Drivers of interest rate dispersion in credit markets

Vittoria Iannotta

September 5, 2026

HEC Paris

Motivation

Credit markets exhibit substantial interest rate variation across firms and banks.

Motivation

Credit markets exhibit substantial interest rate variation across firms and banks.

Most is explained by observables at loan issuance:

- for example: macroeconomic conditions, firm and loan characteristics and bank-firm relationships [Altavilla et al. (2024)]

Motivation

Credit markets exhibit substantial interest rate variation across firms and banks.

Most is explained by observables at loan issuance:

- for example: macroeconomic conditions, firm and loan characteristics and bank-firm relationships [Altavilla et al. (2024)]

However, a non-negligible share of variation remains unexplained

Cross-country evidence: US [Amiti et al., 2026 WP], Italy [Bocola et al., 2026 WP], Portugal [Ferreira et al., 2024 WP], Brazil [Cavalcanti et al. (2023)] Dispersion in France

Motivation

Credit markets exhibit substantial interest rate variation across firms and banks.

Most is explained by observables at loan issuance:

- for example: macroeconomic conditions, firm and loan characteristics and bank-firm relationships [Altavilla et al. (2024)]

However, a non-negligible share of variation remains unexplained

Cross-country evidence: US [Amiti et al., 2026 WP], Italy [Bocola et al., 2026 WP], Portugal [Ferreira et al., 2024 WP], Brazil [Cavalcanti et al. (2023)] Dispersion in France

What are the drivers of unexplained rate dispersion?

This paper: overview

Empirics: Using **French loan-level data**, I show that:

- $\tilde{r}_t \equiv r_{t,b,f} - E[r_{t,b,f}|\Omega_t]$ rate residuals contain **forward information** about changes in firms' credit rating: $\tilde{c}_{t+k} \equiv c_{t+k,f} - E[c_{t+k,f}|\Omega_t]$
- **Heterogeneous** across market segments: stronger for young, small firms, and in crises
- **Fixed vs variable rates** test rules out $\tilde{r}_t \to \tilde{c}_{t+k}$

suggesting $\tilde{c}_{t+k} \to \tilde{r}_t$ (i.e. banks acquire information)

This paper: overview

Empirics: Using **French loan-level data**, I show that:

- $\tilde{r}_t \equiv r_{t,b,f} - E[r_{t,b,f}|\Omega_t]$ rate residuals contain **forward information** about changes in firms' credit rating: $\tilde{c}_{t+k} \equiv c_{t+k,f} - E[c_{t+k,f}|\Omega_t]$
- **Heterogeneous** across market segments: stronger for young, small firms, and in crises
- **Fixed vs variable rates** test rules out $\tilde{r}_t \to \tilde{c}_{t+k}$

suggesting $\tilde{c}_{t+k} \to \tilde{r}_t$ (i.e. banks acquire information)

Theory: A new model of loan pricing:

- imperfect competition + adverse selection + information acquisition
- Banks acquire information when **the cost of screening is smaller than the loss from adverse selection**, which is decreasing in competition
- $\uparrow$ **screening reduces (increases) costs borne by safer (riskier) firms**

This paper: overview

Empirics: Using **French loan-level data**, I show that:

- $\tilde{r}_t \equiv r_{t,b,f} - E[r_{t,b,f}|\Omega_t]$ rate residuals contain **forward information** about changes in firms' credit rating: $\tilde{c}_{t+k} \equiv c_{t+k,f} - E[c_{t+k,f}|\Omega_t]$
- **Heterogeneous** across market segments: stronger for young, small firms, and in crises
- **Fixed vs variable rates** test rules out $\tilde{r}_t \rightarrow \tilde{c}_{t+k}$

suggesting $\tilde{c}_{t+k} \rightarrow \tilde{r}_t$ (i.e. banks acquire information)

Theory: A new model of loan pricing:

- imperfect competition + adverse selection + information acquisition
- Banks acquire information when **the cost of screening is smaller than the loss from adverse selection**, which is decreasing in competition
- $\uparrow$ **screening reduces (increases) costs borne by safer (riskier) firms**

The calibration of my model rationalizes the empirical findings

Implications and literature

Unexplained dispersion can be:

1. **mispricing** due to frictions in credit markets (search, bargaining, etc.)
    - [Cavalcanti et al. (2021)], [Altavilla et al. (2024)], [Mazet-Sonilhac (2025)], [Amiti et al. (2026)], [Ferreira and Kozeniauskas (2026)], [Bocola et al. (2026)]
2. **screening** due to unobserved risk and costly information acquisition
    - [Lester et al. (2019)]

My contribution: a mix of both Why it matters:

- **Policy**: if dispersion is due to mispricing, it can be reduced by increasing competition; if due to screening, it is a feature of the market

Literature

Rate dispersion in loan markets

Cavalcanti et al. (2021), Altavilla et al. (2024), Mazet-Sonilhac (2025), Amiti et al. (2026), Ferreira and Kozeniauskas (2026), Bocola et al. (2026)

→ the unexplained component is not only inefficiency: it carries forward information

Search and adverse selection

Burdett and Judd (1983), Guerrieri et al. (2010), Lester et al. (2019)

→ banks buy a costly noisy signal, rather than screening through menus

Information acquisition and market power in banking

Boot and Thakor (2000), Dell'Ariccia (2001), Hauswald and Marquez (2006), Agarwal and Hauswald (2010), Crawford et al. (2018), Cahn et al. (2024)

→ competition matters for screening incentives

Empirical Strategy

Firm-level datasets

1. Loan-level survey (NCE, 2006–2024)

Loan-level survey: all new loan issuance in the first month of each quarter

Includes banks' id, loan terms and firms' accounting, credit, and risk data (observable to the bank).

Cannot observe: full loan history for firms.

2. Credit Registry

Tracks outstanding stock of credit across banks-firms (thresholds: loan exposures $\geq$ €25,000 and/or firm balance-sheet $\geq$ €750,000)

3. Balance Sheets (FIBEN)

Annual accounting data from tax filings. Firms' demographics, additional controls.

4. Banque de France credit ratings (COTA)

Forward-looking over 3 years; incorporates quantitative and qualitative data, historical trends and payment incidents

I turn ratings into default probabilities using historical default frequencies ⏩ PD

Rate residuals contain forward information

I use unexpected rating reviews as a signal of the firm's riskiness at t.

I estimate

$$r_{ilbt} = \alpha \qquad\qquad\qquad\qquad + \mathbf{x}'_{ilbt}\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt},$$

r_{ilbt} is the rate on loan l granted by bank b to firm i in quarter t
$\Delta P_{i,t+k}$ is the change in default probability associated with an upgrade/downgrade of firm i between $k-1$ and k years after issuance.
$\mathbf{x}_{ilbt}$ holds what the bank and the econometrician observe at issuance
$\mu_{bt\tau s}$ absorbs month $\times$ lender $\times$ loan-type $\times$ two-digit-sector effect
Balanced sample, non-defaulting firms at time t

Rate residuals contain forward information

I use unexpected rating reviews as a signal of the firm's riskiness at t.

I estimate

$$r_{ilbt} = \alpha + \sum_{k=1}^{K} \beta_k \Delta P_{i,t+k} + \mathbf{x}'_{ilbt}\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt},$$

r_{ilbt} is the rate on loan l granted by bank b to firm i in quarter t

$\Delta P_{i,t+k}$ is the change in default probability associated with an upgrade/downgrade of firm i between $k-1$ and k years after issuance.

$\mathbf{x}_{ilbt}$ holds what the bank and the econometrician observe at issuance

$\mu_{bt\tau s}$ absorbs month $\times$ lender $\times$ loan-type $\times$ two-digit-sector effect

Balanced sample, non-defaulting firms at time t

Rate residuals contain forward information

I use unexpected rating reviews as a signal of the firm's riskiness at t.

I estimate

$$r_{ilbt} = \alpha + \sum_{k=1}^{K} \beta_k \Delta P_{i,t+k} + \mathbf{x}'_{ilbt} \gamma + \mu_{bt\tau s} + \varepsilon_{ilbt},$$

r_{ilbt} is the rate on loan l granted by bank b to firm i in quarter t

$\Delta P_{i,t+k}$ is the change in default probability associated with an upgrade/downgrade of firm i between $k-1$ and k years after issuance.

$\mathbf{x}_{ilbt}$ holds what the bank and the econometrician observe at issuance

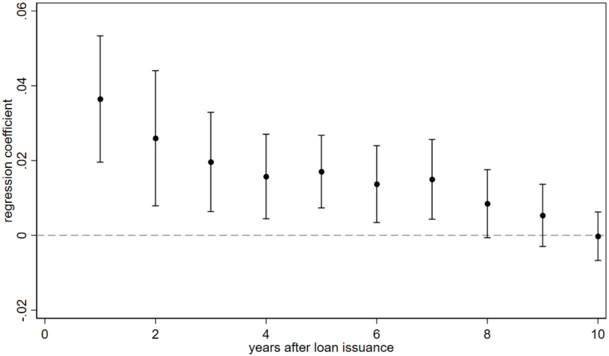
$\mu_{bt\tau s}$ absorbs month $\times$ lender $\times$ loan-type $\times$ two-digit-sector effect

Balanced sample, non-defaulting firms at time t

One-step estimation: absorbs expected changes, robust standard errors. actual default controls $\mathbf{x}_{ilbt}$

Correlation residuals vs default probability

$$r_{ilbt} = \alpha + \sum_{k=1}^{K} \beta_k \, \Delta P_{i,t+k} + \mathbf{x}'_{ilbt}\,\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt},$$



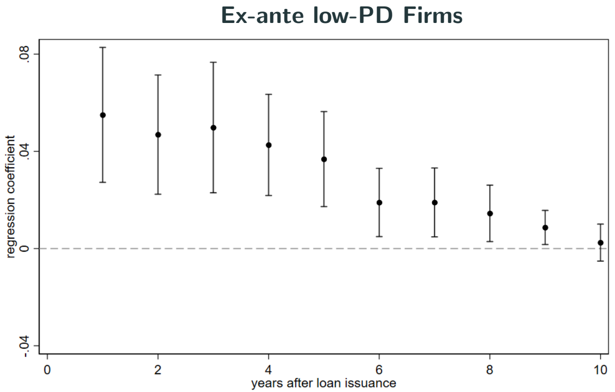
β_k at horizon k, with 95% CI. All $K = 10$ surprises enter jointly; balanced sample.

- Positive and significant, weaker at longer horizons

Information, or a leverage effect?

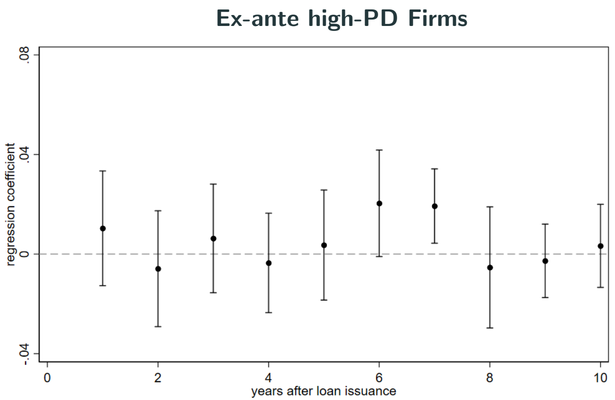
1. I explore how the **correlation varies in the cross-section**
2. **Fixed vs variable rates** test rules out $\tilde{r}_t \rightarrow \tilde{c}_{t+k}$

Correlation: stronger for better rated firms



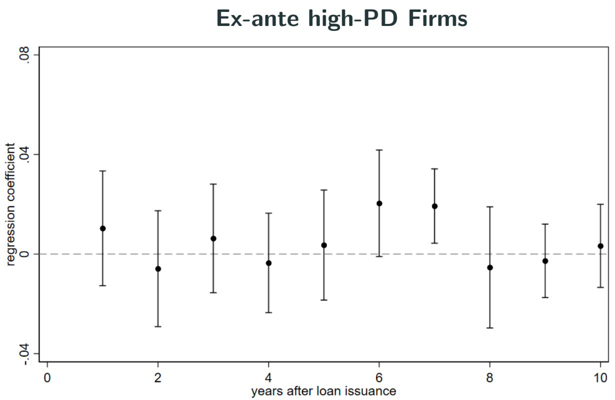
Computed for firms with ex-ante PD$<$ 0.62%.

Correlation: stronger for better rated firms



Computed for firms with ex-ante PD> 3.45%.

Correlation: stronger for better rated firms



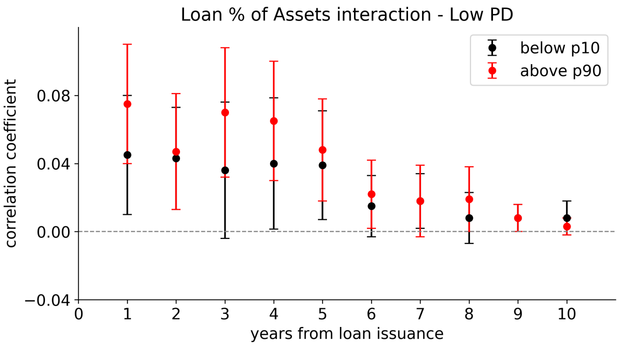
Computed for firms with ex-ante PD$>$ 3.45%.

Predictive power of rate residuals varies by ex-ante riskiness.

Correlation: does not depend on loan size

Mechanical effect → stronger if the loan is large!

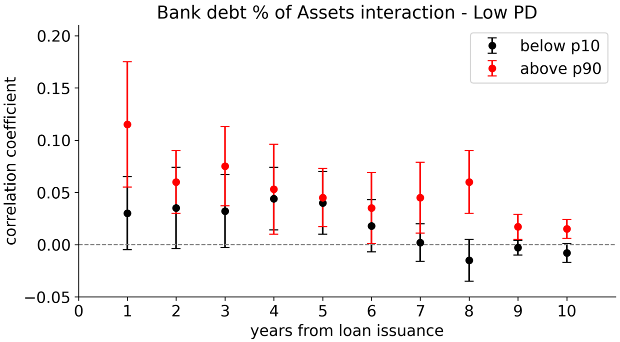
Focusing on the group of better rated firms (low PD):



Excludes firms in liquidation. Balanced sample. Firms with ex-ante good rating. Interactions at 10th-90th percentile of loan over assets.

Higher PD. Prediction or consequence?

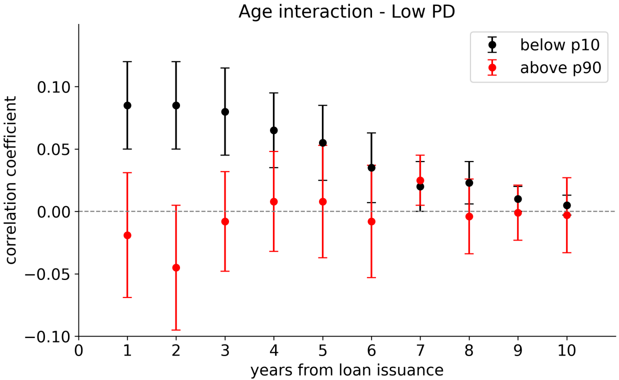
Mechanical effect → stronger if the loan is large!



Probability of default, by year. Excludes firms in liquidation. Balanced sample. Rating: 1 to 3, from best to worst rating. Interactions at 10th-90th percentile of bank debt over assets.

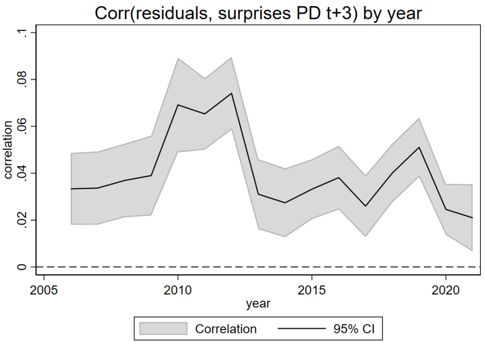
Correlation: stronger for younger firms

Focusing on the group of better rated firms (low PD):

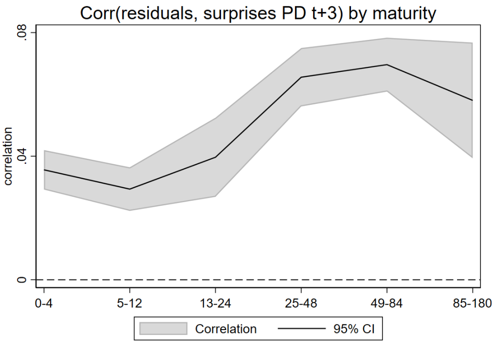


Excludes firms in liquidation. Balanced sample. Firms with ex-ante good rating. Interactions at 10th-90th percentile of age.

Correlation: demographics



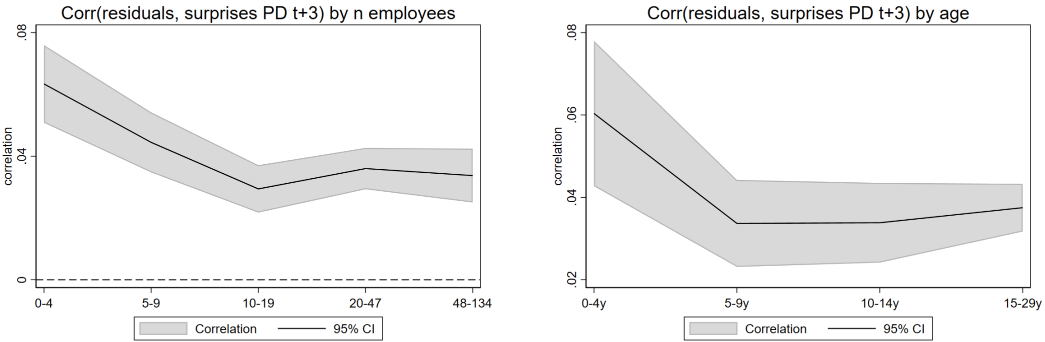
(a) By year



(b) By loan **maturity** (months)

Figure 1: Correlation $\hat{\rho}_g$ between the unexplained rate component $\tilde{r}_t \equiv r_{t,b,f} - E[r_{t,b,f}|\Omega_t]$ and the unexpected 3-year change in default probability $\tilde{PD}_{t+3} \equiv PD_{t+3,f} - E[PD_{t+3,f}|\Omega_t]$, both computed in the entire population and correlated by group g.

