"Into the Shadows": Banks and Transparency

Steven Ongena, *University of Zurich, Swiss Finance Institute, KU Leuven, NTNU Business School, CEPR*

Keynote
ECMI I NBS I CEPS I SUERF Research Conference
Financial deepening – how can we finance productivity growth and transition in small and medium sized economies?
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Information Asymmetry

A key ingredient that helps explain the existence of banks, bank relationships, banking geography, …

Diamond (RES 1984), Sharpe (JF 1990), Fisher (1990), von Thadden (FRL 2004), Hauswald & Marquez (RFS 2003), …

Fama (JME 1985), James (JFE 1987), Morgan (AER 2002), Petersen & Rajan (JF 2002), …

Boot (JFI 2000), Ongena and Smith (2000), Berger and Udell (EJ 2002), Elyasiani and Goldberg (JEB 2004), …

Heisenberg Uncertainty Principle

"If we know everything about where a particle is located, we know nothing about its momentum. Conversely, if we know everything about its momentum, then we know nothing about where the particle is located."

In Psychology: "Measurement systems exert a psychological influence that affects people's behavior we aim to measure."

Diamond-Rajan-Suarez-von Thadden … Information Asymmetry Principle

"If we can easily and almost cost-free estimate something, why couldn`t the banker do so as well?

Hence, are we sure we are looking in the right place?"

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Information Asymmetry /2

- **Hence empirically still an interesting and challenging setting to explore?**
    - In essence, it is challenging (and maybe even fun) to assess a phenomenon when the *absence of information* is its core (business)?

    - Banks collect private information, possibly creating informational rents? How? To what use?

      Claessens, Ongena & Wang (2025); Li & Ongena (2025); Di, Ongena, Qi & Yu (2025)
    - Risks may end up hiding on banks` balance sheets?

      Beyene, Delis, Greiff & Ongena (2025)
    - Banks may at times even actively obfuscate, and bankers may self-deal?

      Giannetti, Jasova, Loumioti & Mendicino (2024); **Danisewicz & Ongena (2025); Eyvazi, Einian, Ongena & Amanzadeh (2025)**

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Banks collate *information*

Banks use *information*

Banks compartmentalize *information*

Banks manage *information display*

Bankers use *information*

Banks collate *information*

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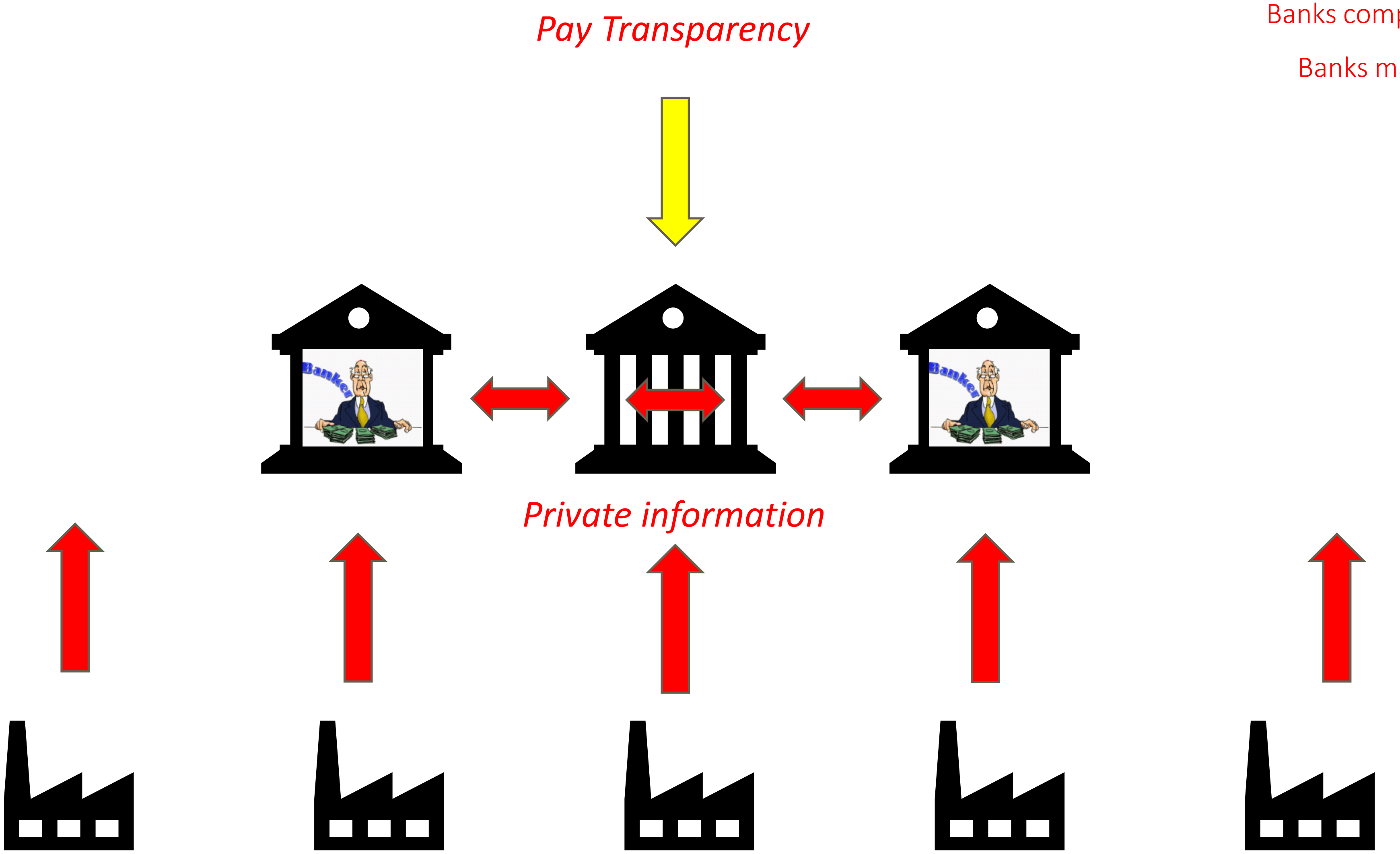

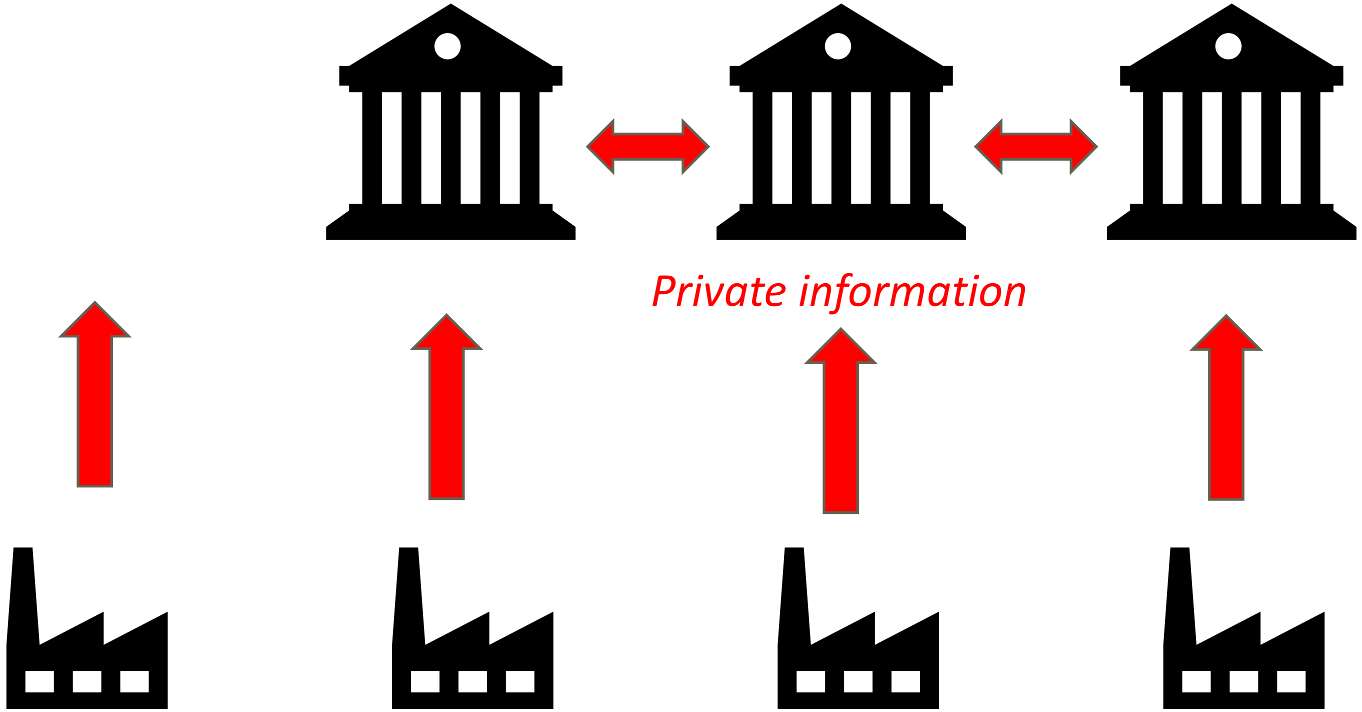

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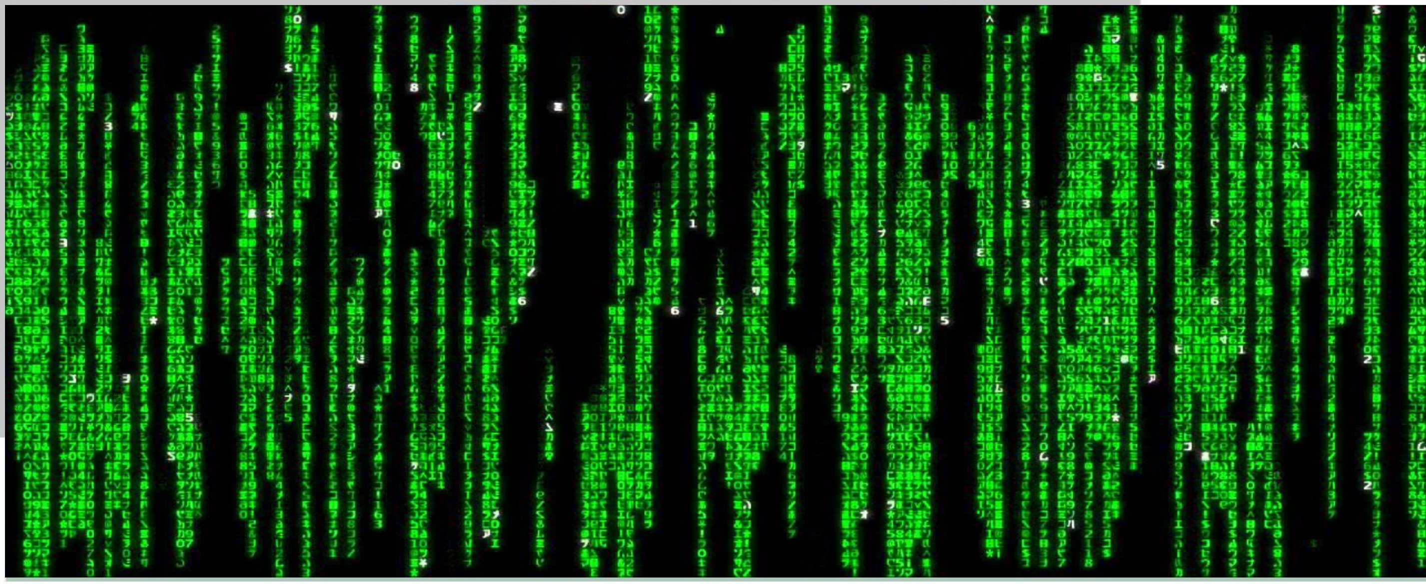
"If You Don't Know Me by Now …"
Banks' Private Information and Relationship Length

Stijn Claessens (*Yale SOM*)

Steven Ongena *(Zurich, SFI, KU Leuven, NTNU, CEPR)*

Teng Wang *(University of Texas at Arlington)*



What We Do

- We aim to quantify the **nature, formation, and implication** of private information embedded in banks' evaluation of borrowers.

- Data
  - Y14Q: Data about U.S. corporate loans held by Comprehensive Capital Analysis and Review (CCAR) banks
    - measure of private information, key characteristics
  - Y9C: Quarterly report filed by bank holding companies (BHCs)

- Simple theory to guide the discussion
  - Identification
    - Exploit the nature of private information contained in the **rating** of corporate loans on banks' balance sheets
    - Compare at a given point in time, the implication of private info set contained in loans to the same borrower by distinct banks, who differ in their relations Khwaja and Mian (AER 2008)

Key Findings

1. What constitutes banks' private information about borrowers?
   - Depth, Positivity, and Negativity
2. How does private information form over time?
   - The "learning process" varies across bank and firm characteristics
3. What is the implication?
   - Private information has significant implications for lending outcomes

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Methodology: Heteroscedastic Regression Model

Mean equation: $y_i = \beta' X_i + u_i$

Variance equation: $\sigma_i^2 = \exp(\gamma' Z_i)$

- Extreme cases:
  - "Rules": R^2 of mean equation → 1
  - "Discretion": R^2 of mean equation → 0

- Model estimated by MLE (normality assumption)

Harvey (ECMA 1976);Cerqueiro, Degryse, & Ongena (JFI 2011, 2013)

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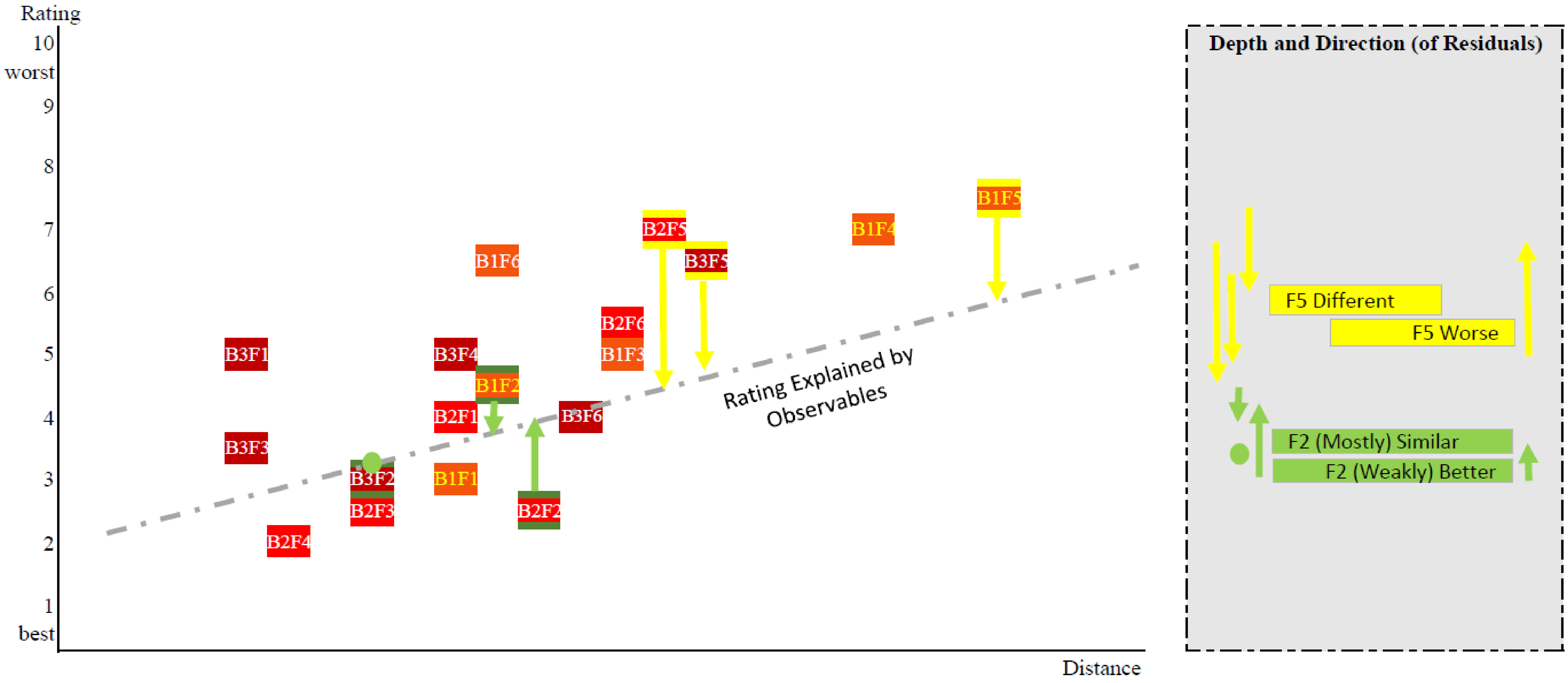
Panel B. Standardized Bank Rating of Firm, and Depth of Private Information and Direction of Private Information



