of observable characteristics between firms taking fixed and variable rate loans. While we find that the two groups differ in some characteristics (variable: fewer firms, larger size, older, riskier, larger financial debt), we include all those characteristics as controls in the following regression, to mitigate the issue of selection bias. We also check the parallel trends assumption by plotting the evolution of rating transitions for firms taking fixed vs variable rate loans, and by including leads of the treatment variable in the regression. We find that rating transitions for firms taking variable rate loans do not differ significantly from those taking fixed rate loans during the period considered. This evidence overall mitigates concerns about selection bias.

Expectations and self selection: firms taking a loan in 2021. To further mitigate the issue of self-selection of firms into fixed or floating rate contracts, we run the exercise at the end of the ZLB period, when firms did not expect a rate hike. We focus on loans issued in 2021, when the policy rate was still at the ZLB and the market did not expect a rate hike. Even for this sample of loans, we do not find a significant effect of reference rate increases on rating worsening. This evidence further supports the idea that the observed correlation is not driven by a mechanical effect of rates on firm fundamentals, but rather by banks' information acquisition.