Correlation: demographics



(a) By **n. of employees**

(b) By firm **age**

Figure 2: Correlation $\hat{\rho}_g$ between the unexplained rate component $\tilde{r}_t \equiv r_{t,b,f} - E[r_{t,b,f}|\Omega_t]$ and the unexpected 3-year change in default probability $\tilde{PD}_{t+3} \equiv PD_{t+3,f} - E[PD_{t+3,f}|\Omega_t]$, both computed in the entire population and correlated by group g.

Information, or a leverage effect?

A positive correlation admits two readings:

Information — the bank recognizes the riskier type and prices it

Leverage — the high rate mechanically increases the size of debt

Two approaches:

1. I explore how the **correlation varies in the cross-section**
2. **Fixed vs variable rates** test rules out $\tilde{r}_t \rightarrow \tilde{c}_{t+k}$

Test: do higher rates induce rating worsening?

Design. Compare **variable**- and **fixed**-rate borrowers; when reference rates rise, are variable-rate borrowers more likely to experience a rating worsening?

Assumptions.

1. Exogeneity: the increase is set by aggregate conditions and monetary policy, so it is exogenous to the individual firm's fundamentals.
2. Sorting on rate expectations: (i) I show that the contract choice is predominantly driven by banks' preferences (ii) I repeat the exercise at the end of 2021 Self-selection
3. Parallel trends: Absent the rate increase, rating transitions of fixed- and floating-rate borrowers would have evolved in the same way. Validity

Test: do higher rates induce rating worsening?

Design. Compare **variable-** and **fixed**-rate borrowers; when reference rates rise, are variable-rate borrowers more likely to experience a rating worsening?

$$\Delta PD_{i,1\to 3} =$$

$$+ \mathbf{x}'_{ilbt}\,\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt}$$

$\Delta PD_{i,1\to 3} = 100 \times (P_{i,3} - P_{i,1})$; $\text{Share}_{i,1}$ = loan- or bank-debt-over-assets.
$\Delta\mathrm{Ref}_{l,1\to 2}$ is loan l's **own** reference rate change: each floating loan is tied to its own index (EONIA, Euribor 1m/3m/1y, TMO), a fixed-rate loan to zero.
Maturity $\geq$ 30 months; SEs two-way clustered by lender and month.

Back

Test: do higher rates induce rating worsening?

Design. Compare **variable-** and **fixed**-rate borrowers; when reference rates rise, are variable-rate borrowers more likely to experience a rating worsening?

$$\Delta PD_{i,1\to 3} = \beta\, \Delta \mathrm{Ref}_{l,1\to 2} + \mathbf{x}'_{ilbt}\,\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt}$$

$\Delta PD_{i,1\to 3} = 100 \times (P_{i,3} - P_{i,1})$; $\mathrm{Share}_{i,1}$ = loan- or bank-debt-over-assets.

$\Delta \mathrm{Ref}_{l,1\to 2}$ is loan l's **own** reference rate change: each floating loan is tied to its own index (EONIA, Euribor 1m/3m/1y, TMO), a fixed-rate loan to zero.

Maturity $\geq$ 30 months; SEs two-way clustered by lender and month.

Variation within a lender $\times$ month $\times$ loan-type $\times$ sector cell: fixed vs floating, and *which index* a floating loan carries.

Back

Test: do higher rates induce rating worsening?

Design. Compare **variable**- and **fixed**-rate borrowers; when reference rates rise, are variable-rate borrowers more likely to experience a rating worsening?

$$\Delta PD_{i,1\to3} = \beta\, \Delta\mathrm{Ref}_{l,1\to2} + \delta \left(\Delta\mathrm{Ref}_{l,1\to2} \times \text{Share}_{i,1}\right) + \mathbf{x}'_{ilbt}\,\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt}$$

$\Delta PD_{i,1\to3} = 100 \times (P_{i,3} - P_{i,1})$; $\text{Share}_{i,1}$ = loan- or bank-debt-over-assets.

$\Delta\mathrm{Ref}_{l,1\to2}$ is loan l's **own** reference rate change: each floating loan is tied to its own index (EONIA, Euribor 1m/3m/1y, TMO), a fixed-rate loan to zero.

Maturity $\geq$ 30 months; SEs two-way clustered by lender and month.

Variation within a lender $\times$ month $\times$ loan-type $\times$ sector cell: fixed vs floating, and *which index* a floating loan carries.

Back

Test: do higher rates induce rating worsening?

	Default Probability						
Variable rate (dummy)	0.1176**		0.1407	0.1039**			
	(0.014)		(0.127)	(0.026)			
cum dRate end y2		0.0433			0.0374		
		(0.229)			(0.254)		
annual dRate end y1			0.0812			0.0524	0.0425
			(0.600)			(0.711)	(0.773)
annual dRate end y2			0.0567			0.0363	0.0128
			(0.330)			(0.551)	(0.879)
Variable rate (dummy) × Loan over assets				0.1932			
				(0.370)			
cum dRate end y2 × Loan over assets					0.0711		
					(0.264)		
annual dRate end y1 × Loan over assets						-0.1330	
						(0.763)	
annual dRate end y2 × Loan over assets						0.0905	
						(0.148)	
annual dRate end y1 × Bank Debt share							0.0058
							(0.980)
annual dRate end y2 × Bank Debt share							0.0986
							(0.623)
Loan over assets	0.2250**	0.2002**	0.2048**	0.1808*	0.1894*	0.1849*	0.1929*
	(0.030)	(0.035)	(0.035)	(0.094)	(0.054)	(0.059)	(0.054)
Bank Debt share	0.0846**	0.1139**	0.1134**	0.0850**	0.1118**	0.1114**	0.1127**
	(0.040)	(0.019)	(0.019)	(0.034)	(0.022)	(0.023)	(0.025)
Lender × Month × Loan Type × 2digit Sector FE	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓
All other observables	✓	✓	✓	✓	✓	✓	✓
Observations	102,463	96,414	96,414	102,463	96,414	96,414	96,414
R^2	0.42	0.40	0.40	0.42	0.40	0.40	0.40

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

Table 1: Data: Nouveaux Crédits (BdF), 2006q1-2024q2. Term loans, at least 30-month maturity, only firms with a rating. Dependent variable: change_PD3. Exclude loans with non-specified reference rate.

Rate exercise: 2021q3–q4, 2022 increase only

	Default Probability - 2021q3-2021q4 only						
Variable rate (dummy)	-0.5698		-6.1935	-0.5121			
	(0.169)		(0.193)	(0.186)			
annual dRate end y2			1.8860			-0.3828*	-0.4445
			(0.261)			(0.095)	(0.218)
Variable rate (dummy) × Loan over assets				-0.6271			
				(0.249)			
annual dRate end y2 × Loan over assets						-0.3410	
						(0.228)	
annual dRate end y2 × Bank Debt share							0.0555
							(0.915)
Loan over assets	-0.5329	-1.1142	-1.1243	-0.1584	-0.6316	-0.6318	-1.1395
	(0.374)	(0.168)	(0.216)	(0.740)	(0.224)	(0.223)	(0.177)
Bank Debt share	0.0986	-0.2614	-0.2672	0.1401	-0.2234	-0.2234	-0.2780
	(0.725)	(0.316)	(0.448)	(0.631)	(0.375)	(0.375)	(0.364)
Lender × Month × Loan Type × 2digit Sector FE	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓
All other observables	✓	✓	✓	✓	✓	✓	✓
Observations	4,324	4,089	4,089	4,324	4,089	4,089	4,089
R^2	0.41	0.41	0.41	0.41	0.41	0.41	0.41

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

Table 2: Data: Nouveaux Crédits (BdF), 2006q1-2024q2. Term loans, maturity at least 24 months, only firms with a rating. Dependent variable: change_PD3. Exclude loans with non-specified reference rate.

▸▸ 2022–23 increase, mat. ≥ 30m ▸▸ 2022–23 increase, mat. ≥ 24m

Test: do higher rates induce rating worsening?

Result: β and δ are not significant.

- a rise in reference rates does not induce a rating worsening
- suggests that the correlation between rate residuals and rating changes **is not mechanically driven by leverage**

Two approaches:

✓ **Information** — the bank recognizes the riskier type and prices it

✗ **Leverage** — the high rate mechanically increases the size of debt

Theory

Environment

Market with search frictions and adverse selection as in [Lester et al. 2019]

- I depart from screening via menus and focus on information acquisition.

A continuum of firms: visit banks to obtain rate quotes

- asymmetric information: two types $i \in \{g, b\}$, measure μ_q^i, default with probability $1 - p^i$ accept maximum rate $\bar{r}^i$
- search frictions: π *shoppers* ($1 - \pi$ *captive*) firms obtain two (one) rate quotes, and accept the lowest one, if lower than $\bar{r}^i$

Two homogeneous banks:

- cost of lending depends on central bank rate and risk: $c^i = \dfrac{r^{CB}}{p^i}$
- cannot distinguish captive/shopper firms, nor types
- can choose to acquire a **costly, symmetric signal** s on all firms, with precision $q \in [0.5, 1]$

Information acquisition

Population shares μ_g and $\mu_b = 1 - \mu_g$.

Each bank can acquire a **binary signal s** $\in \{\mathbf{g}, \mathbf{b}\}$ at cost C_q on all firms, with **precision q**$_\theta$ (probability of correctly identifying a $\theta \in \{g, b\}$ 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, $\sigma_g + \sigma_b = 1$.

The bank updates its prior belief μ_g to a **posterior belief of facing a good type**, given s=g or s=b:

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

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.

Banks' profit maximization

Bank chooses CDF of rates $F^{s_i}(r)$ to maximize expected profits:

$$\Pi^{s_i}(r) = \begin{cases} & \text{if } r \leq \bar{r}^g \\ & \text{if } \bar{r}^g < r \leq \bar{r}^b \end{cases}$$

with $\bar{r}^g < \bar{r}^b$

Banks' profit maximization

Bank chooses CDF of rates $F^{s_i}(r)$ to maximize expected profits:

$$\Pi^{s_i}(r) = \begin{cases} \underbrace{[1-\pi+\pi(1-F^{s_i}(r))]}_{\text{acceptance probability}}\underbrace{(r-c^{avg,s_i})}_{\text{profit per trade}} & \text{if } r \leq \bar{r}^g \\ & \text{if } \bar{r}^g < r \leq \bar{r}^b \end{cases}$$

with $\bar{r}^g < \bar{r}^b$

- below $\bar{r}^g$, **both types accept**
- **Trade-off:** a higher rate raises the profit per trade and lowers the probability of acceptance

Banks' profit maximization

Bank chooses CDF of rates $F^{s_i}(r)$ to maximize expected profits:

$$\Pi^{s_i}(r) = \begin{cases} \underbrace{[1-\pi+\pi(1-F^{s_i}(r))]}_{\text{acceptance probability}}\underbrace{(r-c^{avg,s_i})}_{\text{profit per trade}} & \text{if } r \leq \bar{r}^g \\ \underbrace{(1-\alpha^{s_i})}_{\text{share bad}}\underbrace{[1-\pi+\pi(1-F^{s_i}(r))]}_{\text{acceptance probability}}\underbrace{(r-c_b)}_{\text{profit per trade}} & \text{if } \bar{r}^g < r \leq \bar{r}^b \end{cases}$$

with $\bar{r}^g < \bar{r}^b$

- between $\bar{r}^g$ and $\bar{r}^b$, **only bad types accept**
- **Trade-off:** $\uparrow$rate $\rightarrow \uparrow$ profit per trade and $\downarrow$ probability of acceptance

Where does the bank lend?

It depends on the severity of adverse selection ϕ^{s_i}.

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

Intuition: compares profits in pooling vs profits when lending to bad types only

$$\begin{cases} \phi^{s_i} > 0 & \text{mild: the bank } \textbf{pools} \text{ both types} \\ \underline{\phi}^{s_i} < \phi^{s_i} \leq 0 & \text{severe: a } \textbf{mix} \text{ of pooling and bad-only} \\ \phi^{s_i} \leq \underline{\phi}^{s_i} & \text{severe: } \textbf{bad types only} \end{cases}$$

with $\underline{\phi}^{s_i} \;=\; -\dfrac{\pi}{1-\pi}\left(\bar{r}^g - c^{avg,s_i}\right) \;<\; 0$, found from $F^a(\bar{r}^g) > 0$.

Rate dispersion

Limit cases of $\pi = \mathbf{0}, \mathbf{1}$ [1]

- Banks operate under monopoly/perfect competition

$\rightarrow$ degenerate distribution

[1] π is the share of shoppers

Rate dispersion

Limit cases of $\pi = \mathbf{0}, \mathbf{1}$ [1]

- Banks operate under monopoly/perfect competition

$\rightarrow$ degenerate distribution

Intermediate case $\pi \in (\mathbf{0}, \mathbf{1})$

- at any r^*, a bank deviating to $r^* - \varepsilon$ gains all shoppers $\rightarrow$ Strict gain
- at $r^* = c$, $\Pi^* = 0$. A bank deviating to any $r > c$ makes profits from captive firms

$\rightarrow$ dispersed equilibrium

[1] π is the share of shoppers

Rate dispersion

Limit cases of $\pi = \mathbf{0}, \mathbf{1}$ [1]

- Banks operate under monopoly/perfect competition

$\rightarrow$ degenerate distribution

Intermediate case $\pi \in (\mathbf{0}, \mathbf{1})$

- at any r^*, a bank deviating to $r^* - \varepsilon$ gains all shoppers $\rightarrow$ Strict gain
- at $r^* = c$, $\Pi^* = 0$. A bank deviating to any $r > c$ makes profits from captive firms

$\rightarrow$ dispersed equilibrium

Isoprofit function, top of the support at $\bar{r}^g$ (pooling, $\phi^{s_i} > 0$):

$$(1 - \pi)(\bar{r}^g - c^{avg,s_i}) = \left[1 - \pi + \pi(1 - F^{s_i}(r))\right](r - c^{avg,s_i})$$

[1] π is the share of shoppers

Equilibrium under a perfect signal

Proposition 1 (Dispersed-rate equilibrium, $q = 1$)
For $\pi \in (0,1)$ and a perfect signal there is a unique symmetric mixed-strategy equilibrium. For each type i, banks randomize over $[\underline{r}^i, \bar{r}^i]$ according to

$$F^i(r) = 1 - \frac{1-\pi}{\pi}\left[\frac{\bar{r}^i - r}{r - c_i(r)}\right],$$

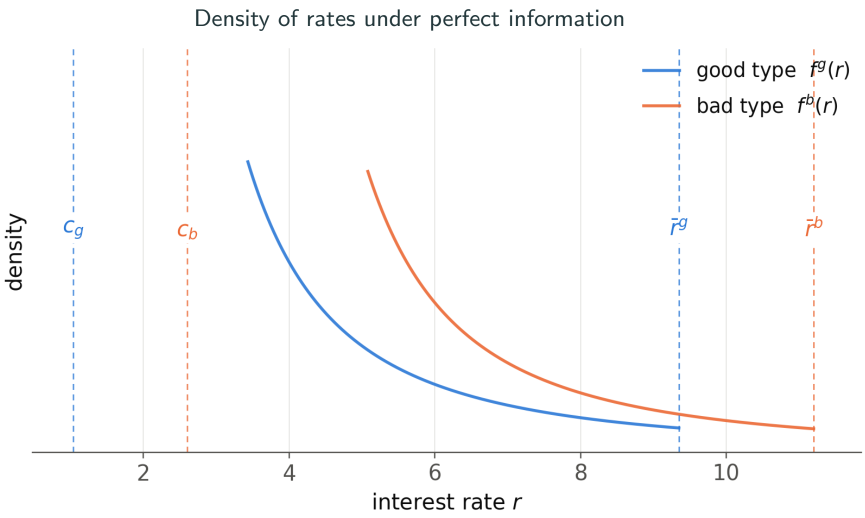
with $\bar{r}^i$ the type's reservation rate and $\underline{r}^i$ defined by $F^i(\underline{r}^i) = 0$.

Observed rates are the mixture $\mu_g F^g(r) + \mu_b F^b(r)$ on $[\underline{r}^g, \bar{r}^b]$.