Data

- Main dataset
  - Comprehensive supervisory dataset at the loan-level from Y14Q H1 schedule, final sample covers over 70% of the total U.S. C&I loans
    - \$1m on banks' balance sheet every quarter
  - Includes characteristics of the firm, loan, and payment information as well as internal ratings, standardized to a common scale time period: September 2012 to March 2021
- Distance, length of relationship
  - Distance: borrower to bank HQ (but also to the nearest branch)
  - Length: in years from the initial loan transaction was observed
- Other data
  - Banks balance sheet variables from Y9C

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Identify Private Information from Loan Rating

Table 1. Main Results: Bank Rating of Firm, Depth and Direction of Private Information	
Model	(1)
Sample	***All bank ratings of firms***
Definition	**Standardized bank rating of firm (1 = best, 10 = worst)**
Dependent Variable Name	*Bank Rating of Firm*
Independent variables	
Firm Variables	
Ln(Firm assets)	-0.110***
	(-36.30)
Firm ROA	-1.942***
	(-88.48)
Firm leverage	0.449***
	(43.92)
Green	-0.032*
	(-1.85)
Brown	0.057
	(1.60)
Bank Variables	
Ln(Bank assets)	0.099***
	(36.09)
Bank equity ratio	3.535***
	(18.63)
Bank NPL ratio	-4.994***
	(-31.15)
Bank liquid asset ratio	0.475***
	(9.18)
Bank ROA	12.326***
	(13.13)
Static Bank-Firm Variable	
Distance bank HQ to firm	0.008***
	(3.68)
Observations	2,717,102
Adjusted R-squared	0.129

Firm and bank characteristics, as well as the distance between the them are strong predictors for banks' internal ratings

Liberti & Petersen (RCFS 2019), Plosser & Santos (RFS 2018)

Private Information at Inception

Private information at inception:
Certain firms are severely disadvantaged
(e.g., firms located afar)

Table 1. Main Results: Bank Rating of Firm, Depth and Direction of Private Information

Model	(2)	(3)	(4)
Sample	***Length bank-firm relationship < 0.25 Years***		
Definition	**Ln(Residual squared)**	**Residual if Residual < 0**	**Residual if Residual > 0**
Dependent Variable Name	*Depth of Private Information*	*Better Private Information*	*Worse Private Information*
Independent variables			
Firm Variables			
Ln(Firm assets)	0.111***	-0.010***	0.038***
	(18.33)	(-5.75)	(19.76)
Firm ROA	0.543***	0.156***	-0.012
	(12.11)	(17.95)	(-1.05)
Firm leverage	1.404***	-0.311***	0.519***
	(19.89)	(-28.33)	(21.90)
Green	-0.159**	-0.027**	-0.016
	(-2.33)	(-2.25)	(-1.27)
Brown	0.140	0.107***	-0.069***
	(1.05)	(3.43)	(-2.78)
Bank Variables			
Ln(Bank assets)	0.084***	0.005**	-0.003
	(6.68)	(2.19)	(-0.94)
Bank equity ratio	-9.831***	1.164***	-4.271***
	(-10.54)	(6.76)	(-20.69)
Bank NPL ratio	-2.646***	1.557***	-1.057***
	(-3.08)	(10.73)	(-4.84)
Bank liquid asset ratio	-1.513***	0.401***	-0.532***
	(-6.23)	(7.75)	(-8.97)
Bank ROA	-25.303***	0.580	-2.004
	(-3.25)	(0.44)	(-0.93)
Static Bank-Firm Variable			
Distance bank HQ to firm	-0.012	-0.007***	0.001
	(-1.32)	(-4.29)	(0.37)
Observations	61,149	61,149	61,149
Adjusted R-squared	0.019	0.030	0.043

Regression Results for the Loan Terms

Depth and negativity information increase rate and lower maturity. Positive information decreases rate and increases mat urity

Uncertainty about borrower's quality leads to higher risk premium and rationing

Table 4. Impact of Private Information on Loan Terms

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent Variable	*Loan Interest Rate Spread*			*Ln(Loan Maturity)*		
Independent variables						
Depth of Private Information	0.023***			-0.001		
	(4.31)			(-1.04)		
Better Private Information		-0.423***			0.042***	
		(-22.34)			(2.80)	
Worse Private Information			0.388***			-0.042***
			(25.78)			(-6.95)
Firm, Bank and Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank and Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,121,365	2,121,365	2,121,365	2,713,058	2,713,058	2,713,058
Adjusted R-squared	0.112	0.121	0.128	0.283	0.283	0.283

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	(1)	(2)	(3)	(1)	(2)	(3)
Dependent Variable	*Ln(Loan Amount)*			*d(Collateralized)*		
Independent variables						
Depth of Private Information	-0.001			-0.003***		
	(-0.53)			(-8.18)		
Better Private Information		0.022			-0.037***	
		(1.45)			(-5.68)	
Worse Private Information			-0.013*			0.013***
			(-1.82)			(8.17)
Firm, Bank and Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank and Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,715,622	2,715,622	2,715,622	2,715,622	2,715,622	2,715,622
Adjusted R-squared	0.393	0.393	0.393	0.148	0.151	0.148

The Formation of Private Information

Banks, in general, collect more information as they learn about the borrowers over time.

- The information collected tends to be positive in nature.

Table 2a. Bank-firm Relationship Length and Banks' Private Information

	(1)	(2)	(3)
Dependent Variable / Independent variables	*Depth of Private Information*	*Better Private Information*	*Worse Private Information*
<u>Dynamic Bank-Firm Variable</u>			
Length bank-firm relationship	3.693***	6.760***	-5.492***
	(3.31)	(19.98)	(-20.95)
Bank and Firm Controls	YES	YES	YES
Observations	2,715,622	2,715,622	2,715,622
Adjusted R-squared	0.010	0.016	0.007

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Geographic Distance and the Formation of Private Info

More private information is collected for distant borrowers as the relationship lengthens

- The private information collected is largely positive in nature

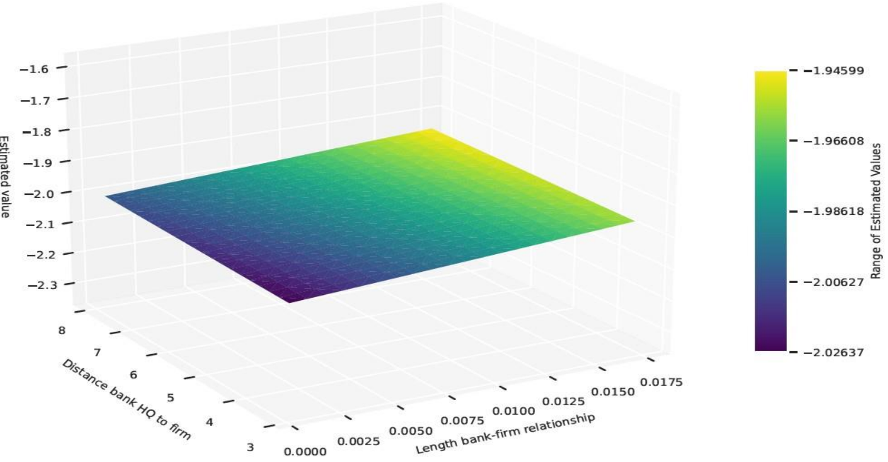
Dependent Variable	Depth	Better	Worse
Independent variables			
Distance bank HQ to firm	-0.019	-0.000	0.001**
	(-1.51)	(-0.60)	(2.27)
Distance bank HQ to firm * Length bank-firm relationship	5.601***	0.224***	-0.065
	(3.67)	(3.85)	(-1.11)
Firm, Bank, and Bank-Firm Relationship Controls	Yes	Yes	Yes
Adjusted R-squared	0.027	0.014	0.013

Notes: The table reports the coefficients with t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

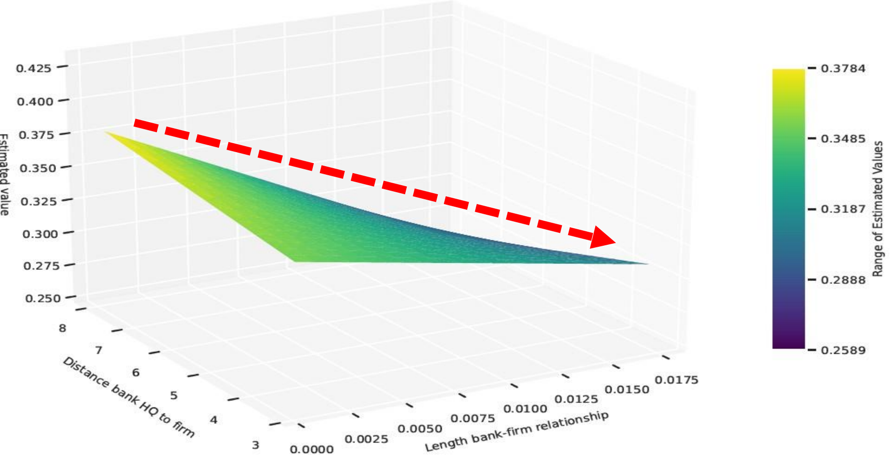
Geographic Distance and the Formation of Private Info

Firms located far away are disadvantaged in the beginning, but banks learn mostly positive information over time.

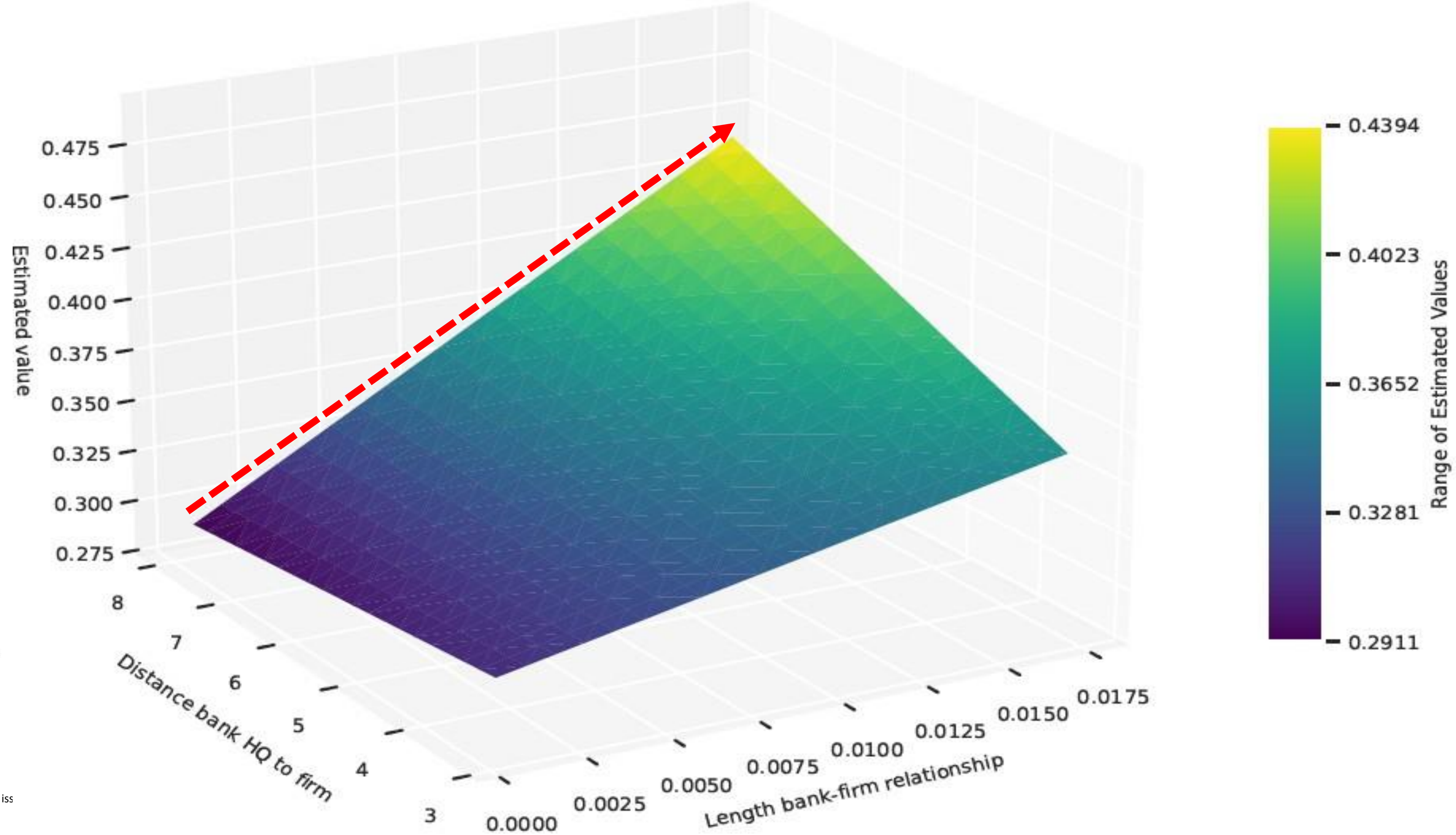
Depth of Private Information



Worse Private Information



Better Private Information



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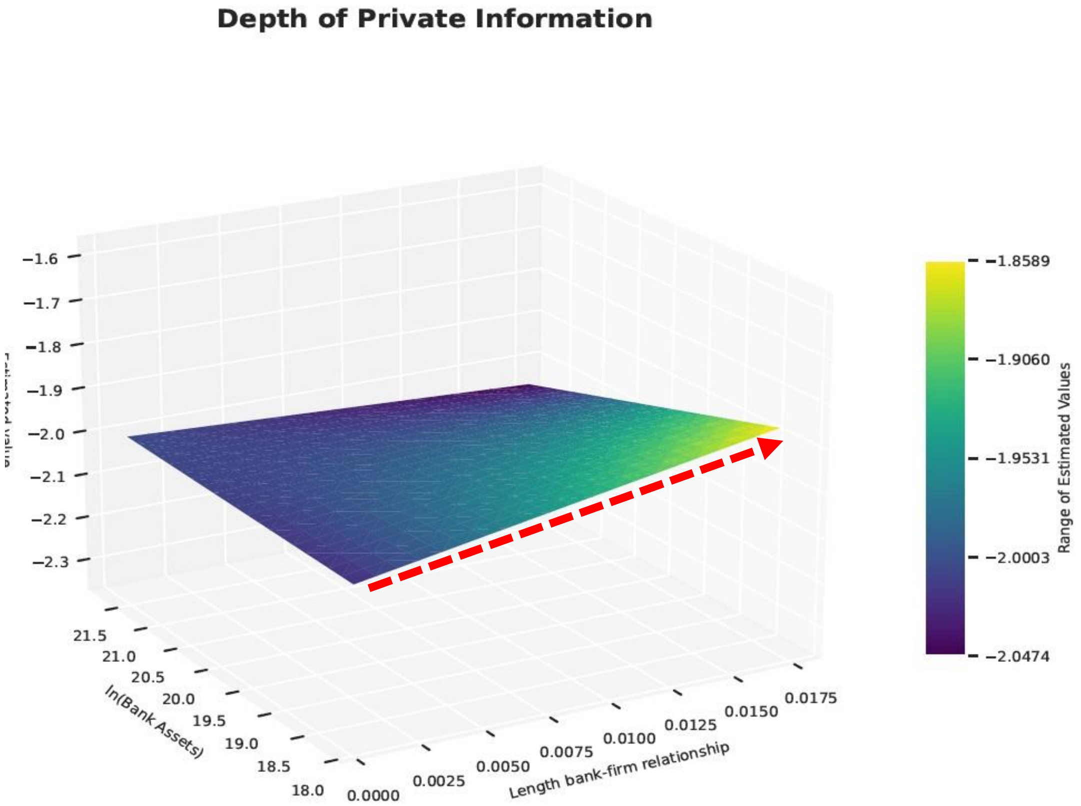
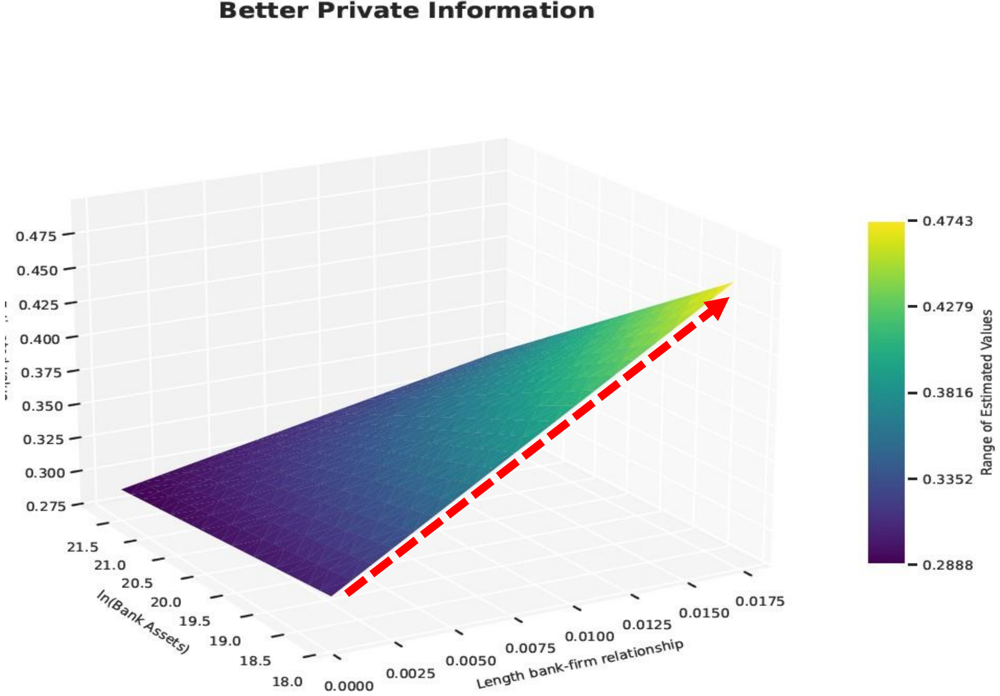
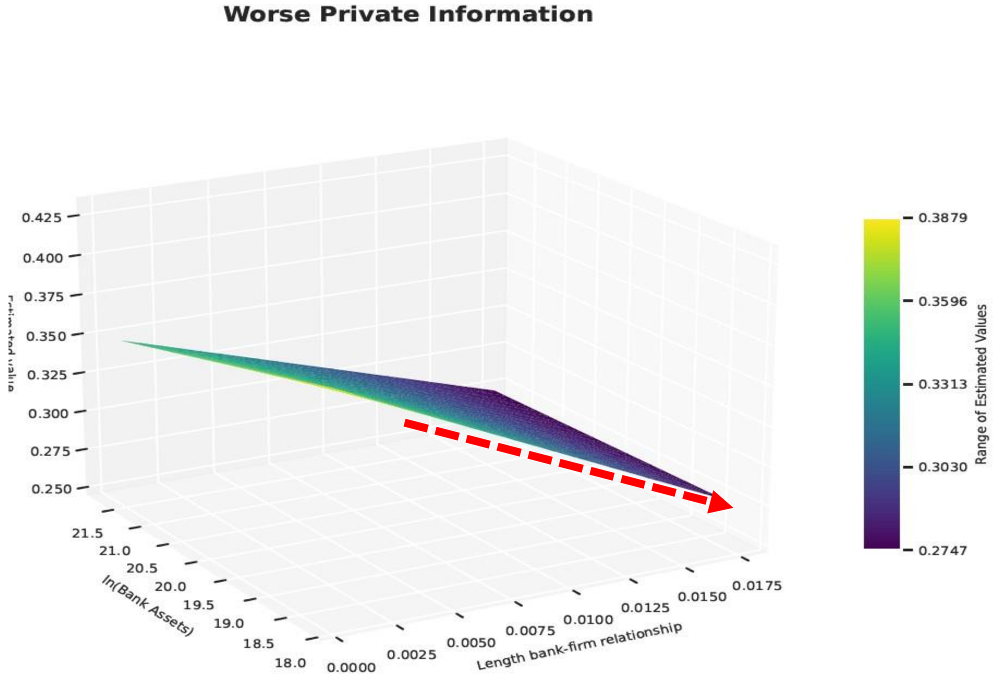
Bank Characteristics and the Formation of Private Info