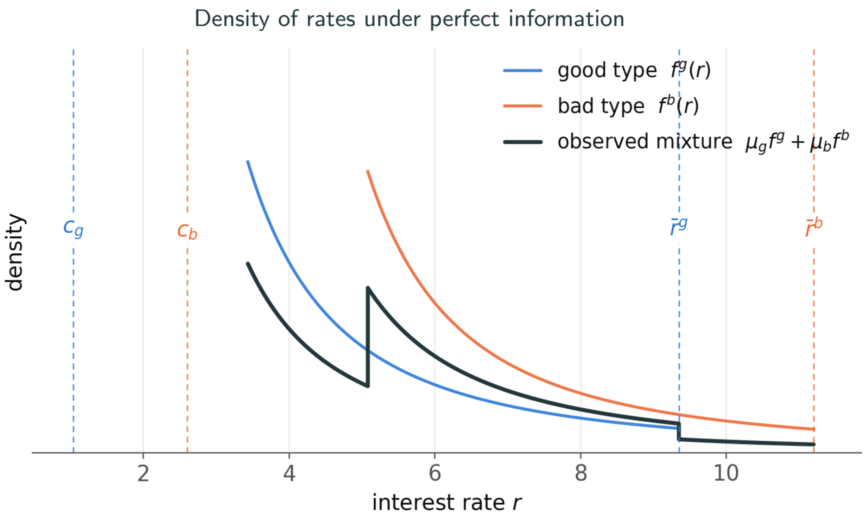
- the bank solves two separate problems, one by type, one per type $\rightarrow$ *between-type* dispersion

Derivation | Example: one type | Example: two types

Example: two types, perfect signal ($q = 1$)



Example: two types, perfect signal ($q = 1$)



Equilibrium without information: two regimes

Proposition 2 (Severe adverse selection, $\phi \leq 0$)
Banks randomize over $[\underline{r}^a, \bar{r}^b]$, mixing a pooling and a bad-only region: $F = F^a$ on $[\underline{r}^a, \bar{r}^g]$ and $F = F^a(\bar{r}^g) + F^b$ on $(\bar{r}^g, \bar{r}^b]$, with

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

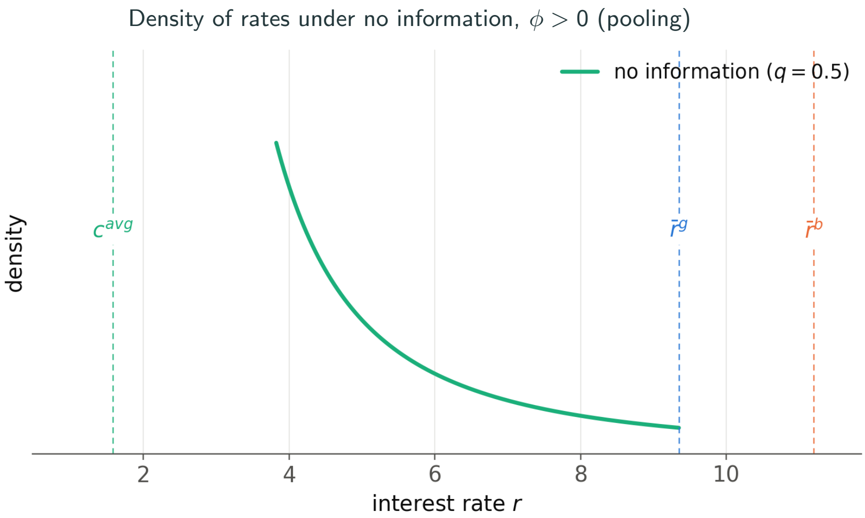
$$F^b(r) = 1 - F^a(\bar{r}^g) - \frac{1-\pi}{\pi}\left[\frac{\bar{r}^b - c_b}{r - c_b(r)} - 1\right]$$

Proposition 3 (Mild adverse selection, $\phi > 0$)
Banks randomize over $[\underline{r}, \bar{r}^g]$ only, at $F(r) = 1 - \frac{1-\pi}{\pi}\left[(\bar{r}^g - r)/(r - c^{avg}(r))\right]$: all firms trade, both types face the same rates.

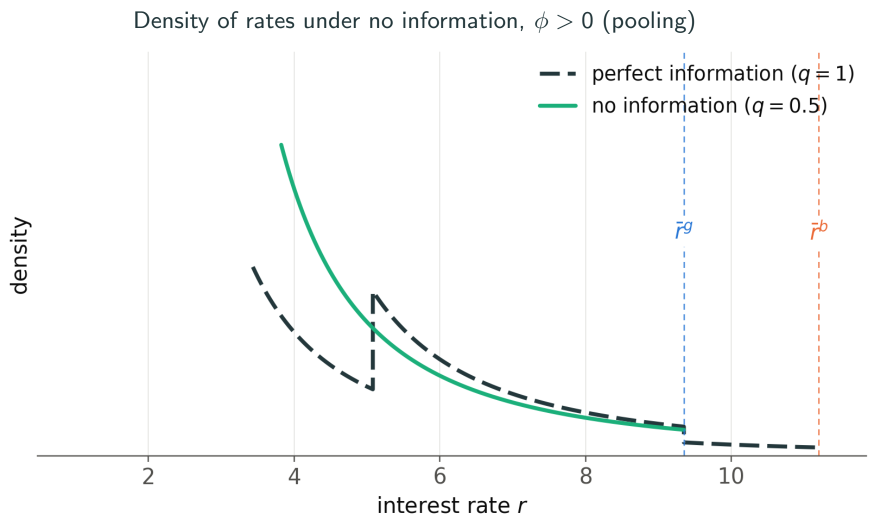
Lemma 1 (When does pooling survive?)
A pooling region exists for $-\frac{\pi}{1-\pi}(\bar{r}^g - c^{avg}) < \phi \leq 0$; below that threshold the bank lends to bad types only.

Example

Example: two types, no signal acquisition ($q = 0.5$)



Example: two types, no signal acquisition ($q = 0.5$)



Back to the data: variance and correlation

Dispersion

$q = 1$

$$\mathrm{Var}(r) = \underbrace{\sum_{i\in\{g,b\}} \mu_i \mathrm{Var}(r \mid i)}_{\textbf{within-type}} + \underbrace{\mu_g \mu_b \big(\mathbb{E}[r|b] - \mathbb{E}[r|g]\big)^2}_{\textbf{between-type}}$$

$q = 0.5,\ \phi > 0$

$$\mathrm{Var}(r)_{q=0.5} \ < \ \mathrm{Var}_{\text{within}} \ < \ \mathrm{Var}(r)_{q=1}$$

Back to the data: variance and correlation

Dispersion

$q = 1$

$$\mathrm{Var}(r) = \underbrace{\sum_{i \in \{g,b\}} \mu_i \mathrm{Var}(r \mid i)}_{\textbf{within-type}} + \underbrace{\mu_g \mu_b \big(\mathbb{E}[r|b] - \mathbb{E}[r|g]\big)^2}_{\textbf{between-type}}$$

$q = 0.5, \ \phi > 0$

$$\mathrm{Var}(r)_{q=0.5} < \mathrm{Var}_{\text{within}} < \mathrm{Var}(r)_{q=1}$$

Correlation rates and riskiness

$q = 1$

$$\rho(r, PD) = \sqrt{\mu_g \mu_b} \frac{\mathbb{E}[r|b] - \mathbb{E}[r|g]}{\sqrt{\mathrm{Var}(r)}}$$

$q = 0.5, \ \phi > 0$

$$0$$

Back to the data: variance and correlation

Dispersion

$$q = 1 \qquad \mathrm{Var}(r) = \underbrace{\sum_{i\in\{g,b\}} \mu_i \mathrm{Var}(r \mid i)}_{\textbf{within-type}} + \underbrace{\mu_g \mu_b \big(\mathbb{E}[r|b] - \mathbb{E}[r|g]\big)^2}_{\textbf{between-type}}$$

$$q = 0.5,\ \ \phi > 0 \qquad \mathrm{Var}(r)_{q=0.5} < \mathrm{Var}_{\text{within}} < \mathrm{Var}(r)_{q=1}$$

Correlation rates and riskiness

$$q = 1 \qquad \rho(r, PD) = \sqrt{\mu_g \mu_b}\,\frac{\mathbb{E}[r|b] - \mathbb{E}[r|g]}{\sqrt{\mathrm{Var}(r)}}$$

$$q = 0.5,\ \ \phi > 0 \qquad 0$$

$\rightarrow$ I will target **Var** and **Corr** to calibrate π and q

Who gets the surplus?

Proposition 4
The banks' share of total surplus is decreasing in competition and increasing in the precision of the signal.

1. **Under a perfect signal**, every firm trades, each type is priced off its own cost, and the bank captures exactly $1-\pi$ of the realized surplus, firms π.
2. **Under no information**, the bank collects strictly less:

$$\mathbb{E}[\Pi(q)] \propto (1-\pi), \qquad \Pi^{LOSS} = \begin{cases} (1-\pi)\,\mu_b\,(\bar{r}^b - \bar{r}^g) & \text{if } \phi > 0 \\ (1-\pi)\,\mu_g\,(\bar{r}^g - c_g) & \text{if } \phi \leq 0 \end{cases}$$

Gains table

Who gets the surplus?

Proposition 4
The banks' share of total surplus is decreasing in competition and increasing in the precision of the signal.

1. **Under a perfect signal**, every firm trades, each type is priced off its own cost, and the bank captures exactly $1-\pi$ of the realized surplus, firms π.
2. **Under no information**, the bank collects strictly less:

$$\mathbb{E}[\Pi(q)] \;\propto\; (1-\pi), \qquad \Pi^{LOSS} = \begin{cases} (1-\pi)\,\mu_b\,(\bar{r}^b - \bar{r}^g) & \text{if } \phi > 0 \\ (1-\pi)\,\mu_g\,(\bar{r}^g - c_g) & \text{if } \phi \leq 0 \end{cases}$$

Banks recover the loss of adverse selection at q=1 $\rightarrow$ incentive to screen

Gains table

... and what do firms get?

Proposition 5 (Firms' surplus and information)
Information reduces the costs borne by good types.

Under no information, *good types*

- *when adverse selection is mild ($\phi > 0$), trade at the higher* **pooling** *rates* $\rightarrow$ **cross-subsidy** *to bad types*
- *when it is severe ($\phi \leq 0$)* **may not trade at all** $\rightarrow$ **exit** *from the market*

Their gains rise with q, fall when adverse selection is severe and fall with competition.

Gains table Back

...and what do firms get?

Proposition 5 (Firms' surplus and information)
Information reduces the costs borne by good types.

Under no information, *good types*

- *when adverse selection is mild ($\phi > 0$), trade at the higher* **pooling** *rates* $\rightarrow$ **cross-subsidy** *to bad types*
- *when it is severe ($\phi \leq 0$)* **may not trade at all** $\rightarrow$ **exit** *from the market*

Their gains rise with q, fall when adverse selection is severe and fall with competition.

Good types bear two costs of asymmetric information — a **cross-subsidy** to bad types where the bank pools, and **exclusion** where it lends to bad types only. Both fall with q.

Gains table Back

... and what do firms get?

Proposition 6 (Firms' surplus and information)
Information increases the costs borne by bad types.

Under no information, *bad types*

- *when* $\phi > 0$, **benefit** *from pooling* $\rightarrow$ *benefit from* **cross-subsidy** *from good types and from banks*
- *when it is severe* ($\underline{\phi} < \phi \leq 0$), *they may gain if* **partial pooling** $\rightarrow$ **cross-subsidy** *from good types*
- *when it is severe* ($\phi \leq \underline{\phi}$), *same as perfect information* $\rightarrow$ **no gain**

Their benefits fall with q, fall when adverse selection is severe and fall with competition..

Gains table Back

Calibration

Calibration summary

Approach

- calibrated directly from the data: μ_i, PD_i, $\bar{r}^b$
- estimated by moment matching within each rating class: π, q, $\bar{r}^g$
- moments matched: mean, variance, correlation with PD of rate residuals

Approach Results Parameters

Calibration summary

Approach

- calibrated directly from the data: μ_i, PD_i, $\bar{r}^b$
- estimated by moment matching within each rating class: π, q, $\bar{r}^g$
- moments matched: mean, variance, correlation with PD of rate residuals

Results

- even when banks acquire a **very precise signal**, the contribution to unexplained dispersion is **at most 5%**
- banks acquire information in the safest rating classes, but not in the riskiest ones

Calibration summary

Approach

- calibrated directly from the data: μ_i, PD_i, $\bar{r}^b$
- estimated by moment matching within each rating class: π, q, $\bar{r}^g$
- moments matched: mean, variance, correlation with PD of rate residuals

Results

- even when banks acquire a **very precise signal**, the contribution to unexplained dispersion is **at most 5%**
- banks acquire information in the safest rating classes, but not in the riskiest ones

Robustness

- local identification checked; competing global optima ruled out

▸▸ Approach ▸▸ Results ▸▸ Parameters

Calibration: Parameters & Moments

Parameters recovered (3):

- π: search friction (share of shoppers visiting both banks)
- q: signal precision (bank's screening quality)
- $\bar{r}_g$: reservation rate for good types

Moments matched (3):

- Mean: $\mathbb{E}[r]$
- Variance: $\mathrm{Var}(r)$
- Correlation with default probability: $\mathrm{Corr}(r, p)$

Calibrated from data (by rating class):

- Success probabilities p_g, p_b and type shares μ_b from rating transitions
- Upper bound bad types $\bar{r}_b$ from observed $\max(r)$
- Fixed: $r_{CB} = 1$ (average policy rate over the sample period)

data moments Back

Calibration: Strategy

Objective:

minimize squared proportional errors across three moments:

$$Q(\theta) = \sum_m \left(\frac{m^{\text{model}} - m^{\text{data}}}{m^{\text{data}}} \right)^2$$

Numerical implementation:

Grid search (20^3 combinations over $\pi, q, \bar{r}_g$) + L-BFGS-B local refinement

Decomposition (information contribution):

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

Results: Search Frictions vs. Screening

Table 3: Calibrated parameters by rating class

Rating	$\hat{\pi}$	$\hat{q}$	$\hat{\bar{r}}_g$	Info Contr. (%)	Obj. Q
3+	0.772	0.997	3.461	4.89	0.41
3	0.759	1.000	3.706	4.56	0.35
4+	0.738	0.999	4.609	3.94	0.15
4	0.757	1.000	5.056	5.06	0.19
5+	0.749	1.000	5.403	3.05	0.20
5	0.729	0.944	6.662	0.04	0.04
6	0.721	0.526	7.057	0.00	0.04
7	0.711	0.526	9.350	0.00	0.00

Key findings:

1. **Competitive market:** $\hat{\pi} \in [0.71, 0.77]$ - high search intensity across all classes.
2. **Screening gap:** Safe ratings (3+–5+) near-perfect screening ($\hat{q}$ close to 1); risky ratings (6–7) essentially none ($\hat{q} \approx 0.53$).
3. **Search dominates:** Information contributes at most 5.1% of residual variance.

Back

Why screening in the safest classes?

All classes are calibrated in the **mild** regime ($\phi^{s_i} > 0$): under no information, the bank **pools** and charges at most $\bar{r}^g$.

Expected gain from screening: **surplus from bad types**

$$\Pi^{LOSS} = \underbrace{(1-\pi)}_{\textbf{mkt power}} \quad \underbrace{\mu_b \left(\bar{r}^b - \bar{r}^g\right)}_{\textbf{extra bad-type surplus}}$$

⏩ Bank surplus ⏩ Inputs ⏩ Surplus sharing

Why screening in the safest classes?

All classes are calibrated in the **mild** regime ($\phi^{s_i} > 0$): under no information, the bank **pools** and charges at most $\bar{r}^g$.

Expected gain from screening: **surplus from bad types**

$$\Pi^{LOSS} = \underbrace{(1-\pi)}_{\textbf{mkt power}} \underbrace{\mu_b\left(\bar{r}^b - \bar{r}^g\right)}_{\textbf{extra bad-type surplus}}$$

- **Safe classes (3+–5+): the expected gain from screening is larger.** Hidden bad types are many ($\mu_b = 0.85$ at 3+, 0.67 at 4) $\rightarrow$ $\hat{q} \approx 1$

Bank surplus | Inputs | Surplus sharing

Why screening in the safest classes?

All classes are calibrated in the **mild** regime ($\phi^{s_i} > 0$): under no information, the bank **pools** and charges at most $\bar{r}^g$.

Expected gain from screening: **surplus from bad types**

$$\Pi^{LOSS} = \underbrace{(1-\pi)}_{\textbf{mkt power}} \underbrace{\mu_b \left(\bar{r}^b - \bar{r}^g\right)}_{\textbf{extra bad-type surplus}}$$

- **Safe classes (3+–5+): the expected gain from screening is larger.** Hidden bad types are many ($\mu_b = 0.85$ at 3+, 0.67 at 4) $\rightarrow$ $\hat{q} \approx 1$
- **Risky classes (6–7): the expected gain from screening is smaller.** Almost every firm is already known to be risky ($\mu_b = 0.07$) $\rightarrow$ $\hat{q}$ at its floor

Bank surplus Inputs Surplus sharing

Why screening in the safest classes?

All classes are calibrated in the **mild** regime ($\phi^{s_i} > 0$): under no information, the bank **pools** and charges at most $\bar{r}^g$.

Expected gain from screening: **surplus from bad types**

$$\Pi^{LOSS} = \underbrace{(1-\pi)}_{\textbf{mkt power}} \underbrace{\mu_b \left(\bar{r}^b - \bar{r}^g\right)}_{\textbf{extra bad-type surplus}}$$

- **Safe classes (3+–5+): the expected gain from screening is larger.** Hidden bad types are many ($\mu_b = 0.85$ at 3+, 0.67 at 4) $\rightarrow$ $\hat{q} \approx 1$
- **Risky classes (6–7): the expected gain from screening is smaller.** Almost every firm is already known to be risky ($\mu_b = 0.07$) $\rightarrow$ $\hat{q}$ at its floor

The wedge $\bar{r}^b - \bar{r}^g$ runs the other way ($0.07 \rightarrow 0.19$), but μ_b falls twelvefold: Π^{LOSS} is about **five times larger** in the safe classes.

⏩ Bank surplus ⏩ Inputs ⏩ Surplus sharing

Conclusion

Main takeaways

Empirics: unexplained rate premia $\tilde{r}_t$ carry forward information on firms' credit outcomes $\tilde{c}_{t+k}$

- **Heterogeneous** across segments: young and small firms, crises
- **Fixed vs variable rates**: rates anticipate a deterioration, not cause it

Main takeaways

Empirics: unexplained rate premia $\tilde{r}_t$ carry forward information on firms' credit outcomes $\tilde{c}_{t+k}$

- **Heterogeneous** across segments: young and small firms, crises
- **Fixed vs variable rates**: rates anticipate a deterioration, not cause it

Theory: loan pricing with imperfect competition + adverse selection + information acquisition

- Banks screen when adverse selection is costly and competition is low
- Screening reduces (increases) the cost borne by safer (riskier) firms

Main takeaways

Empirics: unexplained rate premia $\tilde{r}_t$ carry forward information on firms' credit outcomes $\tilde{c}_{t+k}$

- **Heterogeneous** across segments: young and small firms, crises
- **Fixed vs variable rates**: rates anticipate a deterioration, not cause it

Theory: loan pricing with imperfect competition + adverse selection + information acquisition

- Banks screen when adverse selection is costly and competition is low
- Screening reduces (increases) the cost borne by safer (riskier) firms

Calibration: information explains **at most 5%** of the dispersion, **search frictions** the rest. Larger incentive to screen in the safest classes, where the bank can extract more surplus from bad types.

Appendix

Example Documents Required for the Application

- Business plan including financial projections (forecast income statement, working capital requirements, financing plan)
- Company information: legal status, share capital, partners/shareholders
- Proof of personal contribution or equity investment
- Proof of guarantees or collateral (optional for “solidarity” loans)
- Documentation of the project cost (quotes, sales offers, franchise agreements)
- Company registration extract (Kbis) if the company is already registered

Survey Evidence: Banks

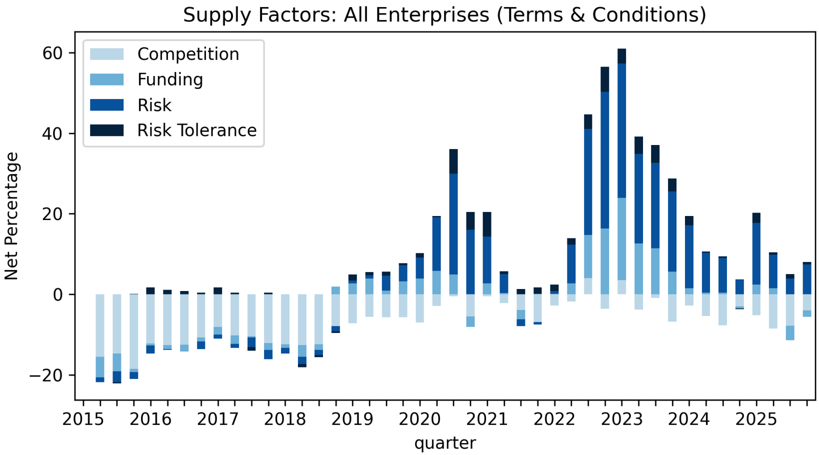


Figure 3: Source: BLS (ECB). Decomposition of Supply-Side Drivers for Loan Terms and Conditions tightening/easing, 3-month backward-looking, country-weighted. Net percentage contribution of primary supply-side factors to the tightening or easing of credit terms and conditions for new loans to

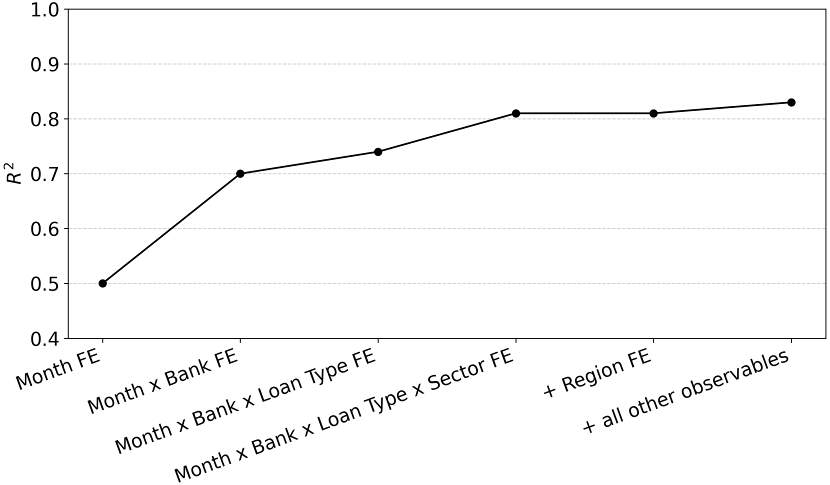
Survey Evidence: Firms

SAFE (ECB):

- 15–30% of firms applying for loans report an increase in financing costs (loan covenants, required guarantees, information requirements, procedures, time required for loan approval)
- 5–14% of firms report financing obstacles to obtaining a bank loan (rejections, high cost, limited amount granted, not applying for fear of rejection)

France: interest rate dispersion

R^2 of interest rates regression on observables



Baseline Specification

Table 4: Data: Nouveaux Credits (BdF), 2006q1-2024q2. Excludes credit lines and undefined maturity products. 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

⏩ back ⏩ explained dispersion ⏩ example ⏩ Firm FE ⏩ sample

The regression sample

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

458 thousand loans, 120 thousand firms, 2006q1–2022q4. Fixed-term products to private companies; credit lines and

Measuring dispersion: empirical approach

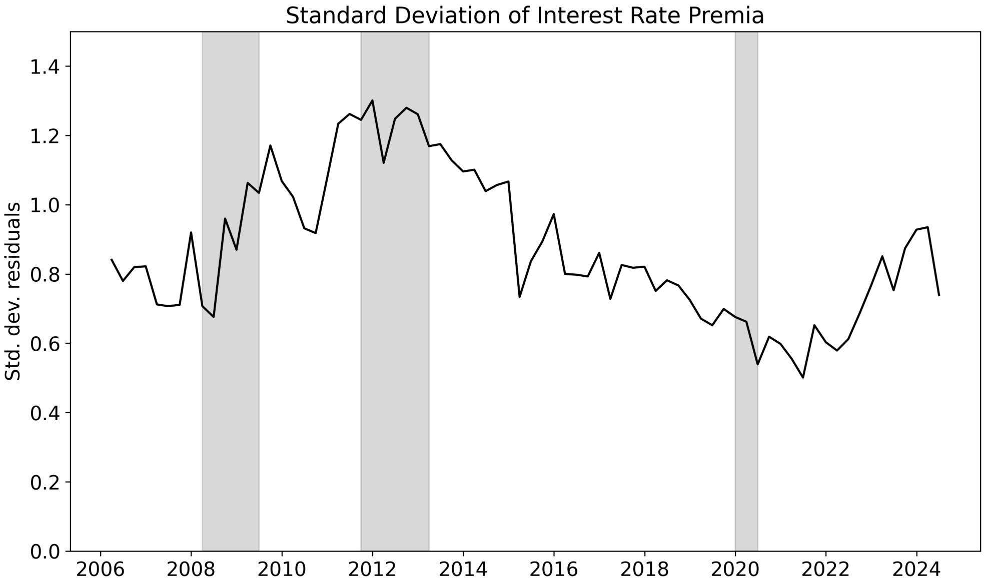
Extract the **unexplained component of rates** by controlling for:

- **Interacted Fixed Effects** $\delta_{b,p,s,t}$: Interact month (t), bank (b), loan type (p), sector (s)
- **Loan (l) characteristic**: amount, maturity, loan purpose, variable rate, personal use, guarantees pledged, bundles
- **Firm (f) characteristic**: region/department, age, new bank relationship, sector, credit rating, group indicator, individual entrepreneur, credit&accounting data

$$\text{Rate}_{f,b,l,t} = \alpha + \beta \cdot \text{LoanChar}_{f,b,l,t} + \gamma \cdot \text{FirmChar}_{f,t} + \delta_{b,p,s,t} + \varepsilon_{f,b,l,t}$$

back

Rate residuals distribution: standard deviation

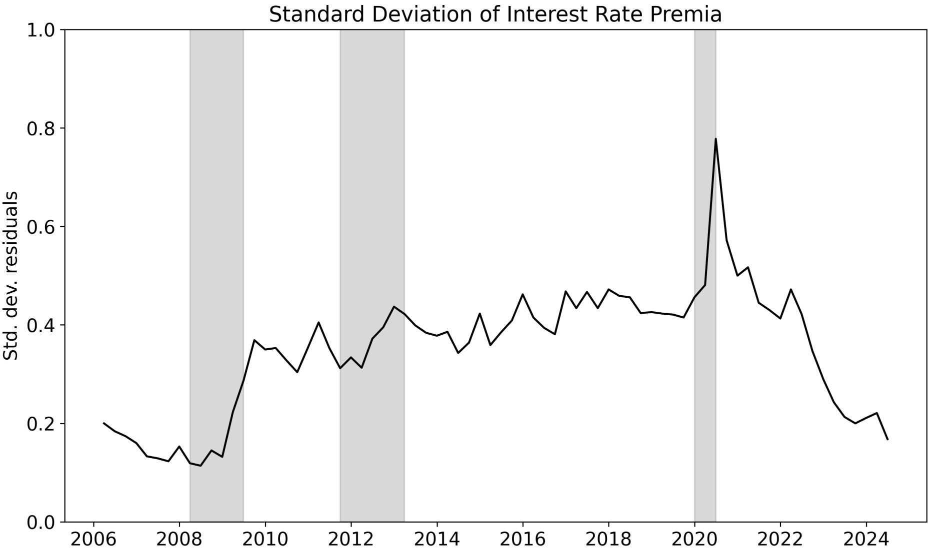


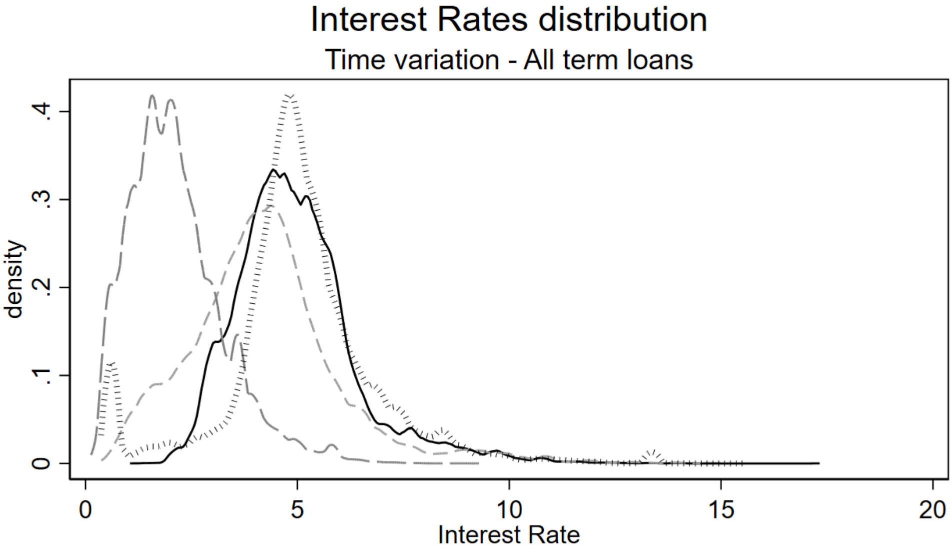
Baseline specification

How are observable characteristics correlated with the rate?

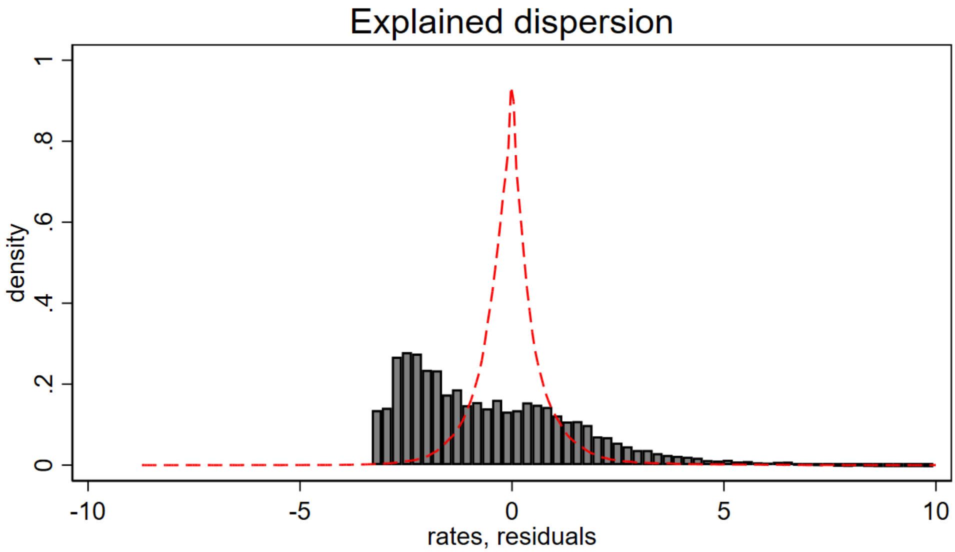
1. **Negatively correlated:** Loan quantity, if Startup, Age, New Relationship reported in Credit Registry, Pledged guarantees, Fraction of drawn credit over assets
2. **Positively correlated:** Maturity, Individual entrepreneur, Bank risk weighting
3. **Not significantly correlated:** Variable or fixed rate, if Personal Loan, Loan over assets, Revenues, Total Bank debt over assets, Short-term debt over assets, Undrawn credit over assets

Baseline Specification

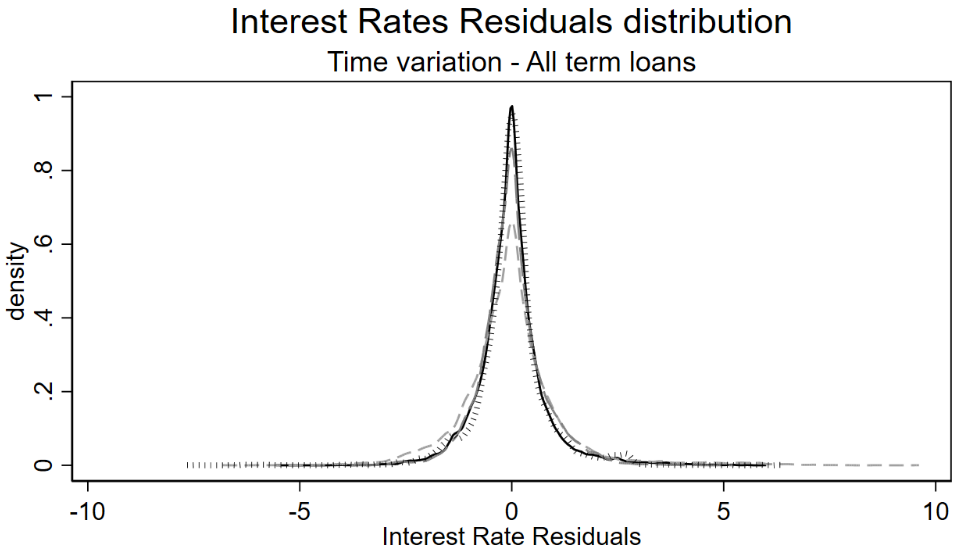



Interest Rates distribution
Time variation - All term loans
density
0
.1
.2
.3
.4
0
5
10
15
20
Interest Rate

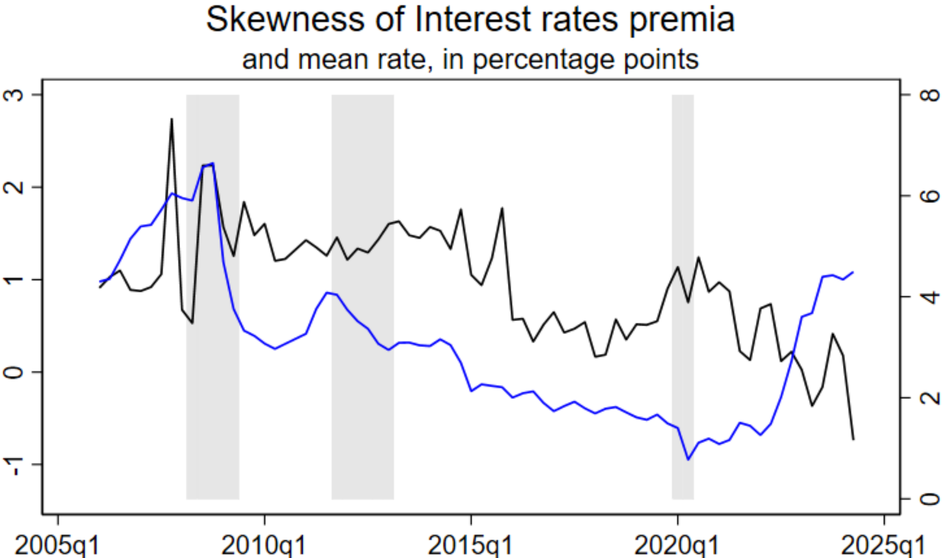
Explained dispersion



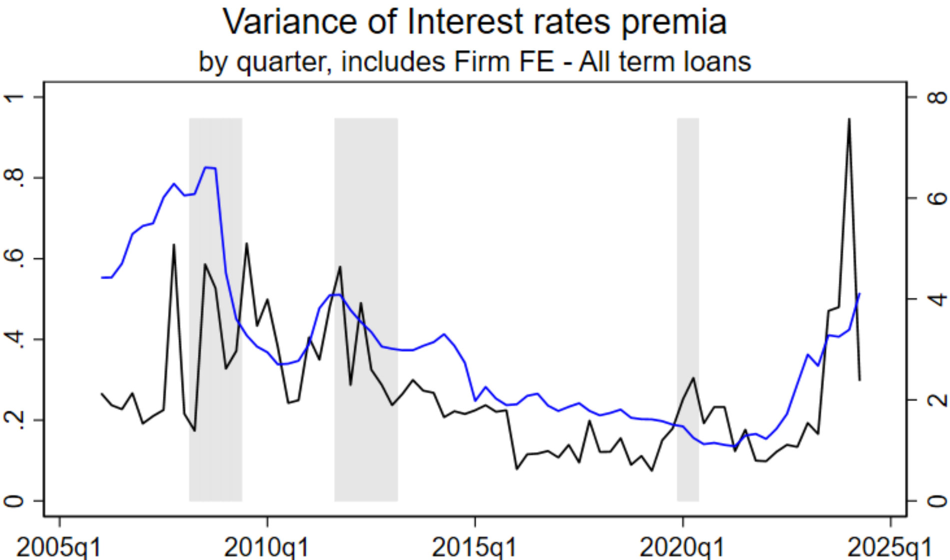
Time variation



Skewness of rate premia



Variance of rate premia - Firm FE

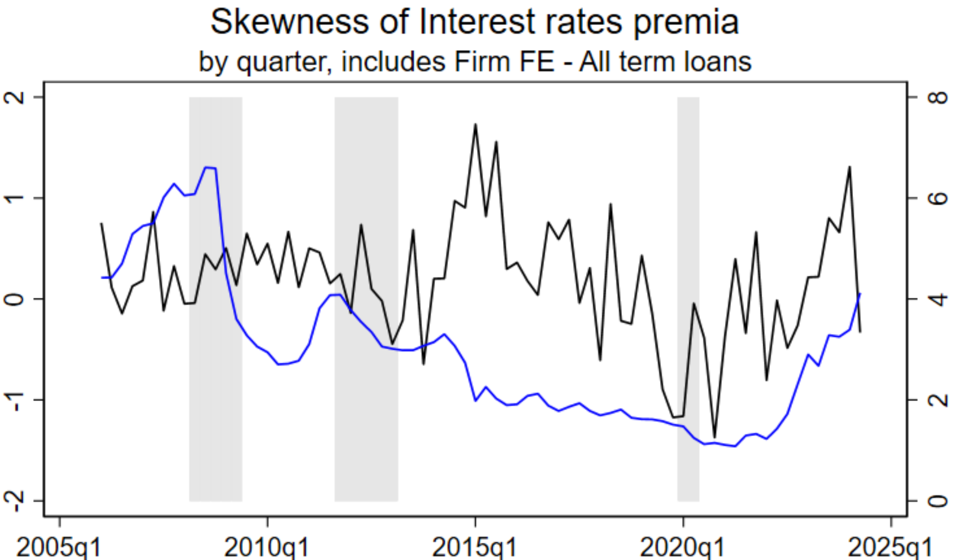


Specification: firm fixed effects

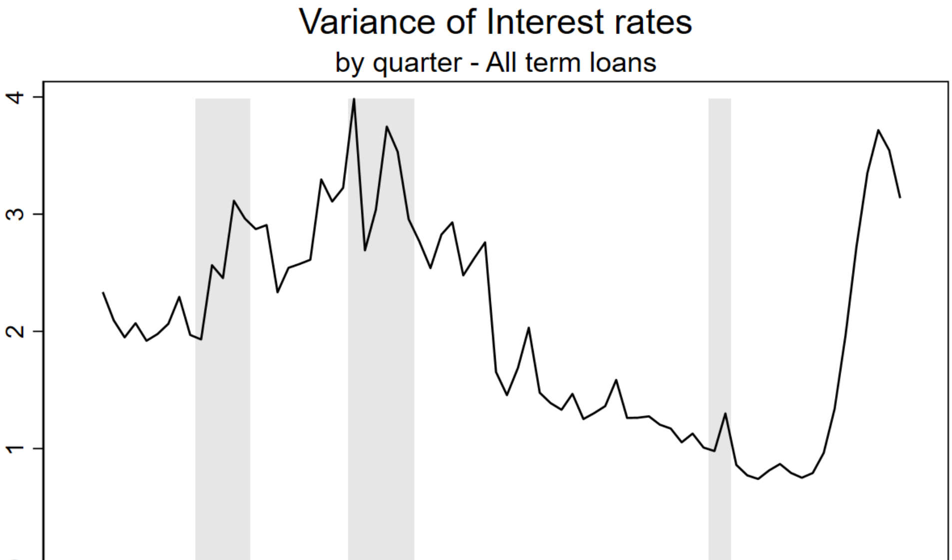
	Total effective rate					
Loan quantity (K-Eur)	-0.0000***	-0.0000***	-0.0000	-0.0000	-0.0000**	-0.0000
	(0.000)	(0.006)	(0.486)	(0.143)	(0.044)	(0.117)
Maturity (months)	-0.0016***	0.0013***	0.0015***	0.0015***	0.0014***	0.0014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variable rate (dummy)	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