Smaller banks are more engaged in private information collection

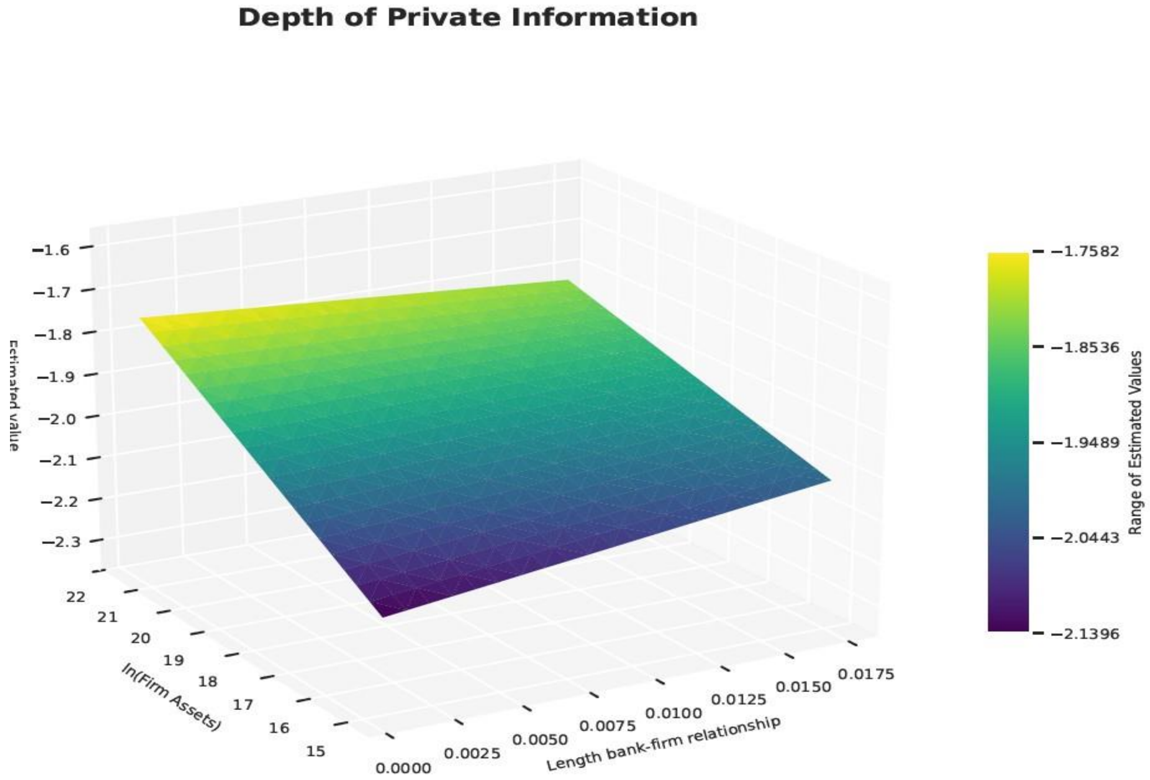


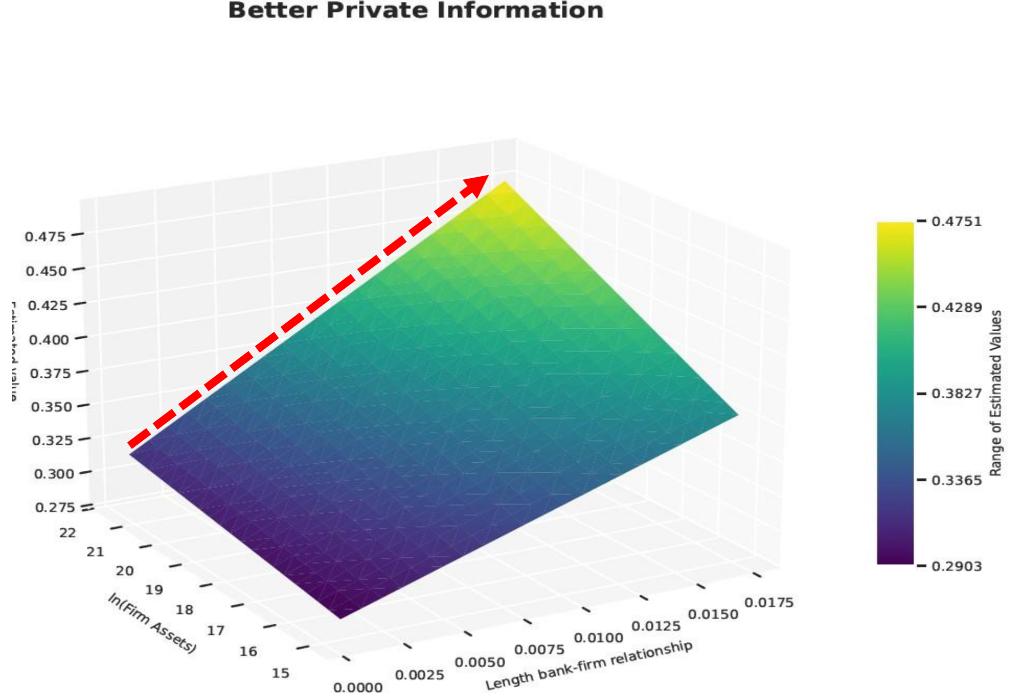


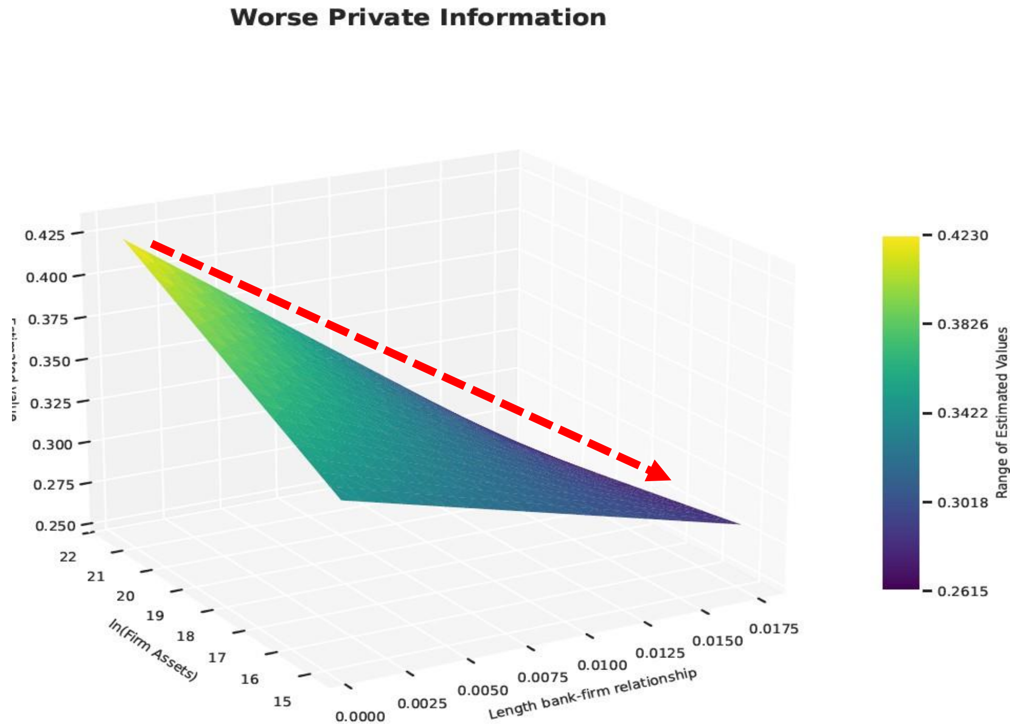


Firm Size and the Formation of Positive Private Info

More positive information is collected for larger private firms over time







COVID-19 and the Formation of Positive Private Info

A smaller amount of private information during the COVID-19 lockdown, especially worse private information

Dependent Variable	Depth	Better	Worse
Independent variables			
COVID-19 Crisis	-0.034*	-0.042***	0.050***
	(-1.69)	(-12.16)	(10.26)
COVID-19 Crisis * Length bank-firm relationship	-4.632**	0.749*	-2.730***
	(-2.41)	(1.87)	(-5.98)
Firm, Bank, and Bank-Firm Relationship Controls	Yes	Yes	Yes
Adjusted R-squared	0.010	0.016	0.007

Notes: The table reports the coefficients with t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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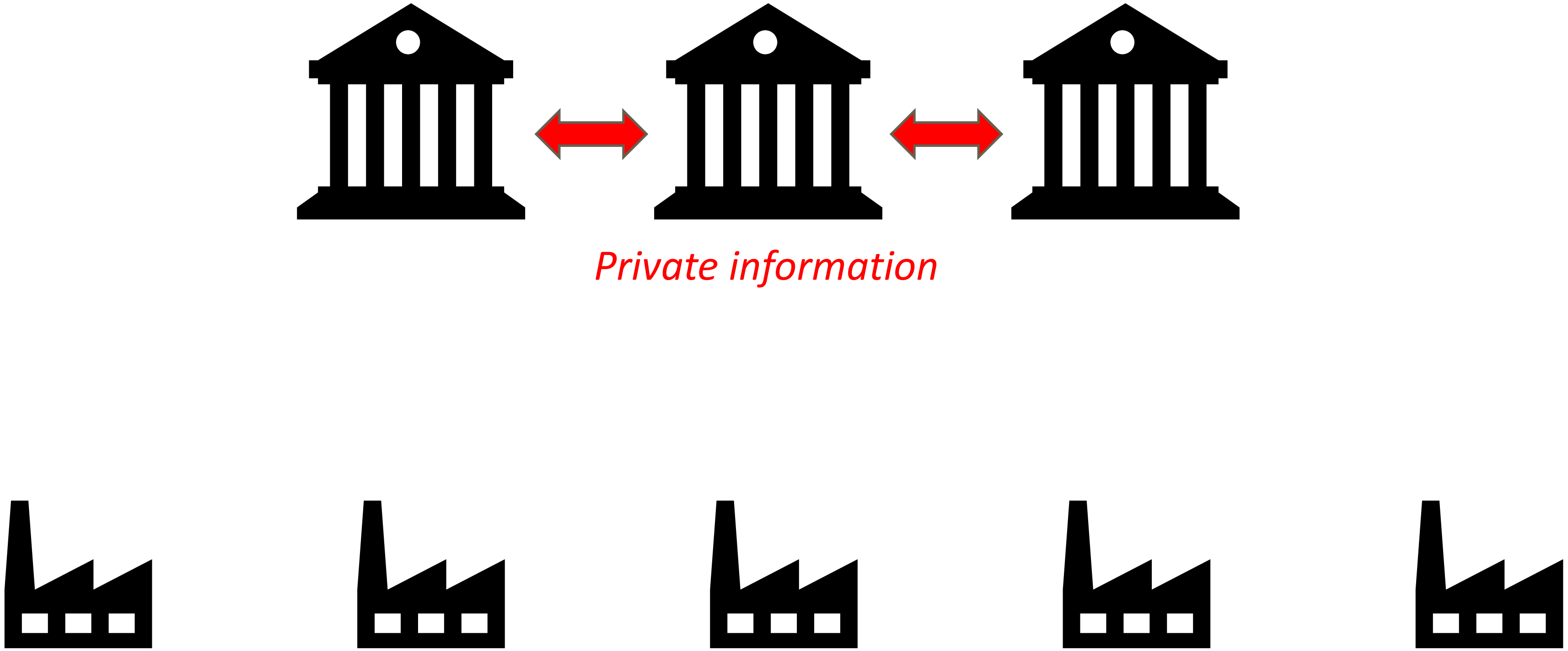
Conclusions

- Banks are special in overcoming information asymmetries in lending
- Banks adjust loan terms according to changes in private information
- We visualize the process in banks' learning of private information embedded in their evaluation of borrowers
- The findings are consistent with the classic banking literature
- Private information matters to banks!


Private information

Global Banks’ Macroeconomic Expectations and Credit Supply

Xiang Li (*Halle IER and Leipzig University*)

Steven Ongena *(Zurich, SFI, KU Leuven, NTNU, CEPR)*

Motivation

- Expectation matters for fundamental economic decisions

Coibion and Gorodnichenko (AER 2015); Gennaioli, Ma, and Shleifer (2016)

  - Consumption, saving, pricing, hiring, ...
  - Macroeconomic expectation as an important driver of boom-bust cycle

Minsky (C 1977)

- Information as a key determinant of capital flows

Portes, Rey and Oh (EER 2001); Tille and Wincoop (JIE 2014)

  - Global banks in facilitating flows
  - Cross-border banking flows

- What do we know about global banks' macroeconomic expectations and their impact?
  - So far very limited

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This Paper

Research Question:

How do global banks' macro expectations affect their credit supply?

- Characteristics of lenders' information process for macroeconomic expectations
- Impact of macroeconomic expectations on international lending

This Paper

- Research Question: How do global banks' macro expectations affect credit supply?
  - Characteristics of lenders' information process for macroeconomic expectations
  - Impact of macroeconomic expectations on international lending
- Major Challenges
  - Data availability: lenders' macro expectation, in particular for foreign countries
  - Endogeneity: macro expectation affected by economic performance, including lending activities

This Paper: What We Do?