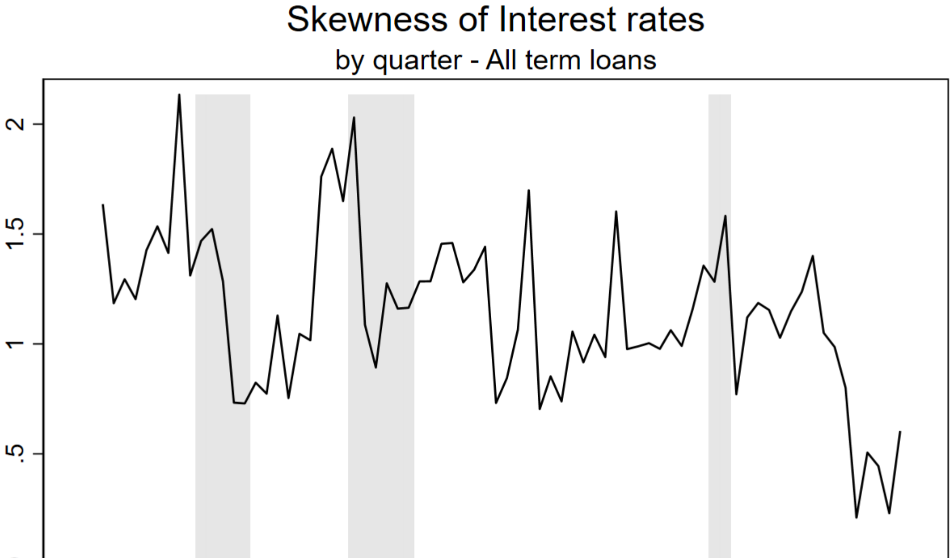
Skewness of rate premia



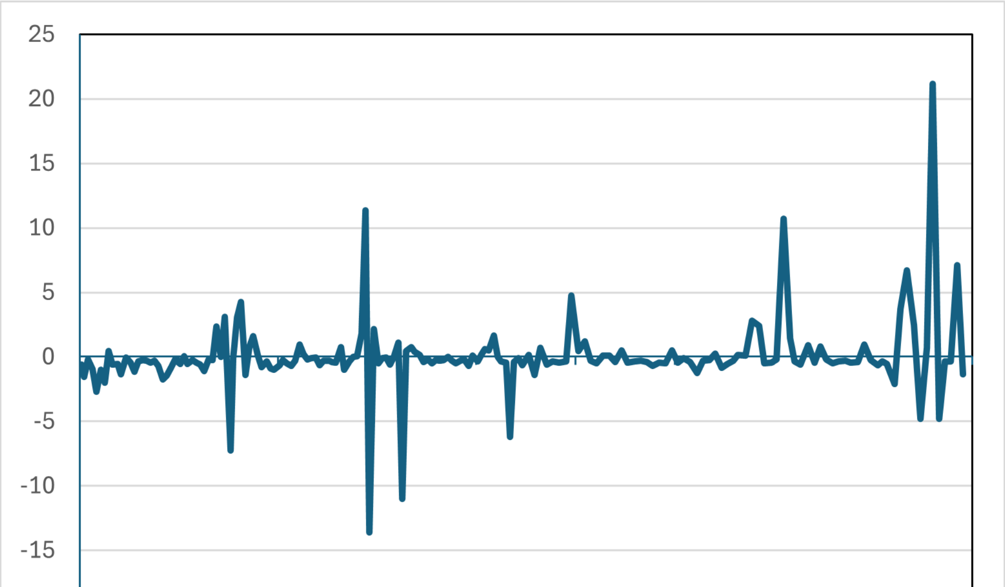
Distribution moments in the time series - Rates



Distribution moments in the time series - Rates



Monetary Policy shock



Effect of an increase of the policy rate

I compute and use high-frequency monetary policy shocks to test the effect of an increase in the funding cost of banks

In levels:[2]

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

And in first differences:[3]

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

⏩ shock series

[2] 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.
[3] γ_1 measures the effect of MP on the change of dispersion of premia. No need to worry about trend.

Effect of an increase of the policy rate

	sandard deviation		delta SD	
L1.rate shock	-0.0096***	-0.0085***	-0.0071**	-0.0049
	(0.000)	(0.003)	(0.028)	(0.175)
L2.rate shock		0.0001		0.0069**
		(0.979)		(0.041)
L3.rate shock		-0.0017		-0.0007
		(0.568)		(0.851)
L1.standard deviation	0.2813***	0.2799***		
	(0.000)	(0.000)		
Lender FE	✓	✓	✓	✓
Observations	7,189	7,077	7,189	7,077
R^2	0.40	0.41	0.01	0.01

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

Table 7: Data: Nouveaux Credits, BdF, 2006q1-2024q2, quarterly shocks. The table shows the effect of a monetary policy rate shock on the standard deviation of the distribution.

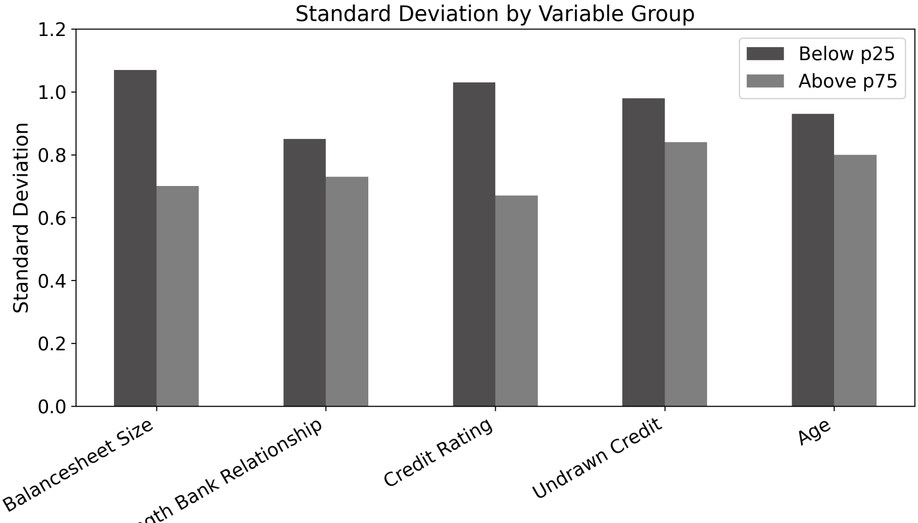
Effect of an increase of the policy rate

	skewness		delta skewness	
L1.rate shock	-0.0135***	-0.0099*	0.0012	0.0053
	(0.010)	(0.093)	(0.860)	(0.490)
L2.rate shock		-0.0227***		-0.0024
		(0.000)		(0.732)
L3.rate shock		-0.0208***		-0.0099
		(0.000)		(0.196)
L1.skewness	0.1294***	0.1171***		
	(0.000)	(0.000)		
Lender FE	✓	✓	✓	✓
Observations	7,189	7,077	7,189	7,077
R^2	0.23	0.24	0.00	0.00

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

Dispersion: heterogeneity over firm characteristics

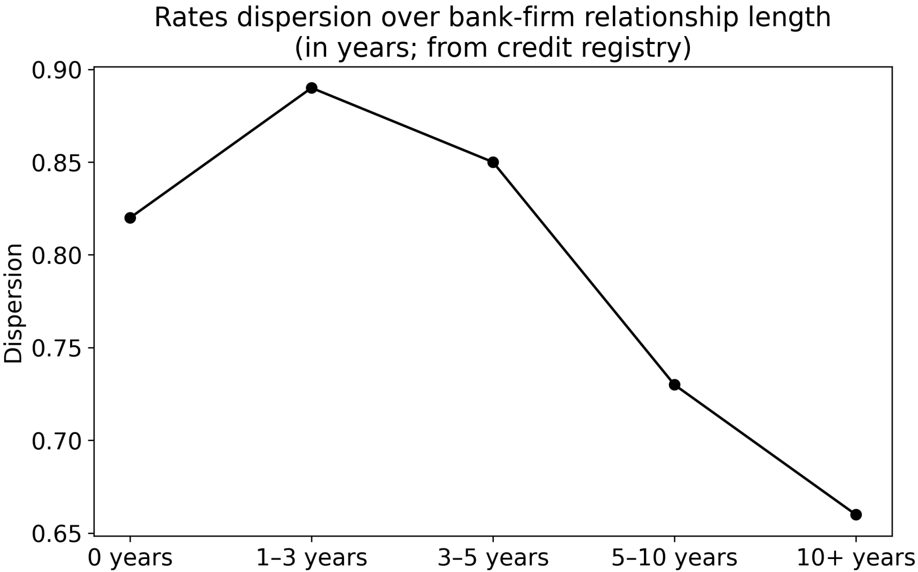
Information asymmetries and imperfect competition are weaker for better firms



Dispersion: descriptives

Rate dispersion - descriptives							
Variables		below p25	above p75	**Variables**		below p25	above p75
balancesheet				undrawn credit			
	s.d.	1.07	0.70		s.d.	0.98	0.84
	n	107	119		n	138	113
turnover over assets				relationship length			
	s.d.	0.74	0.93		s.d.	0.85	0.73
	n	107	123		n	41	81
credit rating				distance last review			
	s.d.	0.67	1.03		s.d.	0.90	0.82
	n	74	73		n	107	4
age				pledged guarantees			
	s.d.	0.93	0.80		s.d.	0.83	0.93
	n	25	192		n	264	193
maturity				short term debt			
	s.d.	1.03	0.69		s.d.	0.71	0.92
	n	202	26		n	106	124

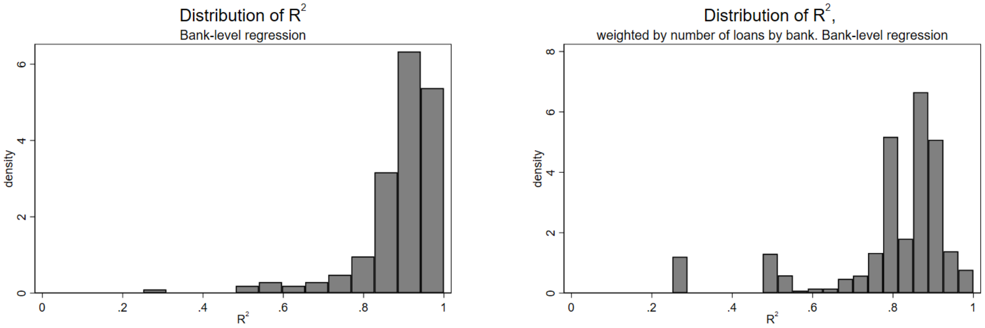
Dispersion over the bank-firm relationship



Within or Between bank dispersion?

Is the dispersion equal across banks, or are some banks "contributing more" to observed dispersion?

- I re-run the analysis separately for all banks and collect R^2



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

Default frequencies by rating

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

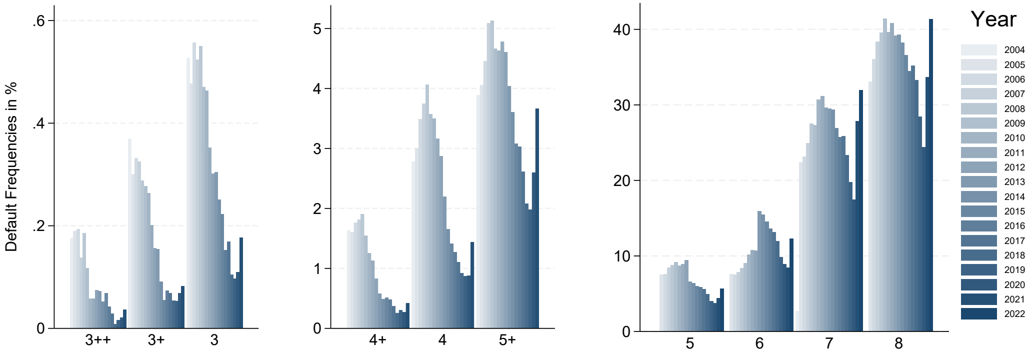


Figure 5: Source: COTA (ratings by BdF), 2004-2025. Following the same approach by BdF in published reports, I consider all firms with a rating at 01/01/year and compute the default frequencies at 31/12/year+2, by year and rating class.

BdF Credit Rating

Three possible entries.

1. **Credit Rating** (= Probability of default)

Rating Category	3++	3+	3	4+	4	5+	5	6	7	8	9
Default Rate	0.02%	0.05%	0.13%	0.35%	0.96%	2.38%	6.30%	9.24%	21.58%	36.98%	36.98%

Table 10: Correspondence of rating categories and default probabilities (Source: BdF)

2. **Actual Default**

   Takes value "P"

3. **Not enough information**

   Takes value "0"

⏩ scale ⏩ back

Banque de France rating scale

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

Can rating be predicted?

	Rating change - 3y ahead				
Interest rate	0.0091***	0.0044	-0.0008	-0.0014	0.0235***
Loan Amount	0.0049*	0.0019	0.0015	0.0052	0.0045
Maturity (months)	0.0000	0.0000	0.0001	0.0002**	0.0002**
Age	-0.0003	-0.0004	-0.0005	-0.0004	-0.0010***
Revenues	-0.0068***	-0.0130***	-0.0131***	-0.0135***	-0.0190***
Bank Debt	-0.1588***	-0.1584***	-0.1552***	-0.1538***	0.0005
Non-Bank Debt	-0.2235***	-0.1952***	-0.1984***	-0.2021***	0.0434*
Short Term Debt	0.0108	0.0301	0.0323	0.0308	0.3190***
Marge disponible crédits confirmés (KEUR)	-0.0147***	-0.0176***	-0.0186***	-0.0181***	-0.0218***
Bank risk weighting	0.0039***	0.0027**	0.0023	0.0025	0.0023
Quarter FE	✓				
Lender × Quarter FE		✓			
Lender × Quarter × 2digit Sector FE			✓		
Lender × Quarter × Loan Type × 2digit Sector FE				✓	✓
Region FE					✓
Group indicator, Rating FE					✓
Observations	306,794	306,794	306,794	306,794	306,794
R^2	0.01	0.06	0.22	0.27	0.34

Which banks use the BdF credit rating?

I compute the δR^2 explained by the credit rating.

- I re-run the analysis separately for all banks, controlling only for time and loan type FEs, and collect the δR^2

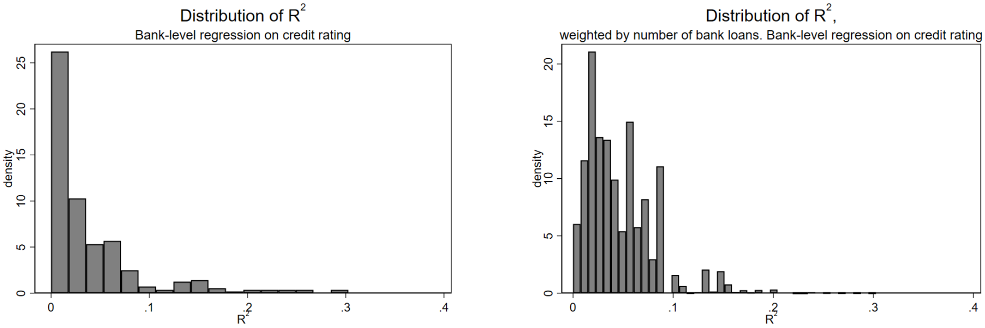


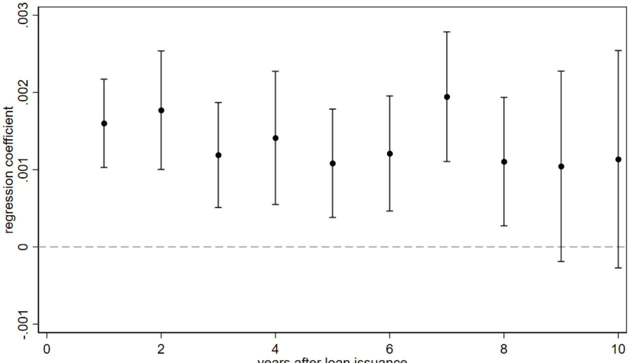
Figure 6: The right image reports the distribution of R^2 weighted by the number of loans issued.

Correlation residuals vs actual default

Same test, replacing the rating revision with the default itself:

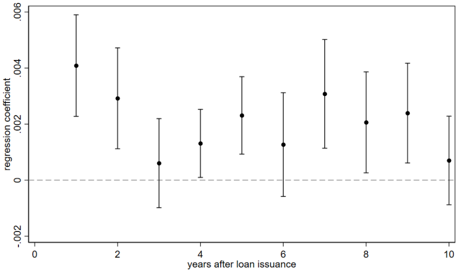
$$r_{ilbt} = \alpha + \sum_{j=1}^{k} \beta_j^D D_{i,t+j} + \mathbf{x}'_{ilbt}\gamma + \mu_{bt\tau s} + \varepsilon_{ilbt}$$

$D_{i,t+j} = 100$ if firm i defaults in year j after issuance. Estimated once per horizon $k = 1, \ldots, 10$; needs no balanced panel; clustered by lender and by quarter.

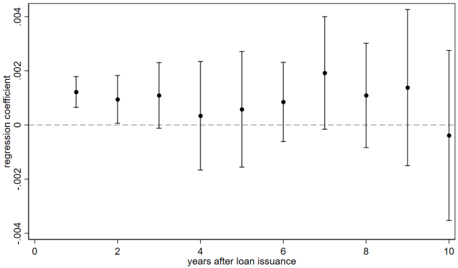


Actual default: by ex-ante rating

Ex-ante low-PD firms



Ex-ante high-PD firms



Computed separately for firms with ex-ante PD$< 0.62\%$ vs PD$> 3.45\%$.

Back

Test: do higher rates induce rating worsening? (2021q3–q4)

	Default Probability - 2021q3-2021q4 only						
Variable rate (dummy)	-0.3953		-38.7291	-0.3499			
	(.)		(0.419)	(.)			
annual dRate end y2			9.8382			0.1178	1.0014
			(0.420)			(0.929)	(0.249)
annual dRate end y3			6.3408			-0.5977	-1.9467
			(0.456)			(0.720)	(0.156)
Variable rate (dummy) × Loan over assets				-0.5306			
				(.)			
annual dRate end y2 × Loan over assets						6.1711	
						(0.743)	
annual dRate end y2 × Bank Debt share							-1.2526
							(0.215)
annual dRate end y3 × Loan over assets						-9.1385	
						(0.732)	
annual dRate end y3 × Bank Debt share							1.8861
							(0.214)
Loan over assets	-0.7120	-1.4514	-1.4851	-0.3328	-0.9459	-0.9777	-1.5080
	(.)	(.)	(0.236)	(.)	(.)	(0.400)	(0.222)
Bank Debt share	0.1002	-0.2848	-0.2949	0.1286	-0.2557	-0.2801	-0.3168
	(.)	(.)	(0.439)	(.)	(.)	(0.456)	(0.585)
Lender × Month × Loan Type × 2digit Sector FE	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓
All other observables	✓	✓	✓	✓	✓	✓	✓
Observations	4,112	3,895	3,895	4,112	3,895	3,895	3,895
R^2	0.42	0.42	0.42	0.42	0.42	0.42	0.42

p-values in parentheses

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

Table 12: Data: Nouveaux Crédits (BdF), 2006q1-2024q2. Term loans, maturity at least 30 months, only firms with a rating. Dependent variable: change_PD3. Exclude loans with non-specified reference rate.

Back Maturity ≥ 24m

Robustness: maturity $\geq$ 24 months

	Default Probability - 2021q3-2021q4 only						
Variable rate (dummy)	-0.5698		-19.6243	-0.5121			
	(0.169)		(0.479)	(0.186)			
annual dRate end y2			5.0816			0.0935	0.6439
			(0.477)			(0.943)	(0.316)
annual dRate end y3			2.6790			-0.7103	-1.5704
			(0.563)			(0.718)	(0.179)
Variable rate (dummy) $\times$ Loan over assets				-0.6271			
				(0.249)			
annual dRate end y2 $\times$ Loan over assets						5.0753	
						(0.781)	
annual dRate end y2 $\times$ Bank Debt share							-0.6506
							(0.424)
annual dRate end y3 $\times$ Loan over assets						-7.6615	
						(0.769)	
annual dRate end y3 $\times$ Bank Debt share							0.9643
							(0.155)
Loan over assets	-0.5329	-1.1153	-1.1298	-0.1584	-0.6351	-0.6550	-1.1379
	(0.374)	(0.168)	(0.233)	(0.740)	(0.216)	(0.287)	(0.283)
Bank Debt share	0.0986	-0.2617	-0.2685	0.1401	-0.2242	-0.2431	-0.2795
	(0.725)	(0.313)	(0.569)	(0.631)	(0.369)	(0.431)	(0.674)
Lender $\times$ Month $\times$ Loan Type $\times$ 2digit Sector FE	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓
All other observables	✓	✓	✓	✓	✓	✓	✓
Observations	4,324	4,089	4,089	4,324	4,089	4,089	4,089
R^2	0.41	0.41	0.41	0.41	0.41	0.41	0.41

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

Table 13: Data: Nouveaux Crédits (BdF), 2006q1-2024q2. Term loans, maturity at least 24 months, only firms with a rating. Dependent variable: change_PD3. Exclude loans with non-specified reference rate.

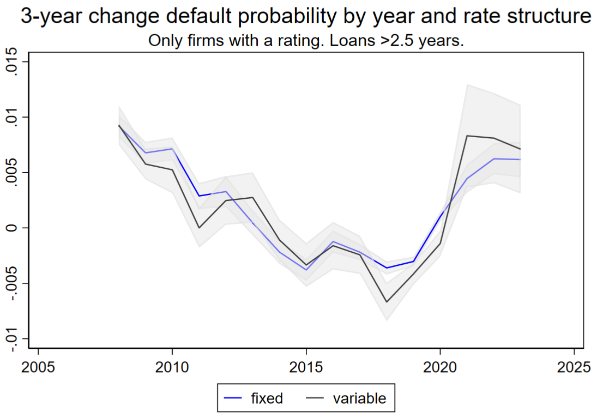
Back

Validity checks

- **Mitigate self-selection issue:**
  - contract choice is predominantly driven by supply-side factors
  - end of ZLB period, firms do not expect a rate hike
- **Balance table** (in 2021):
  - some characteristics differ (variable: fewer firms, larger size, older, riskier, larger financial debt)
  - All of those are included as controls
- **Parallel trends test**:
  - visually: rating transitions for firms taking $> 2.5y$ loans do not differ significantly Figure
  - Pre-treatment betas are close to zero (not ***)

back

Parallel trends: fixed vs. floating



Mean three-year change in the default probability by year, for fixed- and floating-rate borrowers separately. Term loans over 2.5 years, firms with a rating. Shaded: 95% confidence bands.

The two groups track each other through the pre-period.

Can variable/fixed rate contract be predicted?

Focusing on firms with a rating at the time of the loan, I estimate:

$$Floating_{loan} = \beta X^{observables} + \delta_{t,b,p,s} + \varepsilon_{loan} \tag{1}$$

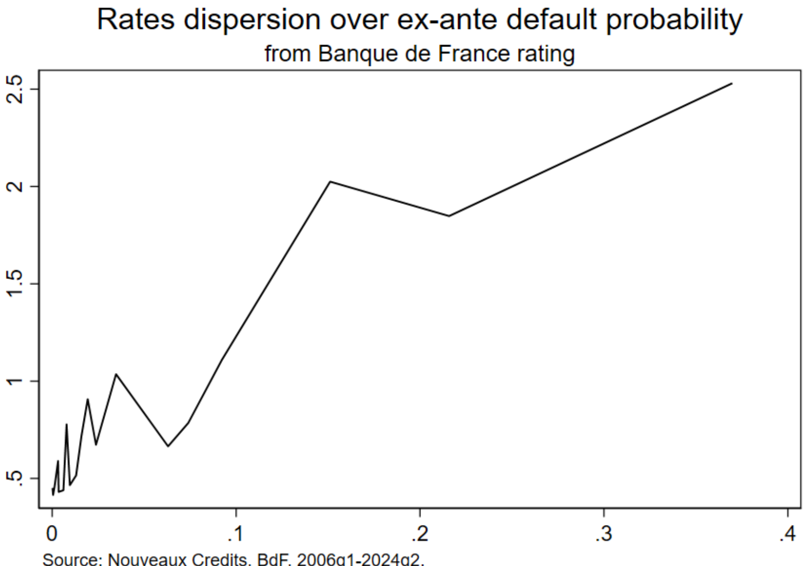
where $Floating_{loan}$ is a dummy for variable-rate loans and $\delta_{t,b,p,s}$ is the fixed effects interaction term for month, bank, loan purpose and firm sector.

Table 14: 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

The contract choice is predominantly driven by supply-side and sectoral factors rather than idiosyncratic firm risk back

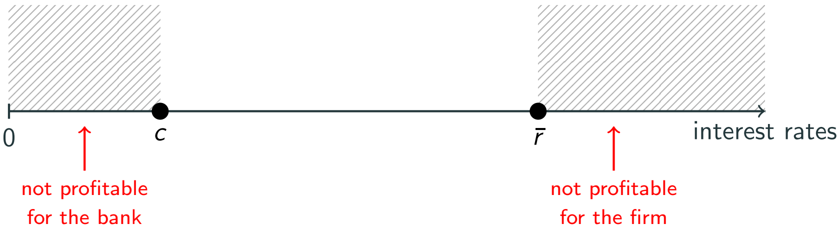
Dispersion over PD



Theory

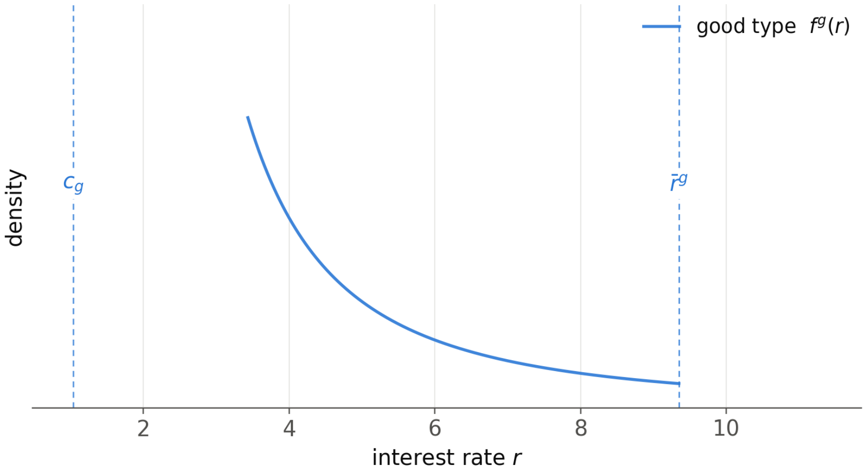
Search frictions only

Example: feasible rates



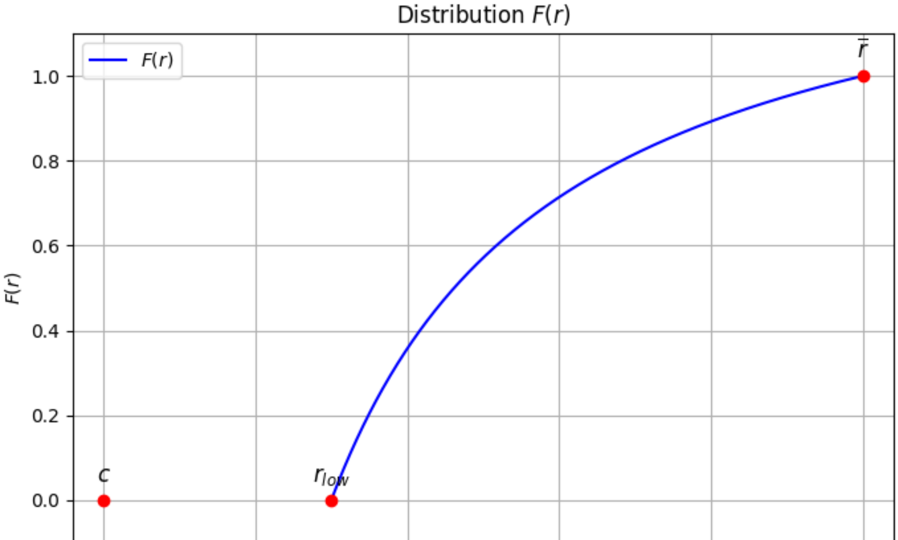
Back

Example: search frictions generate within-type dispersion



- Bank profits: $\Pi(r) = (1 - \pi + \pi(1 - F(r)))(r - c)$

Dispersed rate equilibrium F(r)



ϕ: how severe is adverse selection?

Lemma 2 (Monopoly benchmark)
Under $\pi = 0$, $c'(r) < 1$ and an uninformative signal, define

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

The unique equilibrium is $\bar{r}^g$ if $\phi > 0$, and $\bar{r}^b$ if $\phi \leq 0$.

- $\phi > 0$: adverse selection is **mild** — the bank earns more by **pooling** both types
- $\phi \leq 0$: adverse selection is **severe** — the bank earns more from **bad types only**, and good types walk away

Lemma 3 (Perfect competition)
Under $\pi = 1$ the unique equilibrium is a pooling contract at the competitive rate $r^c = c^{avg}$, accepted by the whole population; profits are zero.

Back

No Info - Monopoly

If monopoly $\pi = 0$

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

The bank evaluates the maximum profit it can extract in each region. It compares:

$$\max\{(1-\pi)(\bar{r}^g - c_{avg}), \mu_b(1-\pi)(\bar{r}^b - c_b)\}$$

Define ϕ:

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

1. $\phi \leq 0$ (strong AS) $\rightarrow$Banks extract more profits from bad types only
2. $\phi > 0$ (weak AS) $\rightarrow$Banks extract more profits from pooling good and bad types

No Info - Perfect competition

If perfect competition $\pi = 1$

1. Banks make zero profits, offering the average cost in the population $c^{avg} = \mu_g c_g + \mu_b c_b$
2. As I consider the case $c^{avg} < \bar{r^g}$, the pooling rate will be always accepted by both types

$$Profits = (\mu_b + \mu_g)(c^{avg} - c^{avg}) = 0$$

If p is a decreasing function of r

$$p = p(r) = \bar{p}^i - \gamma r$$

Case 1: γ is sufficiently small

- Firm: cares about profit if success R-r, same $\bar{r}$
- Bank requires compensation for risk $\uparrow c = \frac{r^{CB}}{p(r)}$

The equilibrium distribution F(r):

$$F(r) = 1 - \frac{1-\pi}{\pi}\frac{\bar{r} - r}{r - \frac{r^{CB}}{p(r)}}, \qquad \text{if } \underline{r(\pi)} < r \leq \bar{r}$$

$$\underline{r(\pi)} = (1-\pi)(\bar{r} - \frac{r^{CB}}{p(r)}) + \frac{r^{CB}}{p(r)}$$

If p is a decreasing function of r

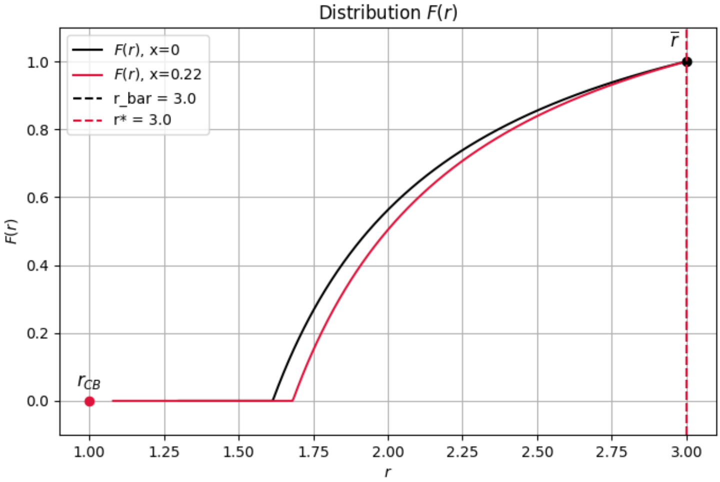


Figure 9: Example: $\bar{r} = 3$, $\pi = 0.7$, $r^{cb} = 1$, $p^{success} = 0.98 - x * r$

If p is a decreasing function of r

Case 2: γ is sufficiently high

- As before, banks require compensation for risk $\rightarrow\uparrow$c
- p(r) may go to zero if r is too high $\rightarrow \bar{r} < R$
- convex cost of lending $\rightarrow$Interior rate r* that maximizes profits

$\rightarrow$ The interval of feasible rates is smaller

Equilibrium distribution $F(r)$:

$$F(r) = 1 - \frac{1-\pi}{\pi} \frac{r^* - r}{r - \frac{r^{CB}}{p(r)}}, \quad \text{for } \underline{r}(\pi) < r \leq \bar{r}$$

If p is a decreasing function of r

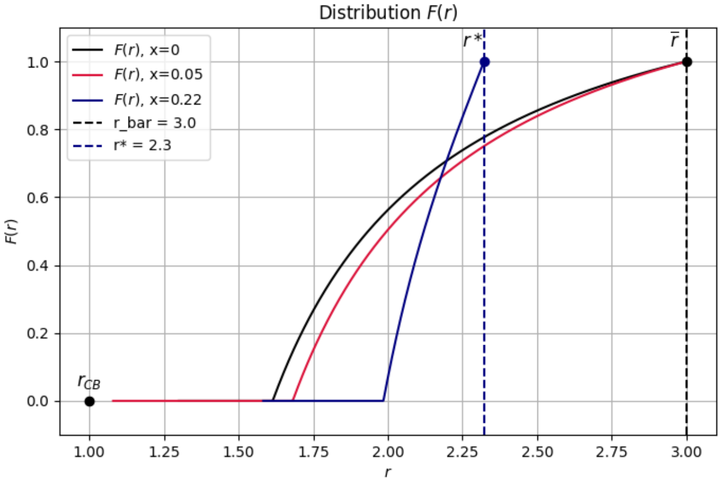


Figure 10: Example: $\bar{r} = 3$, $\pi = 0.7$, $r^{cb} = 1$, $p^{success} = 0.98 - \gamma * r$, values of $\gamma = [0, 0.05, 0.22]$.