Lender-month-level macroeconomic expectation: forecasts in *Consensus Economics*

Match lender names in *DealScan* and *BankFocus*: syndicated loans and balance sheet

⇒ banks with different expectations lend to the same firm at same time:

controls for credit demand and mitigates reverse causality

⇒ IV to tackle endogeneity: initial forecast made at least one year ago

This Paper: Main Findings

Lenders' information process show information rigidity

Expectations matter! GDP expectation ↑ 1 SD, lending share ↑ 8.46 pp ≈ $75.35 mn

More pronounced effect in borrower country currency and with optimistic news shock

Short-run inflation expectations show insignificant impact

Related Literature

Information structure in expectations

- Framework to test FIRE Coibion and Gorodnichenko (AER 2015); Bordalo et al. (JF 2020)
- Determinants of inflation expectation Afrouzi et al. (QJE 2023); Benhima and Bolliger (REStat 2022); Malmendier and Nagel (QJE 2016); Dräger et al. (JME 2024)
- This paper: characterize the macro expectations of global banks

Role of expectations in business cycle

- Firms' expectations on investment, production, and debt issuance Minsky (C 1977); Gennaioli et al., (NBER M 2016); Ropele et al. (2022); Gulen et al. (RFS 2024); He et al. (JFE 2024)
- Banks' lending standard, optimism/pessimism beliefs Bassett et al. (JME 2014); Ma (2015); Ma et al. (2021); Falato and Xiao (2023)
- This paper: directly measure global banks' macroeconomic expectations for various countries

Macro expectation and capital flows

- Experience-based learning and portfolio investment Malmendier and Nagel (QJE 2016)
- Financial intermediary's expectation in bond and mutual fund flows Benhima and Cordonier (JIE 2022); Benhima et al. (2022) Benhima et al. (2023)
- This paper: focus on global banks' lending

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Data: Expectation

Expectation data used in the literature: mostly of firms

- US survey of professional forecasters (SPF)
- Duke/CFO Magazine Business Outlook Survey
- Institutional Brokers Estimate System (IBES)

Lenders' expectation: limited data for US

- Fed's Senior Loan Officer Opinion Survey (SLOOS): around 100 banks, expectations for changes in lending standards, loan demands and loan performance
- Blue Chips: around 40 major financial institutions
- Fed's FR Y-14A data: banks' expectation for each MSA, 8-11 banks, 2014-, annually
- **Consensus Economics**: over 400 forecasters, of which 200 are banks, international lenders' macroeconomic expectations regarding foreign economies

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Data: Consensus Economics

Survey among professional forecasters: (1) commercial banks, (2) non-bank financial institutions (NBFI), (3) consulting and rating agencies, (4) non-financial firms (NFI); (5) industry associations; (6) university and research institutes

CE reports average values across respondents as the consensus forecast

We access the micro-level data, each institution's individual forecasts

- Monthly forecasts of GDP growth rate and inflation rate in the current and next year
- For a given year k, each institution makes 24 forecasts, starting in January of year $k - 1$ and ending in December of year k

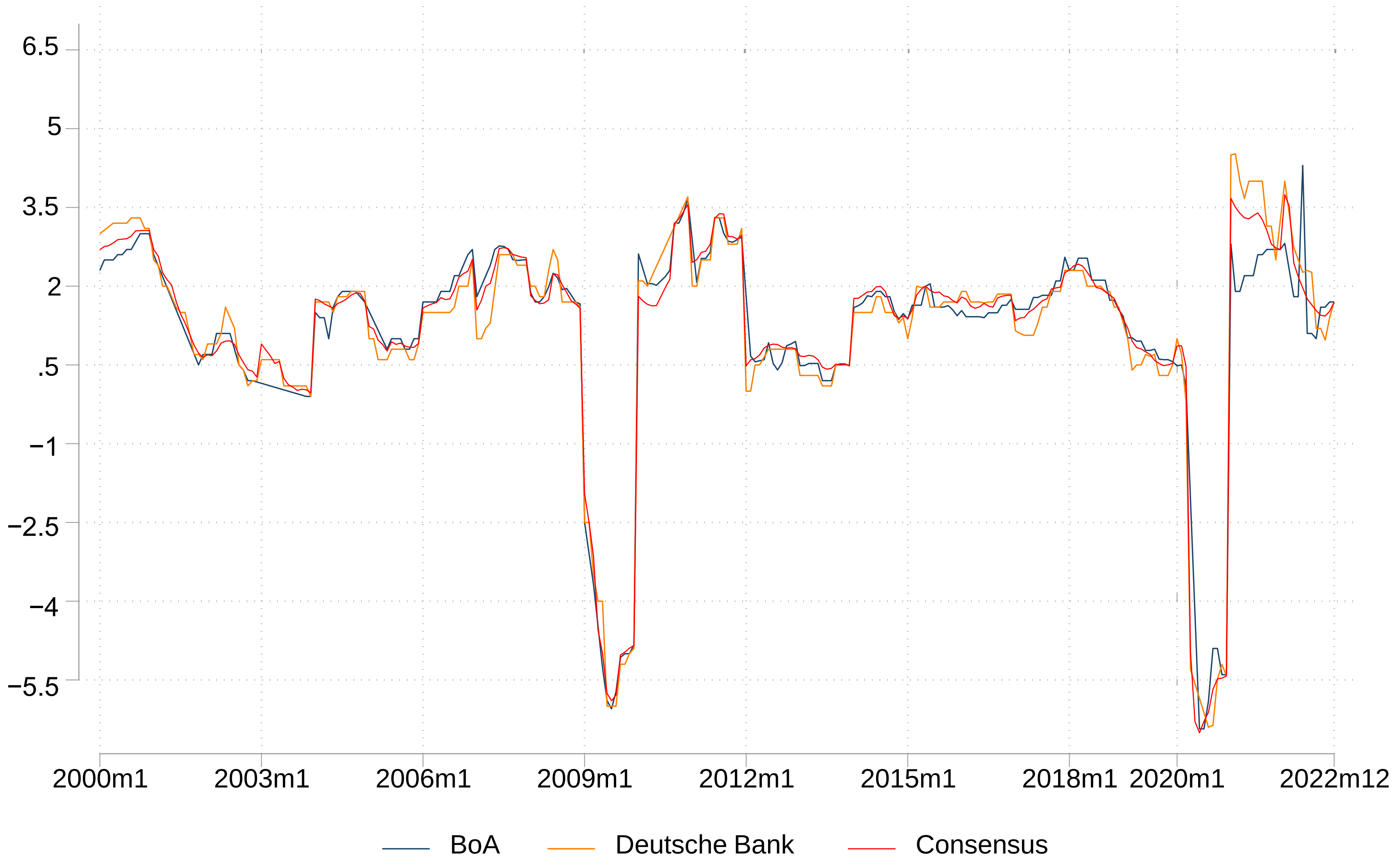
Clean: remove forecasts that deviate by more than five interquartile ranges from the median; only keep forecasters with at least ten observations

Data: Consensus Economics

Example for US GDP Forecast

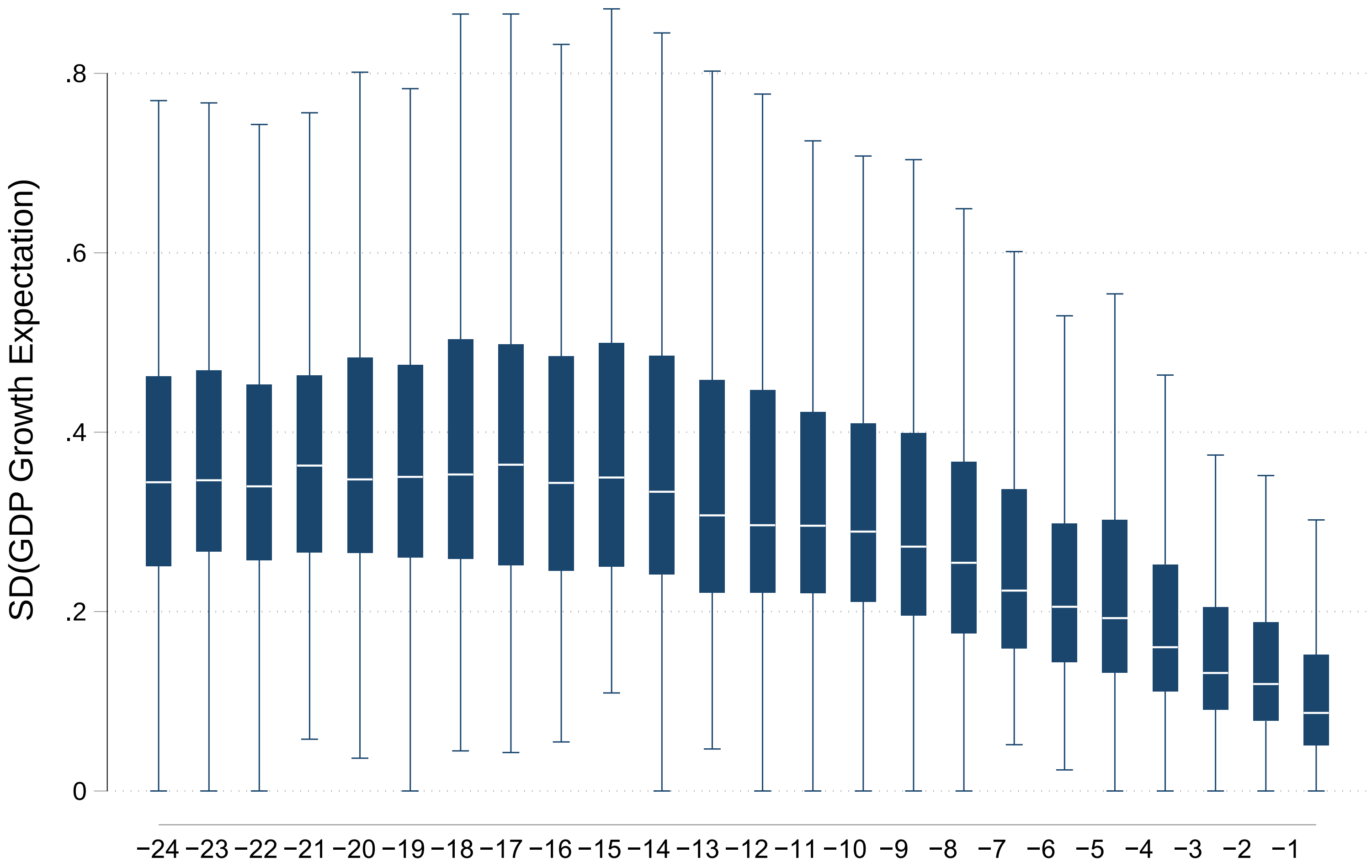
Data: Consensus Economics

Example for Germany GDP Forecast



Data: Consensus Economics

Variation Across Forecasting Horizon



Significant disagreement in initial forecasts, diminishes with forecasting horizon

Data: Syndicated Loans

Loan-level data: Thomson Reuters LPC, universe of syndicated loans

Deal (Package) - Tranche (facility), each tranche is treated as an individual loan

Origination date, lender and borrower identity, loan amount, interest rate, maturity

Variations across banks within a loan tranche: **lender shares**

- Big issue: large fraction of missing values (60%-70%)
- Small sample of unimputed lender → main analysis
- Imputing by allocating equally → robustness check

Bank characteristics: BankFocus

Merge with CE expectation: manually match lender names

Final data: 9,145 deals, 12,230 tranches, from 70 global banks headquartered in 16 countries and 5,209 borrowers headquarters in 17 countries, all Adv Ec, 1992M1-2022M12

Data: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
Lender Share	14.670	13.150	0.460	100.000	37725
GDP Growth Expectation	2.096	1.706	-6.700	7.400	37725
L.Ln(Asset)	14.038	2.838	7.428	21.543	37725
L.Equity/Asset	5.587	3.415	-2.145	111.449	37725
L.Depository Funding/Asset	63.696	23.672	0.291	187.897	37725
L.Ln(Outstanding Loans)	11.109	1.570	1.847	13.446	37725
Number of Lenders	12.218	9.046	1.000	156.000	37725
Ln(Tranche Amount)	5.339	1.756	-2.040	10.800	37725
Tranche Maturity	50.862	33.630	1.000	462.000	37725

Data: Granularity Illustration

- June 2015, a loan tranche totaling $3.77 billion issued to PepsiCo, financed by 22 banks
- Consensus U.S. GDP growth forecast for 2015: 2.48%

Characterize Global Banks' Expectation

FIRE Test

Aggregate consensus for banks in our sample

	Consensus			
	(1) GDP	(2) GDP	(3) Inflation	(4) Inflation
FR	0.319**	0.344***	0.099	0.106
	(2.47)	(2.72)	(0.35)	(0.37)
N	2315	2315	2070	2070
Horizon FE	NO	YES	NO	YES

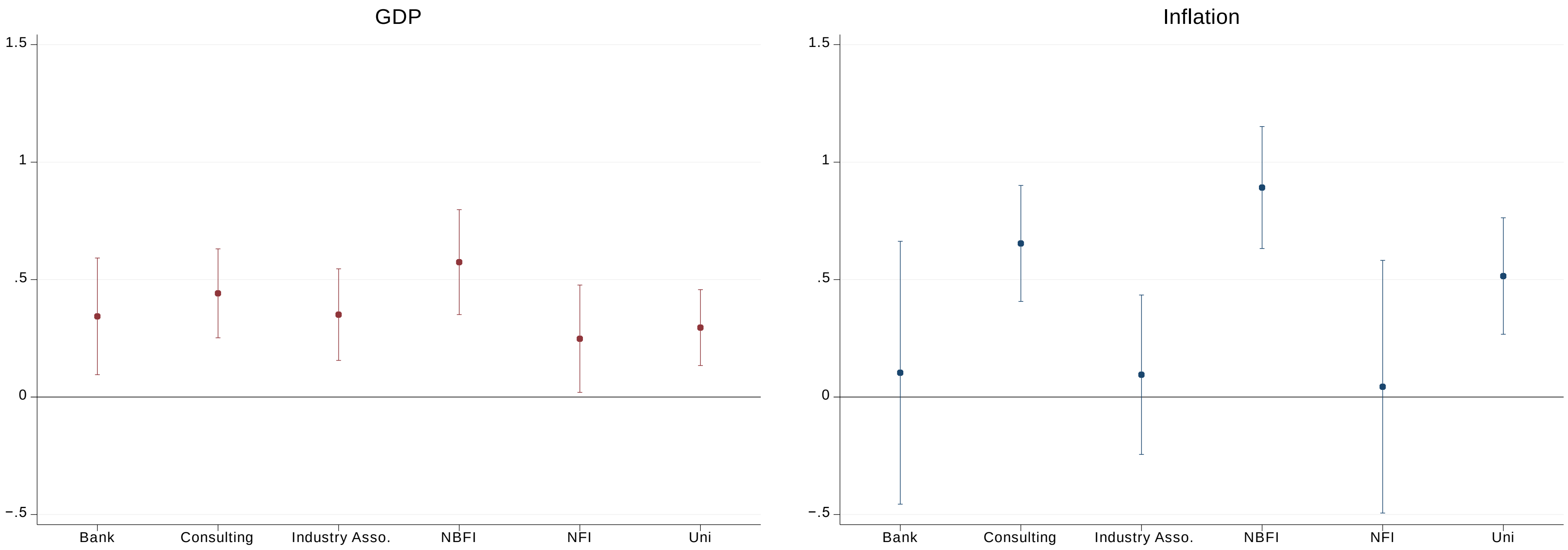
Probability of updating info/weight on new info for GDP: 0.74

Insignificant rigidity for inflation expectation

Characterize Global Banks' Expectation

FIRE Test

Compare with other types of forecasting institutes



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Baseline Specification

$$LenderShare_{b,i,l,t} = \alpha_0 + \beta Expect_{b,i^t,t-1} + \alpha_1 Bank_{b,t-1} + \alpha_2 Loan_{b,i^t,t-1} + \theta_l + \lambda_{b^t,t} + \eta_{b^t,i^t} + \epsilon_{i,b,l,t}$$

b, i, l, t: bank, borrower firm, loan tranche, month, b^l, i^l: borrower country, lender country

$\beta > 0$: lender's more optimistic expectations associated with more credit supply

Control

- $Bank_{b,t-1}$: bank size, equity ratio, deposit ratio
- $Loan_{b,i^t,t-1}$: outstanding loans issued by the bank in the country → mitigate reverse causality

Granular FE → credit demand captured (Khwaja and Mian, AER 2008)

- Tranche FE θ_l → tranche terms captured (amount, maturity, number of lenders)
- Alternatively, firm-month FE $\theta_{i,t}$ and control for tranche terms
- Lender country-month $\lambda_{b^t,t}$ and country pair FE η_{b^t,i^t}