Perfect vs asymmetric information

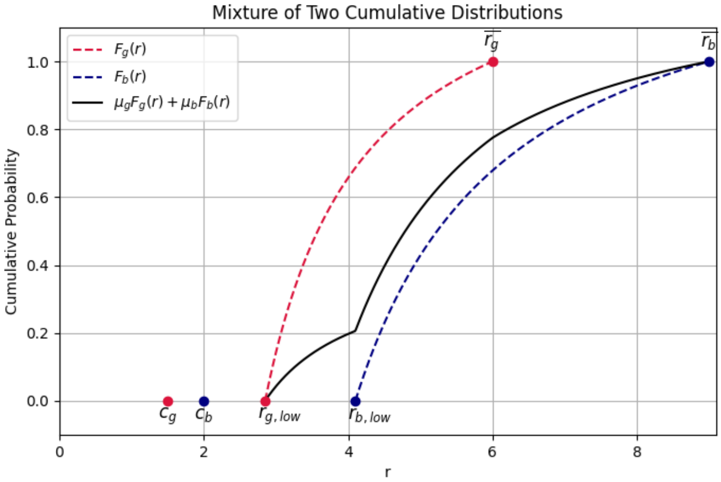
1. **Perfect information / perfect signal q=1:**
   $\rightarrow$The bank can perfectly identify each firm's type
   $\rightarrow$Positive correlation between rates and riskiness

2. **Asymmetric information / q=0.5**
   $\rightarrow$The bank cannot distinguish types

3. The bank can **acquire costly information** $q \in 0.5, 1$ about firm types
   $\rightarrow$extreme precision q_θ values coincide with no/perfect information cases

Perfect information - Total CDF

Duplicate the one-firm problem. $F(r)$ is now the sum of both distributions



Perfect information - Density

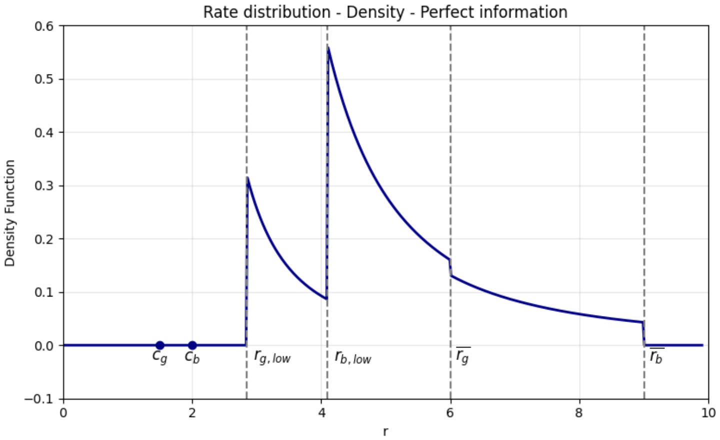


Figure 12: Simulation. Parameter values $c_g = 1.5$, $c_b = 2$, $\bar{r}^g = 6$, $\bar{r}^b = 9$, $\pi = 0.7$, $\mu_b = 0.7$

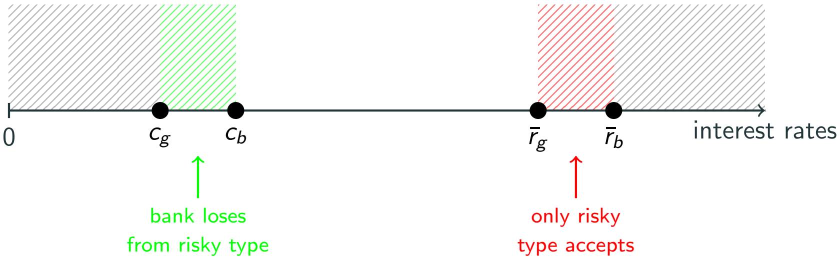
$$f^i(r) = \begin{cases} \frac{1-\pi}{\pi} \frac{\bar{r}^i - c_i}{(r-c_i)^2}, & \text{if } \underline{r}^i(\pi) < r \leq \bar{r}^i, \end{cases}$$

Asymmetric information

Example: feasible rates

- Hp: bad type has higher default probability but higher reservation rate (delivers consistent correlation patterns)
- the bank cannot perfectly recognize types, but knows μ_{bad}, π, $\bar{r}_{bad}$, $\bar{r}_{good}$, p_g, p_b

Example: feasible rates



- Hp: risky type has higher default probability but higher reservation rate (delivers consistent correlation patterns)
- the bank cannot perfectly recognize types, but knows μ_{bad}, π, $\bar{r}_{bad}$, $\bar{r}_{good}$, p_g, p_b

No info - $\phi \leq 0$

Case 1. Banks extract more profits at $\bar{r}^b$.

The **CDF** on both regions can be expressed as:

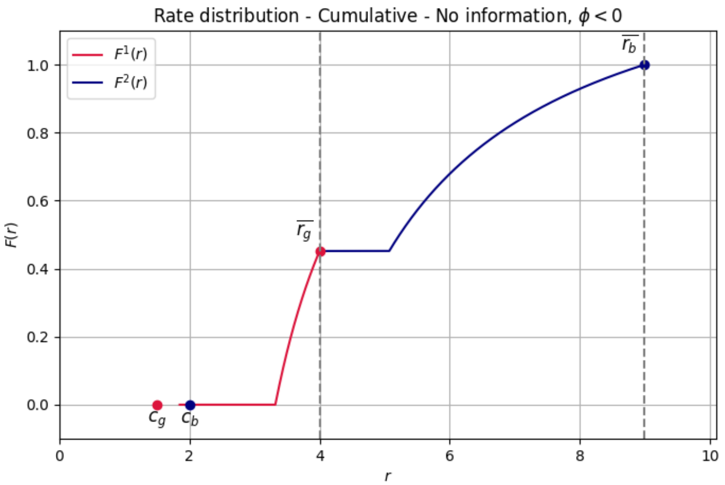
$$F(r) = \begin{cases} 0 & \text{if } r < \underline{r}^a \\ F^a(r) & \text{if } \underline{r}^a \leq r \leq \bar{r}^g \\ F^a(\bar{r}^g) + F^b(r) & \text{if } \bar{r}^g < r \leq \bar{r}^b \\ 1 & \text{if } r > \bar{r}^b \end{cases}$$

Then, the **equal profit condition**:

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

back

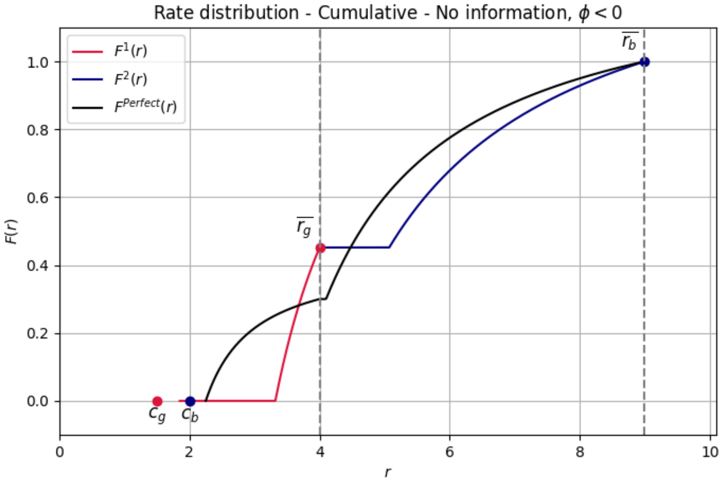
No info - $\phi \leq 0$



Parameter values: $c_g = 1.5, c_b = 2, \bar{r^g} = 6, \bar{r^b} = 9, \pi = 0.7, \mu_b = 0.7$

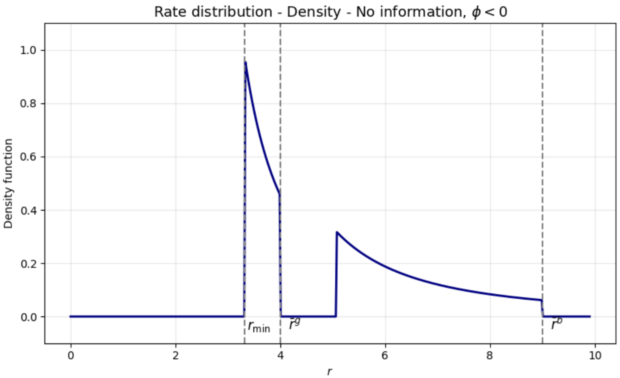
$$F^a(r) = 1 \quad \frac{1-\pi}{} \left[\frac{\mu_b(\bar{r}^b - c_b)}{} \quad 1 \right]$$

No info - $\phi \leq 0$



Parameter values $c_g = 1.5, c_b = 2, \bar{r^g} = 4, \bar{r^b} = 9, \pi = 0.7, \mu_b = 0.7$

No info - $\phi \leq 0$



Parameter values $c_g = 1.5, c_b = 2, \bar{r^g} = 4, \bar{r^b} = 9, \pi = 0.7, \mu_b = 0.7$

$$f(r) = \begin{cases} \dfrac{1-\pi}{\pi} \dfrac{\mu_b(\bar{r}^b - c_b)}{(r - c^{avg})^2}, & \text{if } \underline{r}^a \leq r \leq \bar{r}^g, \\ \dfrac{1-\pi}{\pi} \dfrac{(\bar{r}^b - c_b)}{(r - c_b)^2}, & \text{if } \underline{r}^b < r \leq \bar{r}^b, \end{cases}$$

No info - $\phi > 0$

Case 2. Banks extract more profits at $\bar{r}^g$.
Intuition: No contract on bad-types-only region is feasible. Full pooling equilibrium.

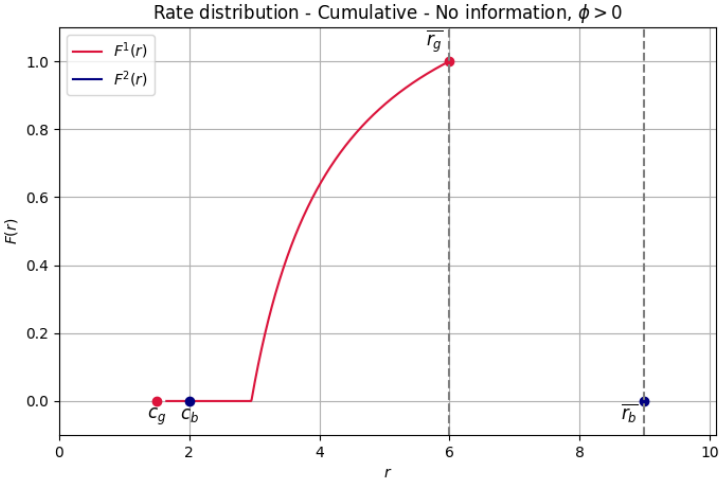
The **CDF** on both regions can be expressed as:

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

Then, the **equal profit condition**:

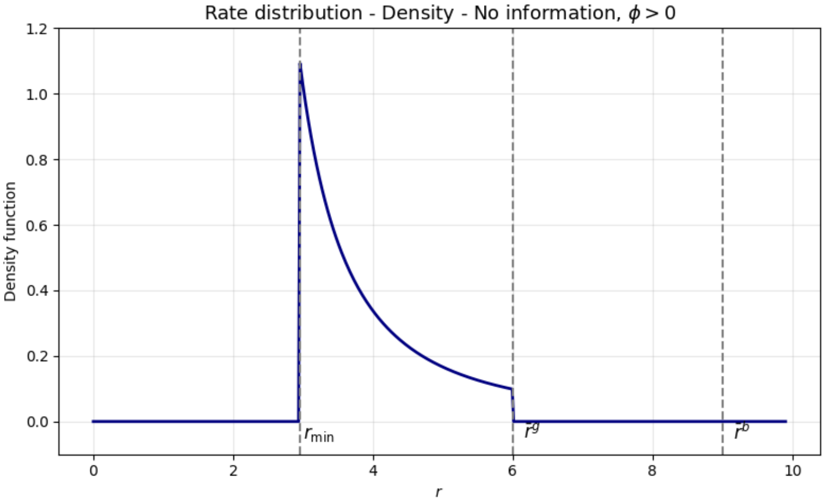
$$[1 - \pi + \pi(1 - F^a(r))](r - c^{avg}) = (1 - \pi)(\bar{r}^g - c^{avg})$$

No info - $\phi > 0$



Parameter values $c_g = 1.5, c_b = 2, \bar{r^g} = 6, \bar{r^b} = 9, \pi = 0.7, \mu_b = 0.3$

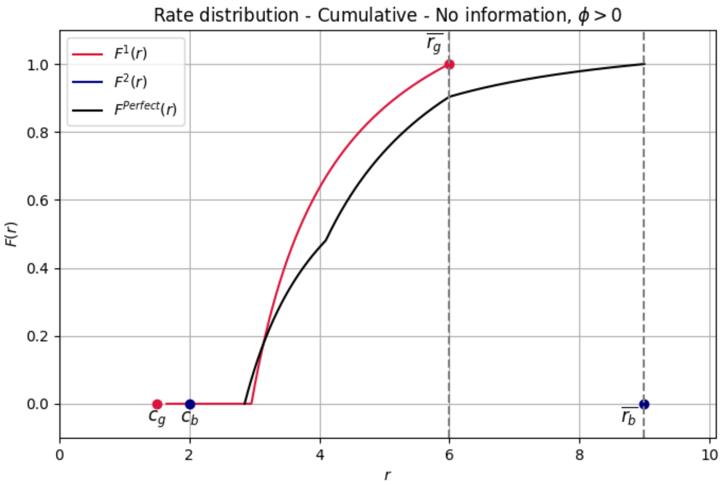
No info - $\phi > 0$



Parameter values $c_g = 1.5$, $c_b = 2$, $\bar{r^g} = 6$, $\bar{r^b} = 9$, $\pi = 0.7$, $\mu_b = 0.3$

No info - $\phi > 0$

Figure 13: Compare pooling eq. (red) and Perfect info eq. (black)



Parameter values $c_g = 1.5$, $c_b = 2$, $\bar{r}^g = 6$, $\bar{r}^b = 9$, $\pi = 0.7$, $\mu_b = 0.3$

Acquire Information

The bank observes the signal s and updates the belief (unconditional probability) using Bayes' rule.

Conditional probabilities: By Bayes' rule, the probability that a firm is good given a good signal is

$$
\begin{aligned}
\Pr(\theta = G \mid s = G) &= \frac{Pr(\theta = G \cap s = G)}{Pr(s = G)} \\
&= \frac{\Pr(s = G \mid \theta = G)\Pr(\theta = G)}{\Pr(s = G \mid \theta = G)\Pr(\theta = G) + \Pr(s = G \mid \theta = B)\Pr(\theta = B)} \\
&= \frac{q_g \mu_g}{q_g \mu_g + (1 - q_b)\mu_b}
\end{aligned}
$$

Signal Precision & Bayesian Updating

Signal precision: For each type $\theta \in \{g, b\}$, the bank observes a binary signal s with

$$\Pr(s = \theta \mid \theta) = q_\theta \geq 0.5$$

$q_\theta = \frac{1}{2}$: uninformative (no information); $q_\theta = 1$: perfect information.

Unconditional signal probabilities:

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

Bayesian updating:

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

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

$$\alpha^{s_g} > \mu_g > \alpha^{s_b}$$

Acquire Information

Expected outcome:

1. Following the same procedure as before, banks compare profits at the two reservation prices using the updated probabilities
2. now, conditional on a good signal, the average population of good types met by the bank is higher than μ_g, and vice-versa for bad signals
3. in equilibrium, two distributions, one for each signal realization

Outcome:

- $\uparrow$informative signal $\rightarrow\downarrow$adverse selection problem, because the average cost and population share are closer to the true ones
- $\uparrow$informative signal $\rightarrow\uparrow$dispersion
- $\uparrow$informative signal $\rightarrow\uparrow$correlation between ex-ante rate and ex-post default probability

One type: equilibrium distribution

Equal-profit condition (highest rate must be the reservation rate $\bar{r}$):

$$(1-\pi)(\bar{r}-c) \;=\; \big[1-\pi+\pi(1-F(r))\big](r-c)$$

CDF and density:

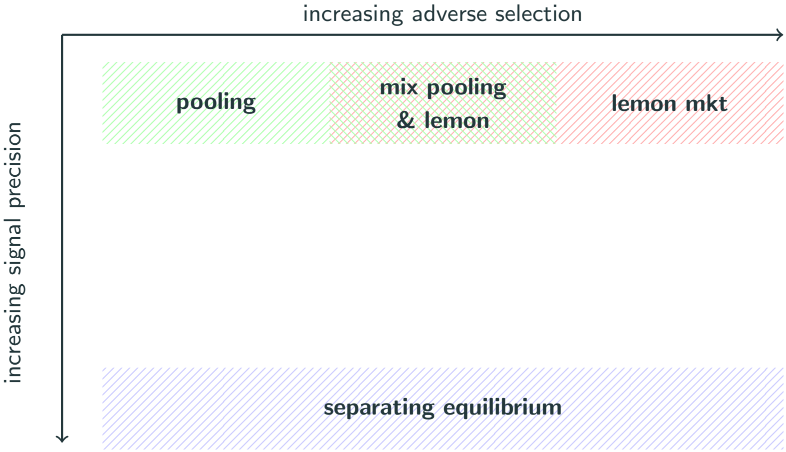
$$F(r) = 1 - \frac{1-\pi}{\pi}\left[\frac{\bar{r}-r}{r-c}\right], \qquad\qquad f(r) = \frac{1-\pi}{\pi}\,\frac{\bar{r}-c}{(r-c)^2}$$

on the support $\underline{r} \le r \le \bar{r}$, with $\underline{r} = (1-\pi)\bar{r} + \pi c$ from $F(\underline{r}) = 0$.

$f'(r) < 0$: the density is right-skewed — most quotes cluster near the competitive rate, but captive firms sustain a tail up to $\bar{r}$.

⏩ Set-up ⏩ Back

Equilibrium: Overview



Back

Gains from moving to a perfect signal

Bank, $\Delta\Pi \equiv \Pi^{q=1} - \Pi^{q=0.5}$, per firm approached by one bank:

Regime at $q = 0.5$	$\Delta\Pi$	the gain is the surplus ...
Full pooling, $\phi > 0$	$(1-\pi)\,\mu_b\,(\bar{r}^b - \bar{r}^g)$	... not extracted from *bad* types
Hybrid, $\underline{\phi} < \phi \le 0$	$(1-\pi)\,\mu_g\,(\bar{r}^g - c_g)$	... mixed, equal to the *good* types that exit
Bad-only, $\phi \le \underline{\phi}$	$(1-\pi)\,\mu_g\,(\bar{r}^g - c_g)$	... of the *good* types that exit

Firms, $\Delta S_i \equiv S_i^{q=1} - S_i^{q=0.5}$:

Regime at $q = 0.5$	ΔS_g	ΔS_b
Full pooling, $\phi > 0$	$\mu_g\,\frac{\pi}{2}\,\mu_b\,(c_b - c_g) > 0$	$-\mu_b\left[(1-\pi)(\bar{r}^b - \bar{r}^g) + \frac{\pi}{2}\mu_g(c_b - c_g)\right] < 0$
Hybrid, $\underline{\phi} < \phi \le 0$	no closed form, > 0	no closed form, ≤ 0
Bad-only, $\phi \le \underline{\phi}$	$\mu_g\,\frac{\pi}{2}\,(\bar{r}^g - c_g) > 0$	0

Good types gain in every regime, bad types never gain. Under full pooling information only redistributes: $\Delta\Pi + \Delta S_g + \Delta S_b = 0$.

⏩ Back ⏩ Calibrated

Calibration

Calibration (moment matching)

Objective: recover parameters of competition π and signal precision q

Moments matched : Mean: $\mathbb{E}[r]$, Variance: $\mathrm{Var}(r)$, Correlation with default probability: $\mathrm{Corr}(r, p)$

Contribution of information:

$$\frac{\mathrm{Var}(\hat{q}) - \mathrm{Var}(q = 0.5)}{\mathrm{Var}(q = 0.5)} \times 100\%$$

▸▸ Details ▸▸ Back

Back to the data

How to rationalize the differences in different markets? ⏩ dispersion over PD ⏩ high vs low

Low PD firms: low dispersion, high correlation.

- Narrow rate region (parameters)
- High information
- Low/high competition?

High PD firms: high dispersion, no correlation

- Wider rate region (parameters, ex. $R^b \gg R^g$, $p^b \ll p^g$)
- Low information (or cost of acquiring is too high) $\rightarrow$pooling is more likely
- Low/high competition?

$\rightarrow$ Calibration results are consistent with these patterns (see Calibration section).

Calibration: Data Moments by Rating Class

Parameters and moments taken from data, by rating class

Rating	Mean	p99 ($\bar{r}_b$)	Var.	Corr.	p_g	p_b	N_g	N_b
3+	1.67	3.532	0.406	0.0251	0.0002	0.0032	1 748	9 569
3	1.83	3.785	0.443	0.0326	0.0005	0.0035	5 567	16 620
4+	2.40	4.703	0.553	0.0315	0.0013	0.0078	10 056	28 499
4	2.37	5.199	0.730	0.0478	0.0032	0.0193	18 266	37 204
5+	2.57	5.527	0.867	0.0478	0.0078	0.0347	24 033	23 178
5	3.36	6.798	0.985	0.0174	0.0193	0.0924	15 869	5 796
6	3.63	7.201	1.137	0	0.0193	0.2158	4 641	329
7	4.79	9.541	1.843	0	0.0347	0.3698	1 049	78

Notes: $\bar{r}_b$ (upper bound for bad types) set at the 99th percentile of the observed rate distribution in each class, an outlier-robust analogue of the literal maximum. p_g, p_b: average 3-year default probabilities. N_g, N_b: number of observations per type. Mean, variance, and correlation are the three moments matched in calibration.

back

Correlation by type

Imagine that within each rating class there are good and bad firms, that you can recognize by looking at the evolution of their default probability.

1. good if PD increases after 10 years, bad if PD decreases, null otherwise
2. Collect residuals and study them separately in each sample

Good rating market:

- good (7th) and bad (28) types .
  Mean: $mean^{good} = -0.04 < mean^{bad} = 0.02$. SD= $sd^{good} = 0.65 < sd^{bad} = 0.78$, correlation is positive

Bad rating market:

- good (6th) and bad (13) types .
  Mean: $mean^{good} = -0.057 < mean^{bad} = 0.05$. SD= $sd^{good} = 0.98 < sd^{bad} = 1.19$, correlation is positive

Model Fit

Table 15: Observed vs. model-implied moments

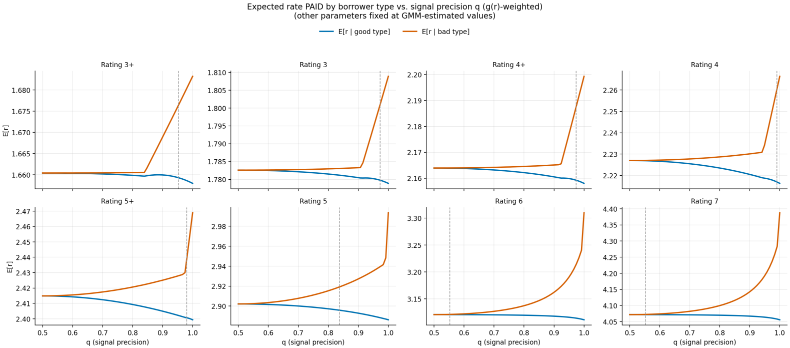
	Mean		Variance		Correlation	
Rating	Data	Model	Data	Model	Data	Model
3+	1.67	1.94	0.406	0.154	0.025	0.025
3	1.83	2.08	0.443	0.188	0.033	0.033
4+	2.40	2.53	0.553	0.338	0.032	0.032
4	2.37	2.63	0.730	0.424	0.048	0.048
5+	2.57	2.80	0.867	0.492	0.048	0.048
5	3.36	3.44	0.985	0.794	0.017	0.017
6	3.63	3.67	1.137	0.913	0.000	0.000
7	4.79	4.78	1.843	1.725	0.000	0.000

Notes: Correlation is matched essentially exactly in every class, and the mean to within roughly 15%. Variance is matched only partially (38–94% of the data value), consistent with a two-type model confronting a continuum of within-class borrower heterogeneity: it should be read as a lower bound on the dispersion the search-and-screening channel alone can generate.

Surplus sharing and stability

Who pays what, as screening improves

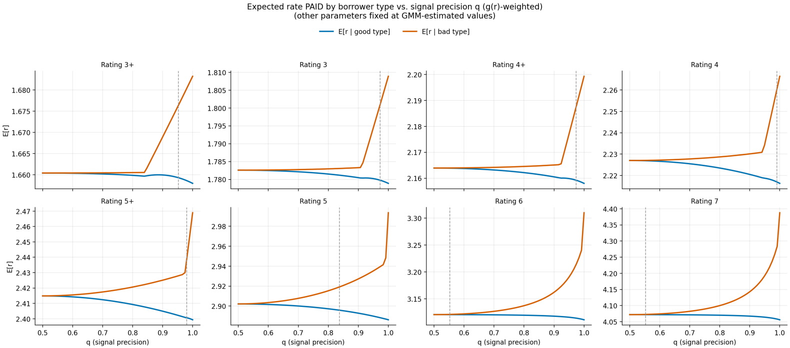
I hold $\pi, \bar{r}^g, \bar{r}^b, \mu_b, p_g, p_b$ at their calibrated values and vary q over $[0.5, 1]$.



Expected rate paid by good vs. bad types, by rating class, under the realized (transaction-weighted) distribution $g(r)$. Dashed line: the class's own $\hat{q}$.

Who pays what, as screening improves

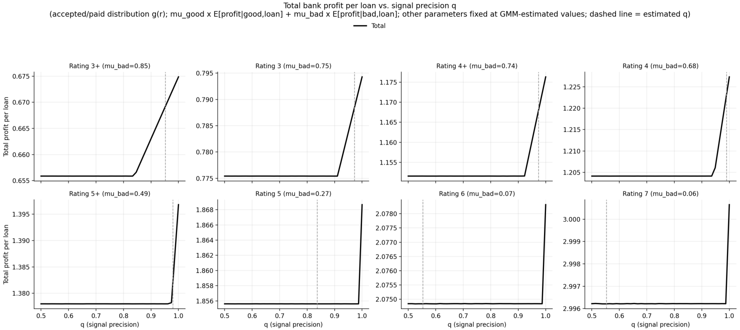
I hold $\pi, \bar{r}^g, \bar{r}^b, \mu_b, p_g, p_b$ at their calibrated values and vary q over $[0.5, 1]$.



Expected rate paid by good vs. bad types, by rating class, under the realized (transaction-weighted) distribution $g(r)$. Dashed line: the class's own $\hat{q}$.

- at $q = 0.5$ every class **pools**: both types pay the same rate
- the gap opens **late**, once ϕ^{s_i} turns negative and pooling is dropped

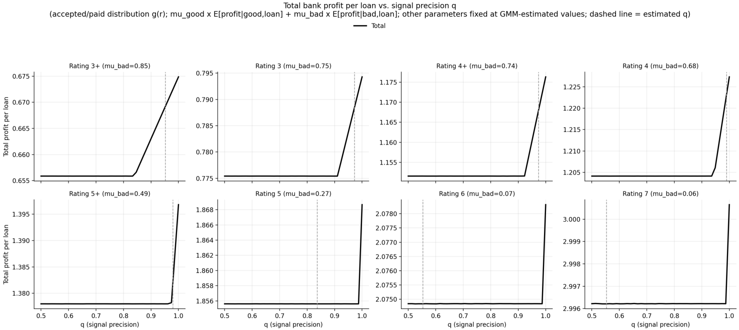
The bank's return to screening



Total expected bank profit per loan, $\mu_g E[\text{profit} \mid g] + \mu_b E[\text{profit} \mid b]$, by rating class. Dashed line: the class's own $\hat{q}$.

By type Back

The bank's return to screening



Total expected bank profit per loan, $\mu_g E[\text{profit} \mid g] + \mu_b E[\text{profit} \mid b]$, by rating class. Dashed line: the class's own $\hat{q}$.

- profit is **flat while the bank pools** — precision it cannot act on is worth nothing
- it rises only once the bank **separates types**, and peaks at $q = 1$
- at $q = 1$ the type gap reaches 0.025 (rating 3+), 0.20 (rating 6), 0.33 (rating 7)

⏩ By type ⏩ Back

Who gains from a perfect signal?

Change in surplus from $q = 0.5$ to $q = 1$, % of the class's total surplus

Rating	Bad types	Banks	Good types
3+	-0.892	0.881	0.010
3	-0.847	0.833	0.013
4+	-0.806	0.786	0.020
4	-0.958	0.907	0.054
5+	-0.646	0.550	0.095
5	-0.438	0.274	0.163
6	-0.217	0.069	0.148
7	-0.308	0.071	0.236

Rows sum to zero: every class is in full pooling at $q = 0.5$, so no firm is rationed at either end and information only redistributes.

⏩ % of own surplus ⏩ Back

Who gains from a perfect signal?

Change in surplus from $q = 0.5$ to $q = 1$, % of the class's total surplus

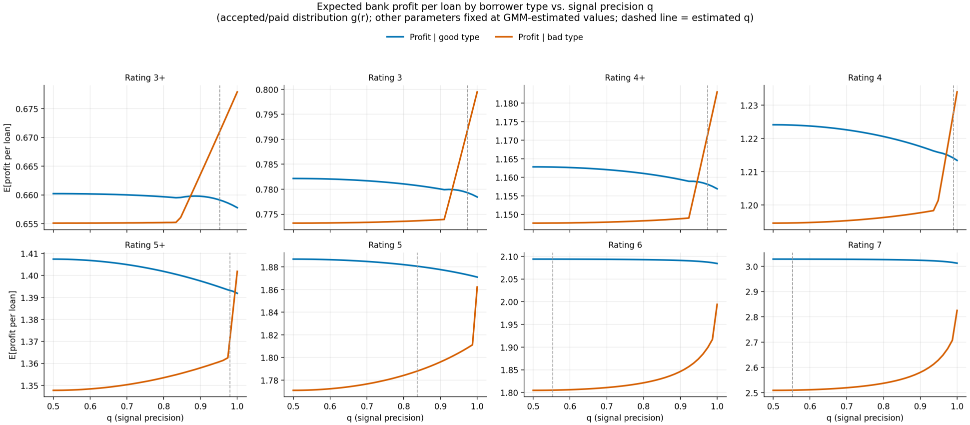
Rating	Bad types	Banks	Good types
3+	−0.892	0.881	0.010
3	−0.847	0.833	0.013
4+	−0.806	0.786	0.020
4	−0.958	0.907	0.054
5+	−0.646	0.550	0.095
5	−0.438	0.274	0.163
6	−0.217	0.069	0.148
7	−0.308	0.071	0.236

Rows sum to zero: every class is in full pooling at $q = 0.5$, so no firm is rationed at either end and information only redistributes.

- information moves surplus from **bad types to banks**
- good types gain in every class, but least where screening is already near-perfect

⏩ % of own surplus ⏩ Back

Bank profit by borrower type



Expected bank profit per loan, $E[r \mid \text{type}] - c_{\text{type}}$, by true borrower type and rating class, over $q \in [0.5, 1]$. Dashed line: the class's own $\hat{q}$.

back

Redistribution, as % of each party's own surplus

Change in surplus from $q = 0.5$ to $q = 1$, % of that party's own surplus at $q = 0.5$

Rating	Bad types	Banks	Good types
3+	−1.65	2.43	0.10
3	−1.80	2.19	0.08
4+	−1.82	1.93	0.13
4	−2.27	2.37	0.27
5+	−2.13	1.39	0.31
5	−2.76	0.65	0.39
6	−5.58	0.16	0.28
7	−7.75	0.16	0.46

Rows do not sum. This is the denominator relevant to a bank weighing the cost of precision, and to a borrower judging the size of the repricing.

back

Is the calibrated $\hat{q}$ an equilibrium?

The calibration holds **both** banks at the same precision. Does either want to deviate?

Hold the rival at $(q^*, F(\cdot; q^*))$ and let one bank pick q_1 and best-respond in price. Changing q_1 moves three objects: the signal shares σ_g, σ_b, the posteriors α^{s_i}, and the pooling cost $c^{avg,s_i} = \alpha^{s_i} c_g + (1 - \alpha^{s_i}) c_b$.

Banks at the same precision agree on every firm; a deviation changes the classification only at the margin. On the share $\min(\sigma_i(q_1), \sigma_i(q^*))$ the two agree and the deviator faces F_i; on the extra share $\max(\sigma_i(q_1) - \sigma_i(q^*), 0)$ they **disagree** and it faces F_{-i}.

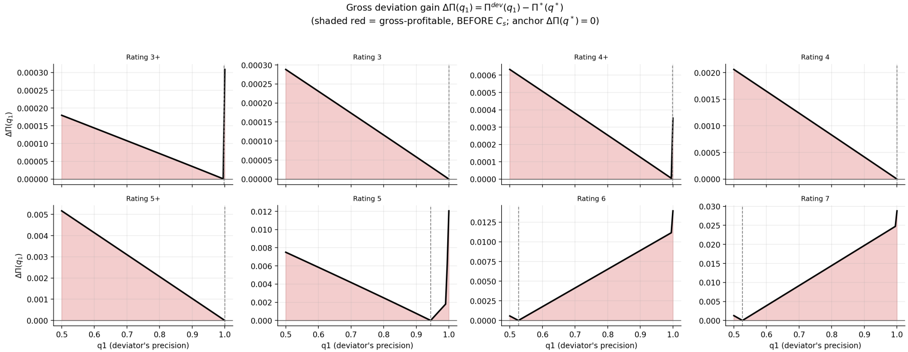
q^* survives a unilateral information deviation iff no Δq satisfies

$$\Delta\Pi(\Delta q) - \Delta C_s(\Delta q) \; > \; 0.$$

The best response is a **pure** strategy: once $c^{avg,s_i}(q_1)$ no longer matches the one F_i was built for, profit is no longer flat in r. Flatness survives only at $q_1 = q^*$.

Results

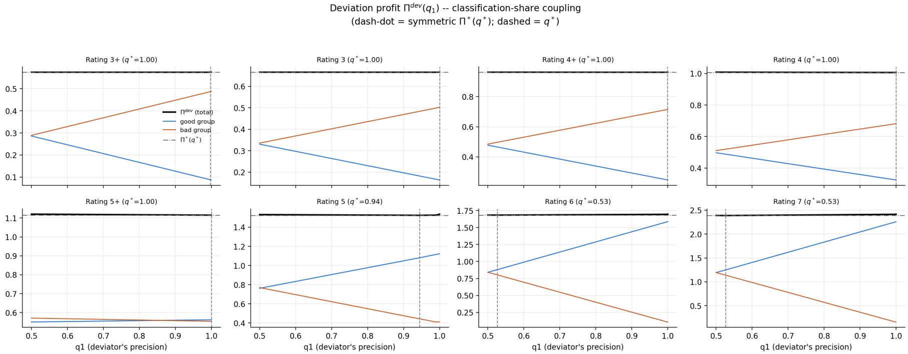
Deviation gains are profitable but small



Gain $\Delta\Pi(q_1) = \Pi^{dev}(q_1) - \Pi^*(q^*)$, by rating class, zero at $q_1 = q^*$ by construction. Shaded: gross-profitable deviations, **before** netting the cost of screening.

$\Delta\Pi$ rises in both directions but stays on the order of 1% of per-encounter profit. Downward deviations are profitable outright (lower gross profit foregone *and* cost savings); upward ones are ruled out whenever the marginal cost of precision exceeds the gross gain.

Deviation profit, levels



Gross deviation profit $\Pi^{dev}(q_1)$ against the symmetric benchmark $\Pi^*(q^*)$ (dash-dot), by rating class.

back