Baseline Results: OLS Estimates

L.GDP Growth Expectation	2.107***	1.840***	1.835***	1.885***	2.193***	1.768***	1.817***	2.131***
	(0.247)	(0.248)	(0.247)	(0.252)	(0.278)	(0.254)	(0.259)	(0.288)
L.Ln(Asset)		-0.097*	-0.094*	-0.061	-0.127**	-0.092*	-0.092	-0.159**
		(0.055)	(0.054)	(0.056)	(0.063)	(0.052)	(0.057)	(0.065)
L.Equity/Asset		-0.023*	-0.023*	-0.036***	-0.038**	-0.023**	-0.032**	-0.033**
		(0.012)	(0.012)	(0.013)	(0.016)	(0.012)	(0.013)	(0.016)
L.Depository Funding/Asset		-0.020***	-0.020***	-0.021***	-0.027***	-0.020***	-0.021***	-0.027***
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
L.Ln(Outstanding Loans)		1.465***	1.449***	1.450***	1.506***	1.461***	1.469***	1.528***
		(0.047)	(0.046)	(0.056)	(0.061)	(0.048)	(0.059)	(0.064)
Number of Lenders			-0.291***	-0.291***	-0.286***			
			(0.045)	(0.045)	(0.046)			
Ln(Tranche Amount)			-0.326***	-0.328***	-0.316***			
			(0.099)	(0.098)	(0.098)			
Tranche Maturity			-0.004	-0.004	-0.004			
			(0.004)	(0.004)	(0.004)			
Observations	37725	37725	37725	37725	37725	37725	37725	37725
R^2	0.709	0.715	0.716	0.717	0.723	0.730	0.731	0.737
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES

1 SD ↑ in banks' growth expectation, loan share ↑ 3.64 pp, ≈ 0.3 SD , 27.22 mn

Baseline Results: Oster Bounds

Coefficients of the key explanatory variable are stable across specifications

Oster (2019) method, bounding sets → mitigate concerns about omitting variables and unobservable selections

R_{max}	Bounding Set	$\tilde{\delta}$ for $\beta = 0$ given R_{max}
$R_{max} = 0.85\ (1.15\tilde{R})$	[2.131,2.594]	-4.561
$R_{max} = 0.92\ (1.25\tilde{R})$	[2.131,2.881]	-2.828
$R_{max} = 0.96\ (1.3\tilde{R})$	[2.131,3.044]	-2.324
$R_{max} = 1$	[2.131,3.208]	-1.972

All bounding sets exclude zero and are positive

Unobservables need to be at least twice as important as the observables to produce a treatment effect of zero

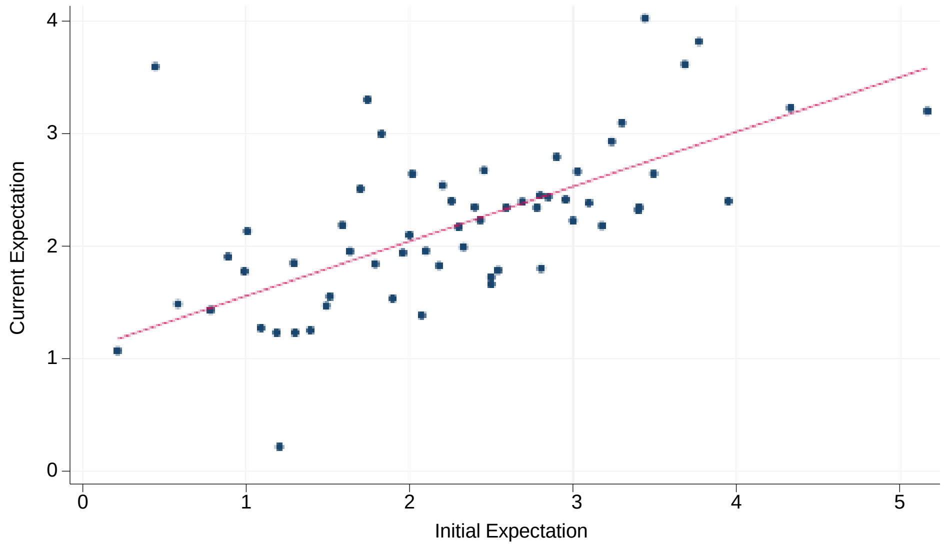
Identification

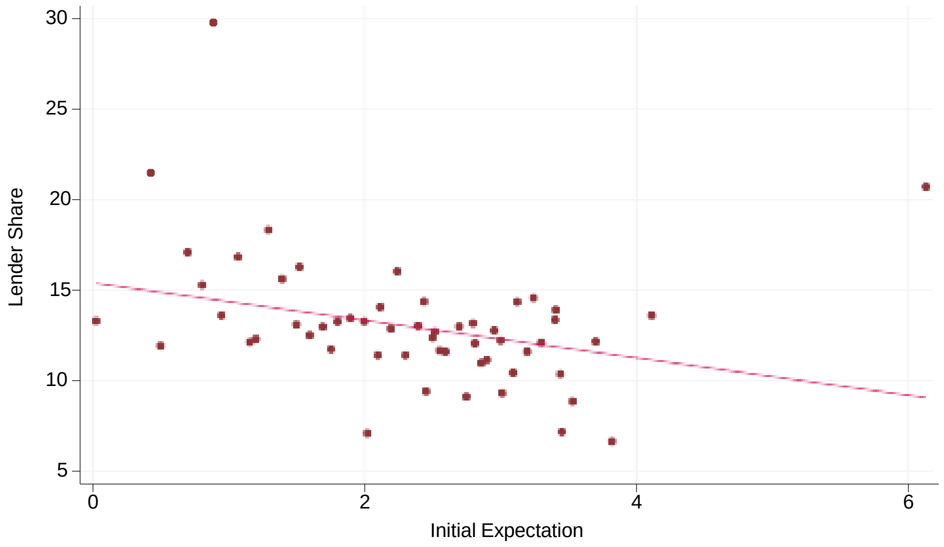
IV: first forecast for a given lender-country year, at least a 12-month gap

- e.g., Credit Suisse's expectation in August 2016 for U.S. GDP growth in 2016 instrumented by its forecast made twenty months earlier, in January 2015

Relevance condition: similar forecasting model and variables

Exclusion restriction: not directly connected to the economic conditions that have evolved in recent months





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Baseline Results: IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Second-Stage Results				
L.GDP Growth Expectation	3.752*** (1.177)	2.737** (1.085)	2.765** (1.079)	3.747*** (1.252)	5.167*** (1.561)	2.912*** (1.111)	3.846*** (1.284)	5.422*** (1.614)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Stat	10.158	165.077	105.477	81.816	78.467	150.991	115.504	110.600
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower $\times$ Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country $\times$ Month FE	NO	NO	NO	NO	YES	NO	NO	YES
				First-Stage Results				
Initial GDP Growth Expectation	0.091*** (0.004)	0.096*** (0.005)	0.096*** (0.005)	0.089*** (0.005)	0.086*** (0.005)	0.096*** (0.005)	0.088*** (0.005)	0.085*** (0.005)
Effective F-Stat	416.006	447.259	447.331	371.876	287.657	396.344	329.255	254.831

High first-stage effective F-test Olea and Pflueger (JBES 2013), Stock and Yogo (2005)

Second-stage: estimates increased by at most 2.5 times

1 SD ↑ in banks' growth expectation, loan share ↑ 8.46 pp, ≈ 75.35 mn

Discussion: Cross-border and Cross-currency Lending

	Crossborder		In Lender Currency		In Borrower Currency		Offshore Currency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	5.201***	5.463***	4.945***	5.222***	1.877	-4.825	5.253***	5.521***
	(1.590)	(1.649)	(1.546)	(1.596)	(2.202)	(3.347)	(1.571)	(1.626)
L.GDP Growth Expectation × D(Crossborder)	6.848	7.056						
	(11.112)	(12.785)						
L.GDP Growth Expectation × D(In Lender Currency)			0.292	0.265				
			(0.200)	(0.192)				
L.GDP Growth Expectation × D(In Borrower Currency)					3.698*	11.533***		
					(2.040)	(3.803)		
L.GDP Growth Expectation × D(Offshore Currency)							-0.633	-0.713*
							(0.423)	(0.400)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Statistics	69.058	91.096	69.693	92.074	69.494	90.421	69.680	92.049
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-
Lender Country-Borrower Country Pair FE	YES	YES	YES	YES	YES	YES	YES	YES
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES
Lender Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES

Impact does not significantly vary with whether the loan is cross-border or denominated in lender currency

Growth expectations matter only when lending is denominated in the borrower's domestic currency

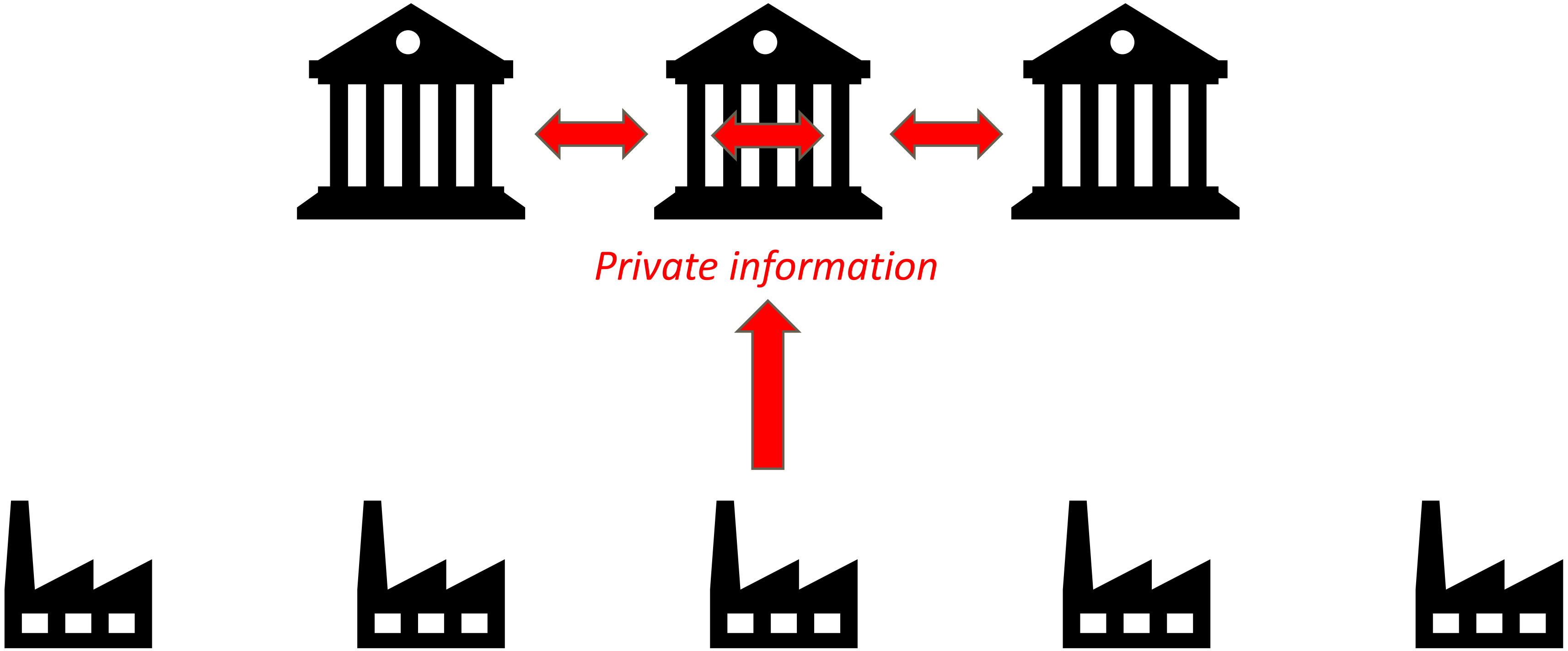
Conclusion

Main Findings

- Global banks' macroeconomic expectation shows information rigidity
- Macroeconomic expectations for borrower countries shape credit supply decisions
- More pronounced effect in borrower country currency and with optimistic news shock
- Short-term inflation expectations do not show a significant effect

Implications

- Monitor the formation and dispersion of expectations as a factor influencing credit availability
- Signaling and communication by governments may help attract international credit


Private information

"Time for a Change of Scenery": Loan Conditions When Firms Switch Bank Branches

Di Gong (*China School of Banking and Finance UIBE*)

Steven Ongena *(Zurich, SFI, KU Leuven, NTNU, CEPR)*

Shusen Qi (*Xiamen University & Peking University*)

Yanxin Yu (*China School of Banking and Finance UIBE*)

This Paper

Questions

- Does hold-up also exist when borrowers switch across branches within the same bank?
  - So what about within-organizational informational asymmetries?

Setting

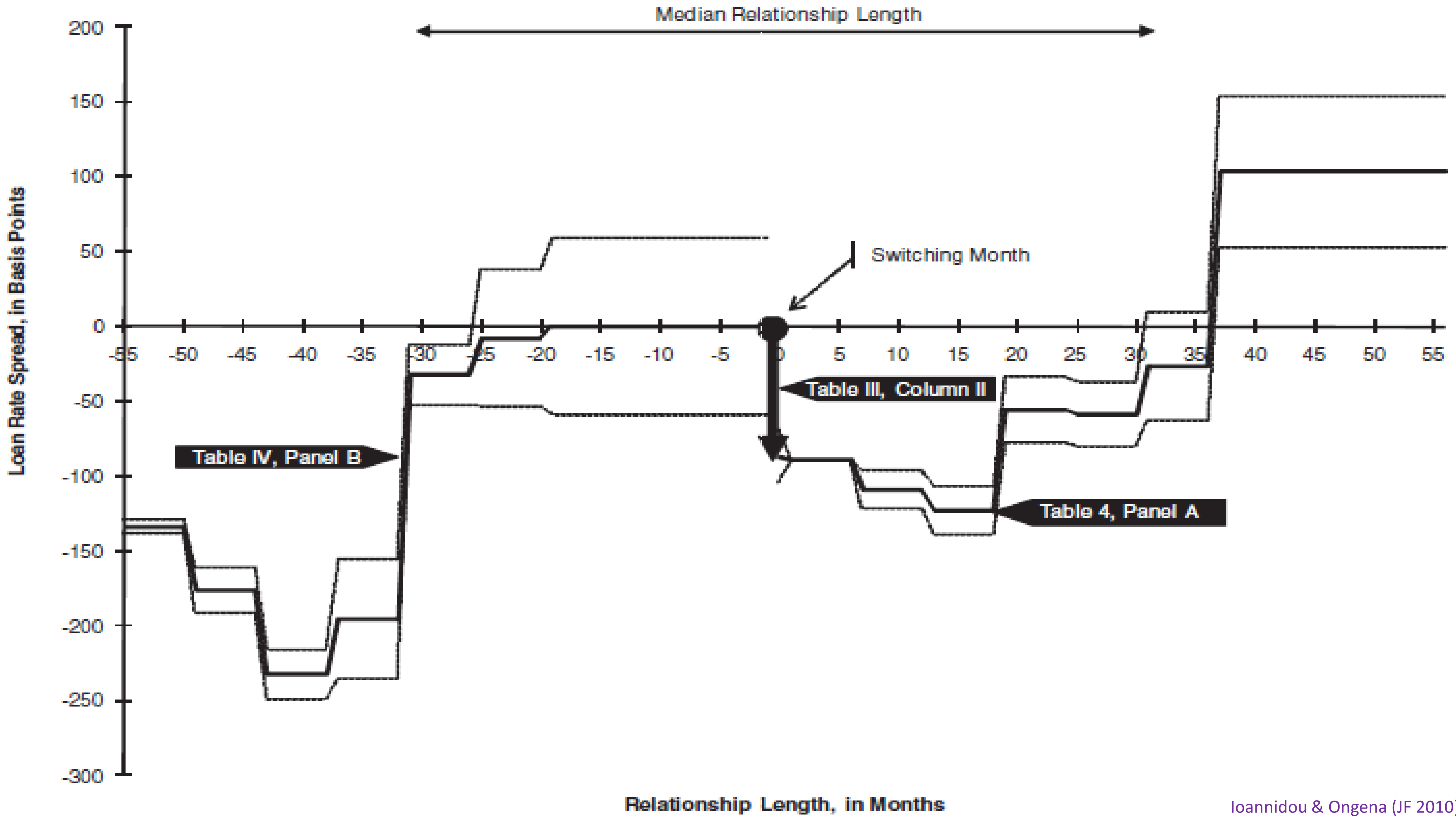
- More then 110,000 loan data from branches in one bank during 2010 and 2020 to 27,118 firms in China

Main Findings

- Better loan conditions when firms switch branches (i.e., lower interest rate, by up to 25 bps)

Switch vs. Transfer

	Across Banks	Within Banks
Switching	Firms switching banks initially receive **a discount**, i.e., a lower loan rate! Ioannidou and Ongena (JF 2010)	?
Transferring	**No discounts** for transfer loans. Bonfim, Nogueira, and Ongena (RF 2021)	A bank branch-firm relationship destruction causes a **higher loan interest** spread for firms. Xu, Saunders, Xiao, Li (JBF 2020)



Ioannidou & Ongena (JF 2010)

Data

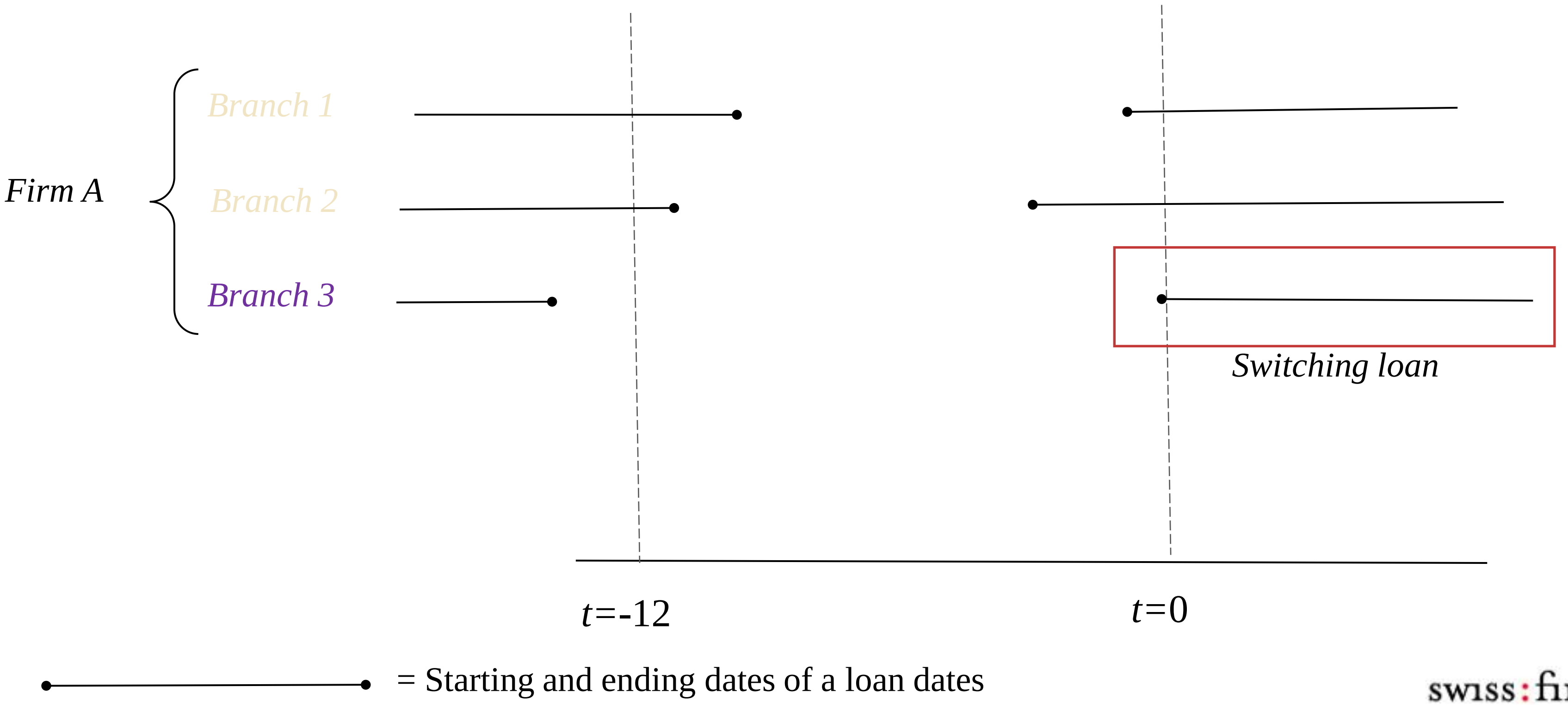
- **Bank**
  - 300 branches in one large bank in China
  - Geographical location, and the establishment dates

- **Firms**
  - 27,118 firms across 203 cities
  - Geographical location, industry, legal structure, ownership structure, and size (78% are small firms).

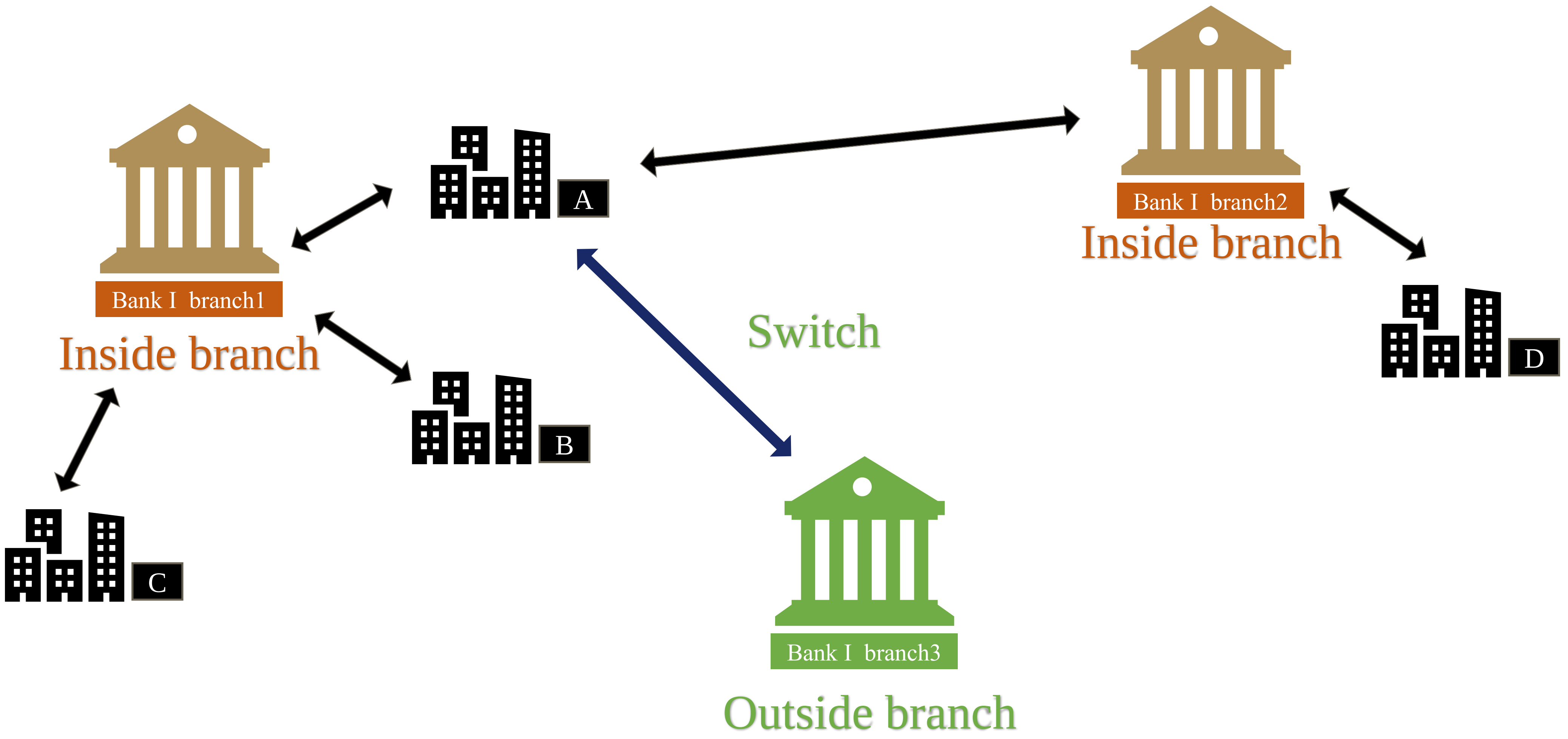
- **Loans**
  - The population of 119,270 new loan initiations
  - 2010~2020
  - The date of origination, maturity, loan rate, amount, collateral, rating, and the existence of a credit line.

Switchers, Inside Branches, and Outside Branches

- Switching loan: a new loan from a branch with which it did not have a lending relationship during the prior 12 months
- Nonswitching loan: any new loan that the inside branch grants to its existing customers.
- Outside branches: those branches offer switching loans.
- Inside branches: those branches with a lending relationship with the firm during the prior 12 months.



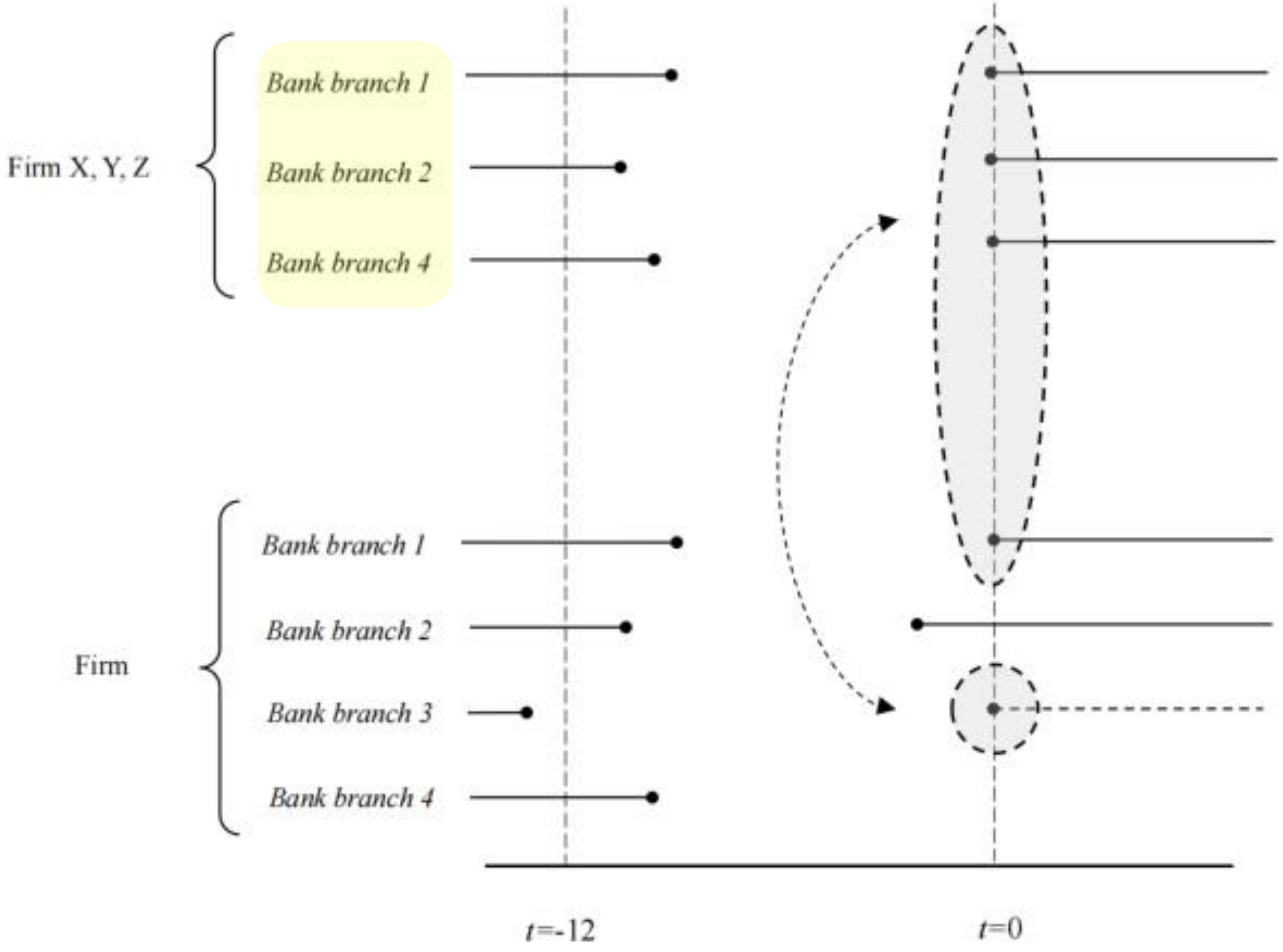
Switching


Bank I branch1
Inside branch
A
B
C
Switch
Bank I branch2
Inside branch
D
Bank I branch3
Outside branch

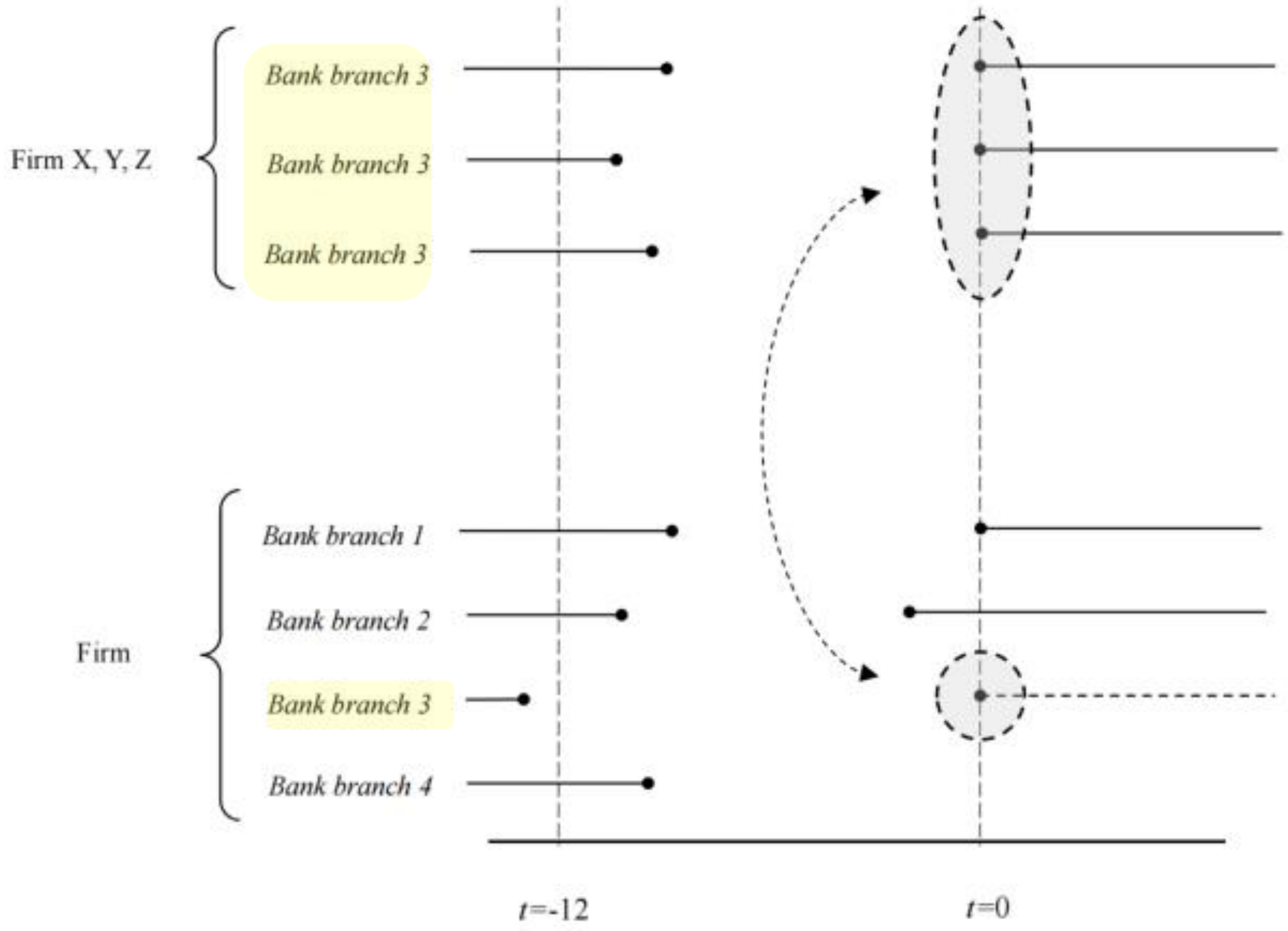
Statistic

	Switching Loans (n = 7,628)		Nonswitching Loans (n = 111,642)	
	Mean	Median	Mean	Median
Loan spread	90.20**	87	88.11	87
Loan amount（in logs）	15.02***	15.42	15.36	15.42
Loan maturity (in months)	13.66***	12	12.29	12
Collateral	0.91***	1	0.89	1
Credit rating	1.09***	1	1.07	1
Credit line	0.59***	1	0.79	1
Corporations	0.97***	1	0.98	1
Private	0.94***	1	0.93	1
SMEs	0.83***	1	0.78	1
Relationship length	25.96***	22***	32.41	25
Relationship num	2.88***	2***	6.11	3
Multiple branch relationships	0.23***	0	0.4	0

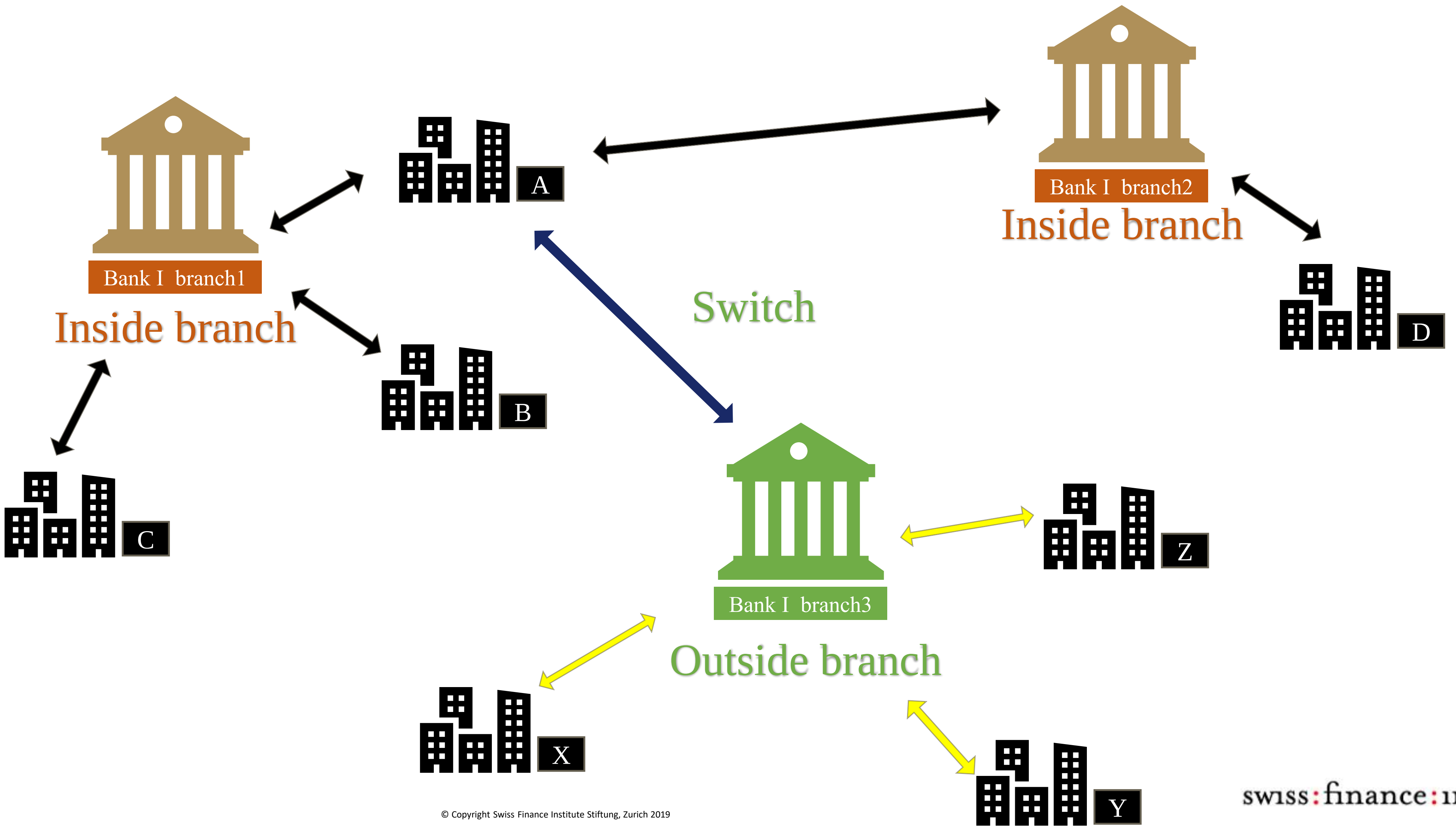
Inside Branch Matching Model



Outside Branch Matching Model



Inside or Outside Branch Matching Model



Data

Category	Matching Variables	#	Possible Values
Macro	Year: month	132	2010.01-2020.12
Bank	Inside branch	2	= 1 if the firm had a lending relationship with the branch in the last 12 months, and = 0 otherwise
Bank	Outside branch	2	= 1 if the firm did not have a lending relationship with the branch in the last 12 months, and = 0 otherwise
Loan	Credit rating	5	pass (= 1), special mention, substandard, doubtful, write-off (= 5)
Loan	Prior credit rating from inside branch	2	= 1 if matched nonswitchers have the same rating as switchers' most recent inside rating prior to the switch, and = 0 otherwise
Loan	Loan amount	2	= 1 if the matched loans have similar amount (using a (-25%, + 25%) window), and = 0 otherwise
Loan	Loan maturity	2	= 1 if the matched loans have similar maturity (using a (-25%, + 25%) window), and = 0 otherwise
Loan	Collateral	2	= 1 if the loan is collateralized, and = 0 otherwise
Loan	Credit line	2	= 1 if the loan comes with a credit line, and = 0 otherwise
Firm	Firm city	203	prefecture-level cities
Firm	Industry	17	domestic trade, technology, construction, building materials, transportation, healthcare, infrastructure construction, foreign trade, real estate, education, tourism, power, electronics, petrochemical, light, postal and telecommunications, finance, and others
Firm	Legal structure	6	corporations, partnerships, collective, sole proprietorships, public institutions, and others
Firm	Ownership structure	5	private firms, central SOEs, local SOEs, government financing platforms, and other government institutions
Firm	Firm size	2	= 1 if the firm is a SME, = 0 otherwise
Firm	Multiple branch relationships	2	= 1 if the firm has outstanding loans with more than one branch, and = 0 otherwise.
Relation	Relationship length	4	length of a firm-branch relationship in months: (0, 12) = 1, (12, 24) = 2, (24, 60) = 3, >60 = 4
Relation	Relationship density	4	number of loans a firm obtained from this branch within the past 5 years: (0, 1) = 1, (1, 3) = 2, (3, 5) = 3, >5 = 4

The table reports the number of values (#) and a range (or list) of values for the matching variables.

Matching Model

Three steps:

- Matching each switching loan with all similar new nonswitching loans to other comparable firms granted by the switcher's inside or outside branches at the time of the switch.

- Calculating the difference between the loan spreads on the switching loans and each matched loan.

- Regress the spreads on a constant:

$$r_{switch} - r_{nonswitch} = \beta + \zeta$$

where β is the constant term and ζ is the error term.

A negative and statistically significant constant term suggests that the rates on switching loans are on average **lower** than the rates on comparable nonswitching loans, which we interpret as estimates of switching costs.

Basic Result

➢ **Columns 1 & 2:**

Loan rates on the switching loans are 5.87 (5.85) bps below the rates on comparable new loans from the inside(outside) branches.

➢ **Columns 3 & 4:**

- Replacing the credit rating that the switchers obtain from their new branch with the most recent rating they obtained from their inside bank prior to the switch.
- Matching directly on the switchers' relationships with their inside banks prior to the switch.

All be consistent with Column 2

Matched Branches	Inside	Outside		
Matching Variables	(1)	(2)	(3)	(4)
Year: month	Yes	Yes	Yes	Yes
Set of insider branch	Yes			
Set of outside branch		Yes	Yes	Yes
Credit rating	Yes	Yes		
Prior credit rating from inside branch			Yes	
Prior relationship length				Yes
Prior relationship density				Yes
Prior multiple branch relationships				Yes
Firm city	Yes	Yes	Yes	Yes
Loan amount	Yes	Yes	Yes	Yes
Loan maturity	Yes	Yes	Yes	Yes
Collateral	Yes	Yes	Yes	Yes
Credit line	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Legal structure	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes
Number of switching loans	1,125	2,095	2,073	624
Number of nonswitching loans	2,619	4,949	4,896	702
Number of observations (matched pairs)	3,210	6,443	6,384	798
Spread in basis points with weighting	-5.87***	-5.85***	-3.86**	-6.86**
	(2.26)	(1.70)	(1.81)	(2.76)

Newly Established Branches——More Discount

Matched Branches	Existing branches	Newly established branches			
Matching Variables	(1)	(2)	(3)	(4)	(5)
Year: month	Yes	Yes	Yes	Yes	Yes
Set of insider branch	Yes	Yes	Yes	Yes	Yes
Credit rating	Yes	Yes			
Prior credit rating from inside branch			Yes		
Prior interest rate from inside branch				Yes	
Prior relationship length					Yes
Prior relationship density					Yes
Prior multiple branch relationships					Yes
Firm city	Yes	Yes	Yes	Yes	Yes
Bank Branch city	Yes	Yes	Yes	Yes	Yes
Loan amount	Yes	Yes	Yes	Yes	Yes
Loan maturity	Yes	Yes	Yes	Yes	Yes
Collateral	Yes	Yes	Yes	Yes	Yes
Credit line	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Legal structure	Yes	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes
Number of switching loans	961	42	44	28	12
Number of nonswitching loans	2,295	108	109	73	17
Number of observations (matched pairs)	2,735	123	127	85	17
Spread in basis points with weighting	-5.50**	-26.79**	-30.69**	-16.79**	-60.55**
	(2.54)	(10.90)	(12.89)	(8.10)	(23.11)

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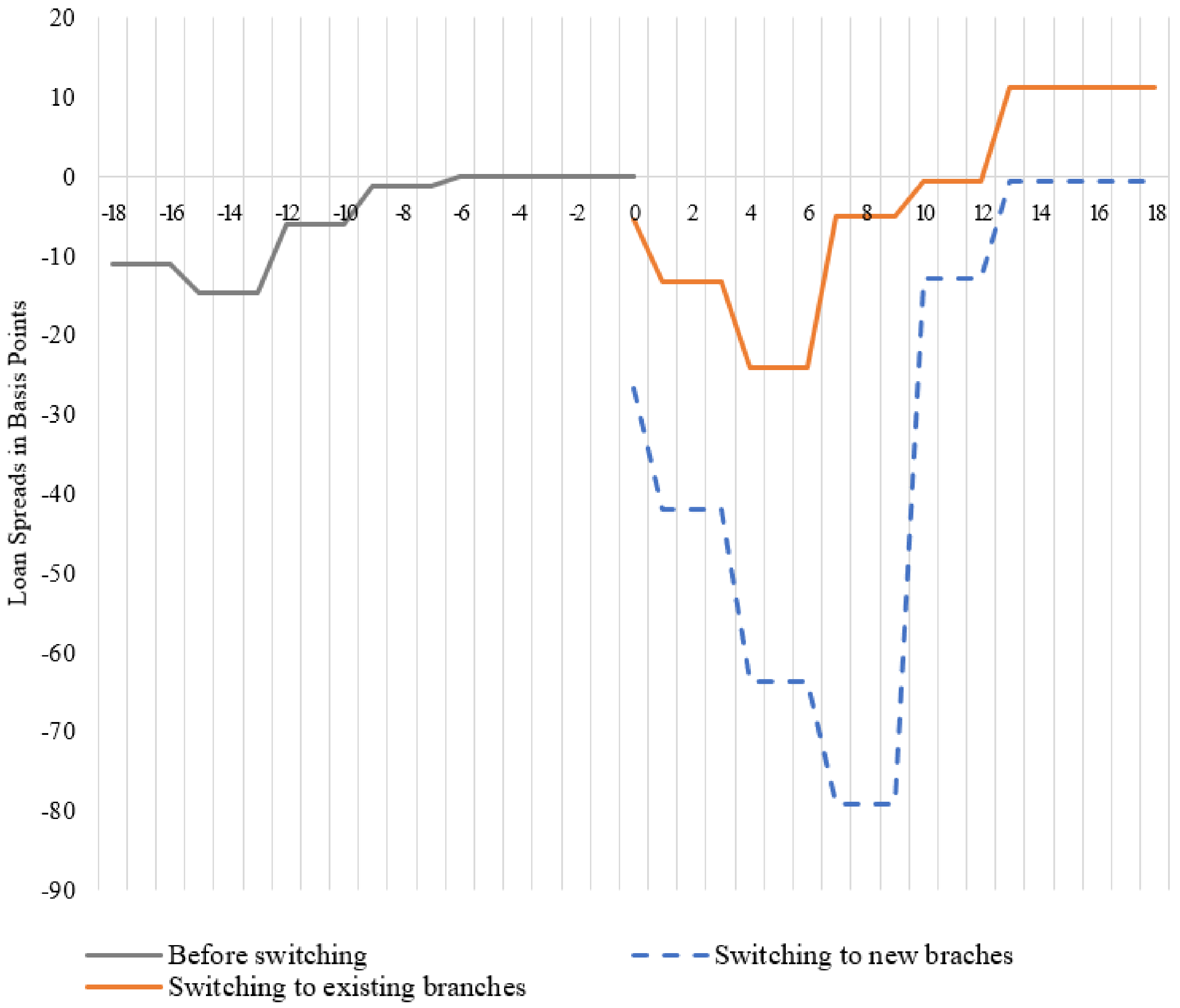
Dynamics after switching

U-shape



Other loan conditions before and after switching

Dependent Variable	Loan amount	Loan maturity	Collateral
Matching Variables	(1)	(2)	(3)
Firm identity	Yes	Yes	Yes
Branch identity	Yes	Yes	Yes
Loan spread	Yes	Yes	Yes
Credit rating	Yes	Yes	Yes
Collateral	Yes	Yes	
Credit line	Yes	Yes	Yes
Loan amount		Yes	Yes
Loan maturity	Yes		Yes
Number of observations (matched pairs)	6,495	6,327	6,771
Periods (in months) since the switching loan			
1-3	0.26***	-0.09***	-0.00***
4-6	0.17***	0.25***	-0.00***
7-9	-0.09***	0.31***	0.01***
10-12	-0.09***	-0.02***	-0.01***
> 13	-0.02***	-0.24***	0.01***

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Deployment of FinTech

How is the hold-up problem affected by the utilization of FinTech in our bank?

Re-estimate our model in column 2 of basic table after adding an index for the application of FinTech in our bank and its squared:

$$r_{switch} - rnonswitch = \beta_0 + \beta_1 FinTech + \beta_2 FinTech^2 + \varepsilon$$

where β_0, β_1, and β_2 are the coefficients to be estimated, and ε is the error term;

FinTech is an index proxying the level of digitalization of bank and market, obtained from the Institute of Digital Finance at Peking University.

$\beta_0 = -5.89$, $\beta_1 = 13.66^{***}$, and $\beta_2 = -3.91^{***}$ → Reversed U-shape

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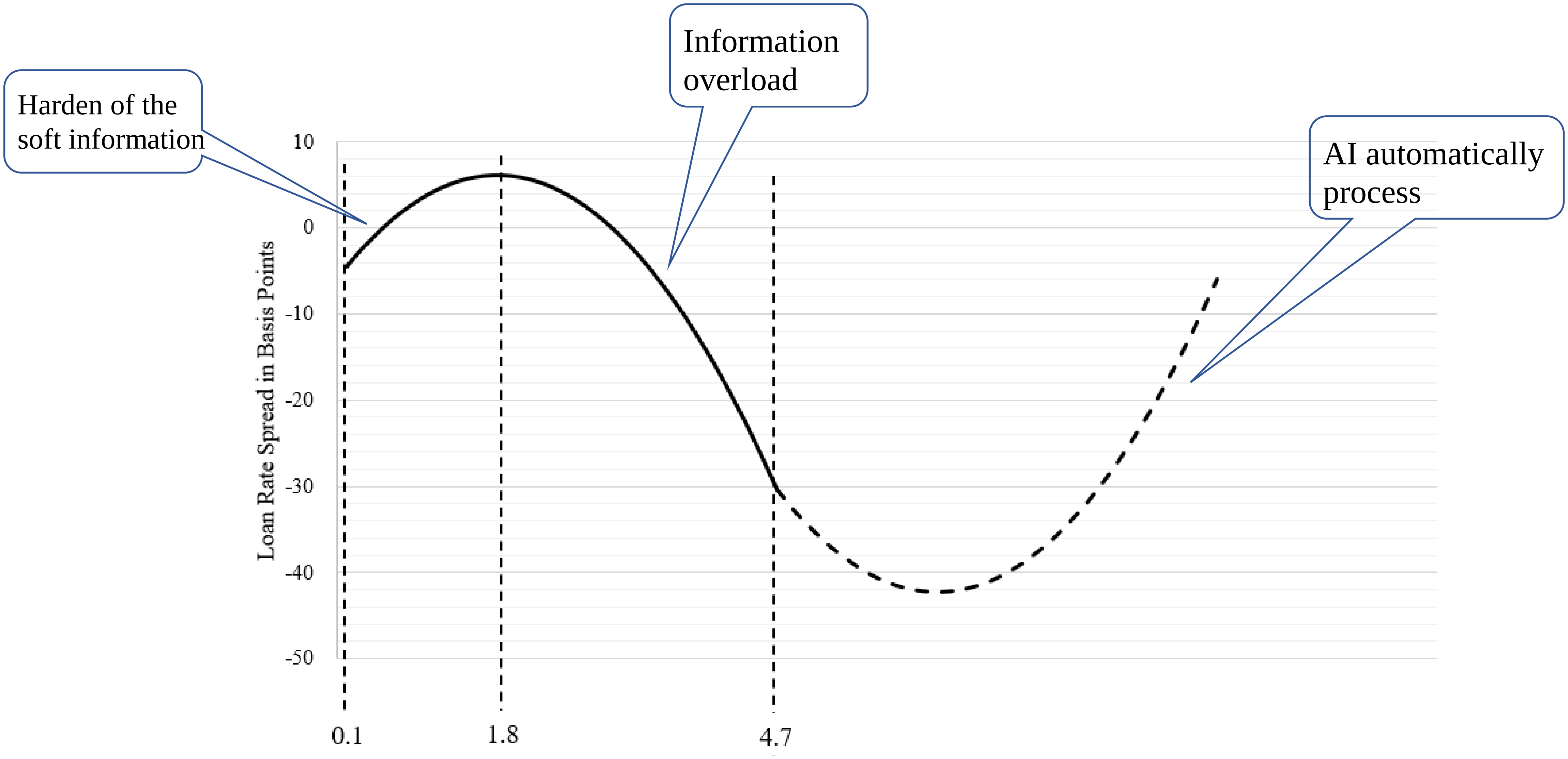
Deployment of FinTech



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A survey among bank employees

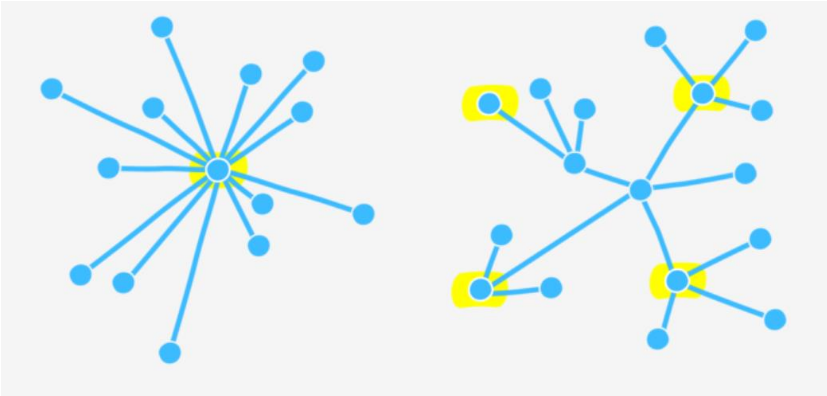
- **Number of surveys:** 141
- **From:** 26 from our sample bank and the other 115 from other banks in China (bank employees).

- **Intra-bank competition**
  ① Meeting their performance targets in the bank is very important (>70%).
  ② Intra-bank comparison across branches outweighs inter-bank rankings (69%).
  ③ Branches directly compete with each other for customers, within the same bank (76%).

- **Information communication within banks**
  ① Information sharing within the bank is important(54% agrees).
  ② A lack of communication, both formally and informally (30%,20%)
  ③ Information, especially soft information, is still hard to be transferred even within the same bank.

- **The application of FinTech**

Conclusion



Findings

- The existence of intra-bank hold-up!
- Switching loans to new established branches have more discounts.
- After switching, the new branch further reduces the loan spreads initially but ratchets it up afterwards.
- The deployment of FinTech in this bank first mitigates but then intensifies hold-up.

Contributions

- Make the first step to document the existence of hold-up within a bank
- New established branches vs. existing branches
- Enhance the understanding of information in bank lending
- Importance of FinTech effect of hold-up-cost

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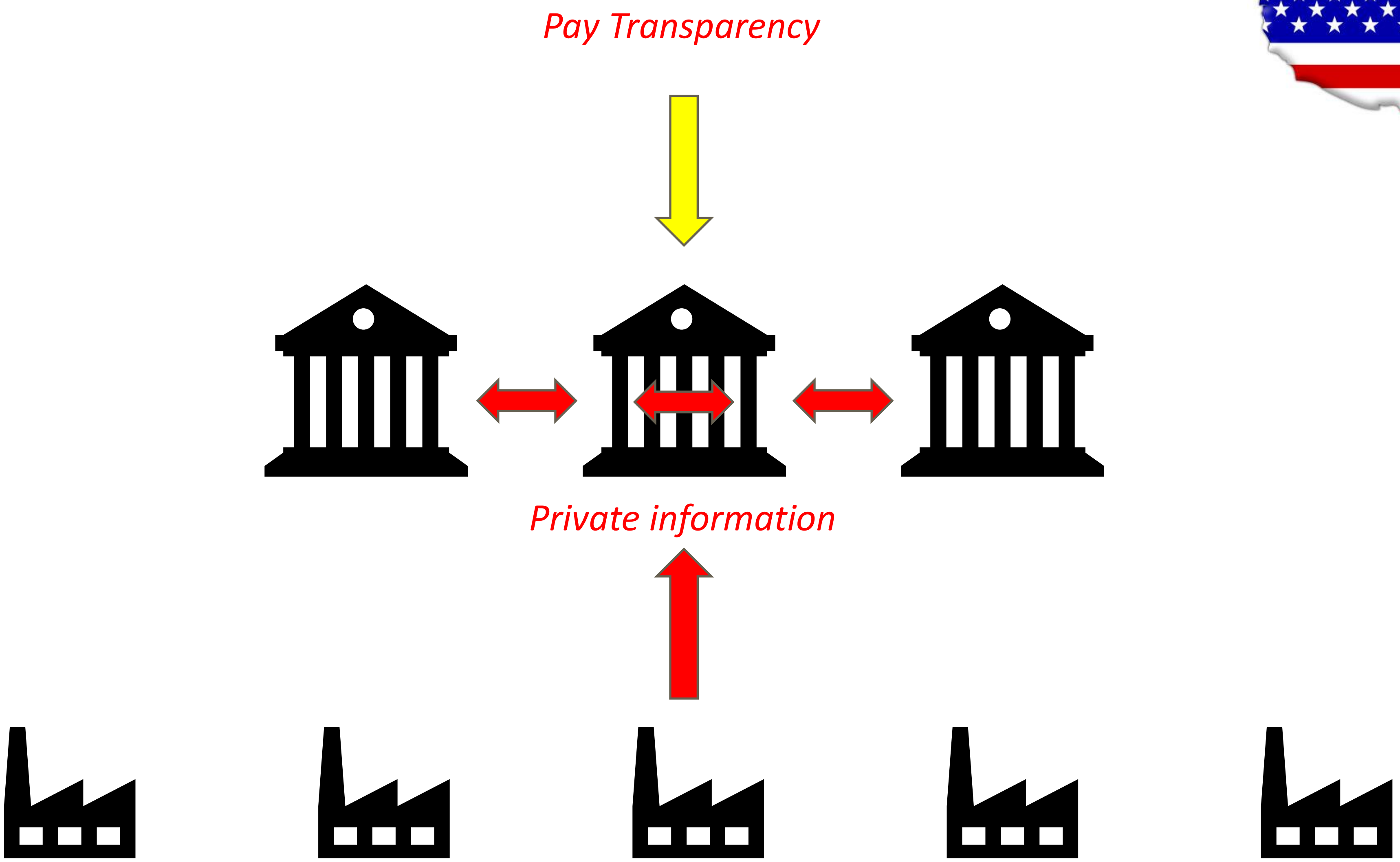

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The Impact of Pay Transparency on Bank Compensation, Employment, Performance and Opacity

Piotr Danisewicz (*Tilburg*)

Steven Ongena *(Zurich, SFI, KU Leuven, NTNU, CEPR)*

Question?

How does pay transparency affect

employment conditions

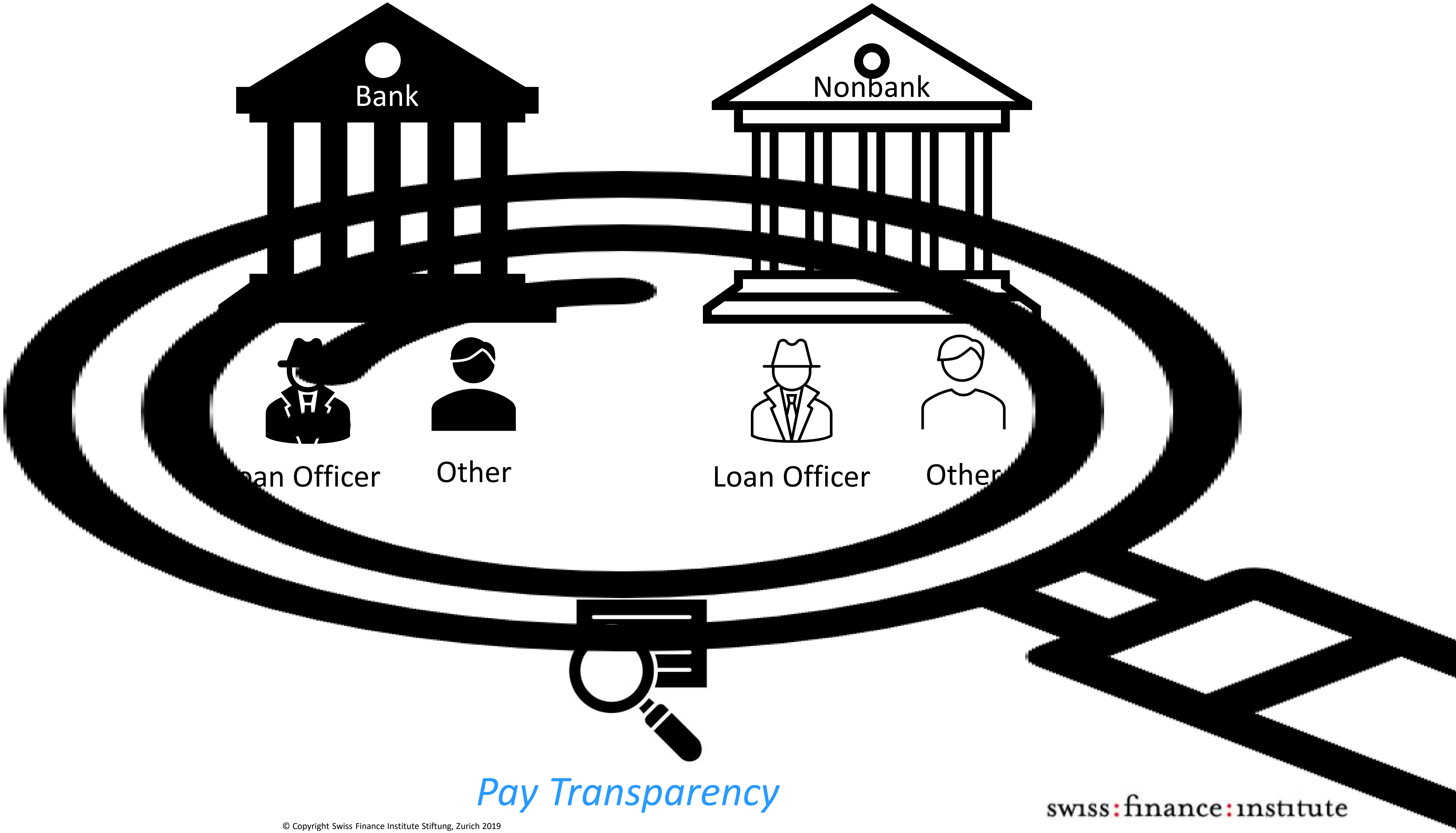
and the

granting of credit

by bank loan officers?

And how does it affect the opacity of the bank itself?

Pay transparency = *Employers required to provide outright or on request salary/salary range in job postings*



Pay Transparency

Pay transparency – Does it matter?

Individuals often lack clear expectations or information about:

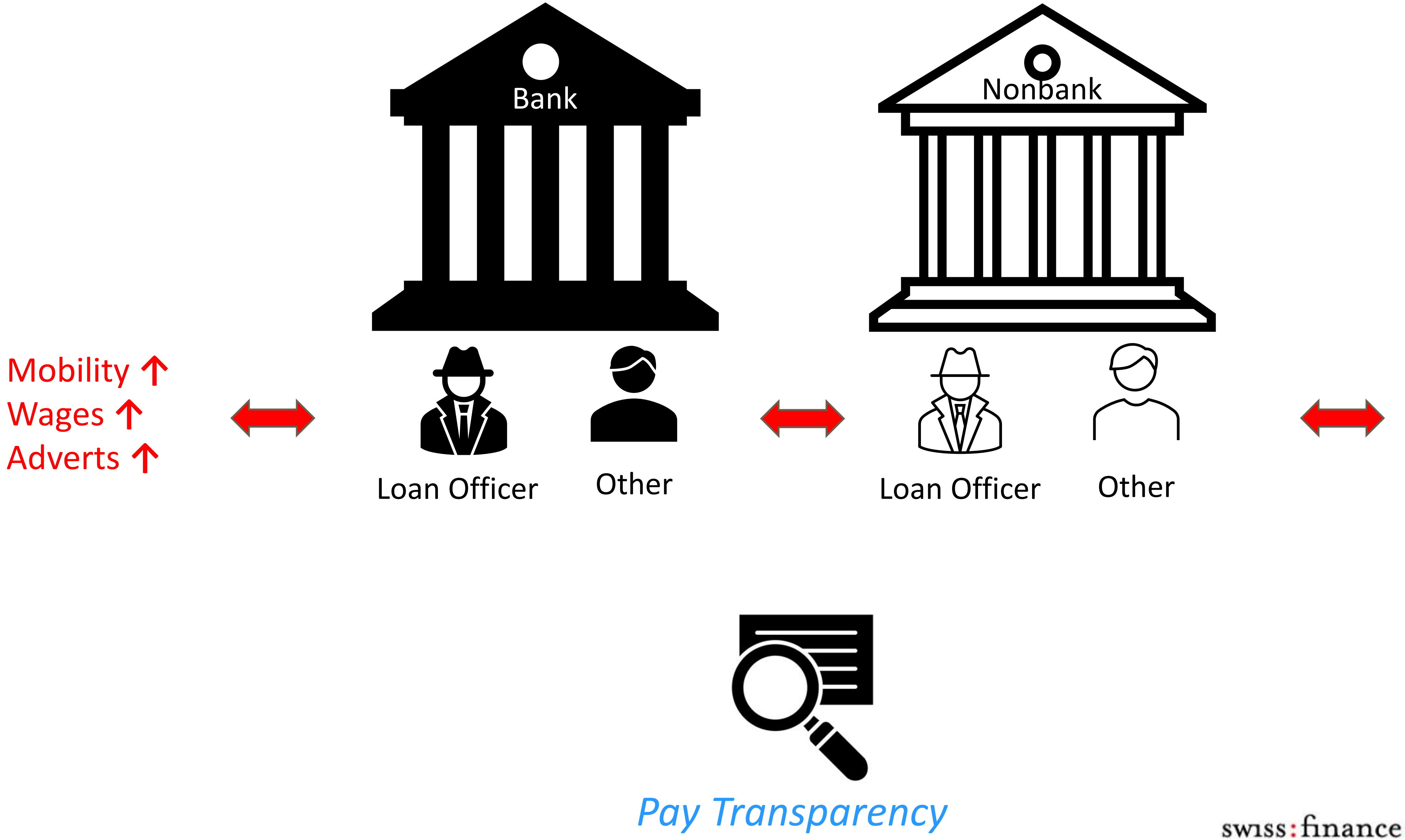
- Pay offered by jobs they interview for (Hall & Krueger AEJ:Macro 2012).
- Salaries earned by their superiors (Cullen & Perez-Truglia JPE 2022).

Cross-firm pay transparency may persuade employees to search for better paid employment (Cullen JEP 2024).

- Individuals with pay information in job adverts broadens the set of jobs they consider (Belot, Kircher and Muller REStud 2019).

Providing salary ranges in job adverts increased wages in the private sector.

- (Skoda 2022; Arnold, Quach & Taska 2023; Frimmel, Schmidpeter, Wiesinger & Winter-Ebmer 2023)



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Pay – Does it matter in banking?

Loan officers' compensation affects the quality of bank assets.

- *Tzioumis & Gee JFE 2013; Cole, Kanz & Klapper JF 2015; Agarwal & Ben-David JFE 2018; Berg, Puri & Rocholl RF 2020*.

Pay transparency – Can it matter for bank asset quality?

Positive effects:

- Banks increase salaries to match competition $\Longrightarrow$ attract and retain higher quality employees $\Longrightarrow$ more accurate risk assessment.
- Information on salaries at different positions may **motivate** current employees to improve their efforts and performance to achieve promotion (Cullen JEP 2024).

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Pay transparency – Can it matter for **bank asset quality**?

Negative effects:

- Banks increase salaries to match competition $\Longrightarrow$ **incentives to generate higher returns** by adopting more risky lending strategies.
- Effect on **employees' morale** $\Longrightarrow$ adverse effect on job satisfaction and performance (Akerlof & Yellen QJE 1990; Card, Mas, Moretti & Saez AER 2012; Breza, Kaur & Shamdasani QJE 2018; Cullen & Perez-Truglia JPE 2022).
- **Employment change** $\Longrightarrow$ loss of soft information $\Longrightarrow$ higher loan defaults (Stein JFE 2002; Berger, Miller, Petersen, Rajan & Stein JFE 2005; Drexler & Schoar MS 2014; Heo & Ongena, 2025).

Pay transparency – Can it therefor matter for **bank opacity**?

Negative effects?

Higher wages and lower employee quality $\Longrightarrow$ Bank profitability and asset quality decreasing

- Banks obfuscate changes in loan values to safeguard asset value and thereby liquidity (Dang, Gorton, Holmstrom and Ordonez, AER 2017)
- Managers may obfuscate versus shareholders as they fear disciplining (Wagner EL 2007)

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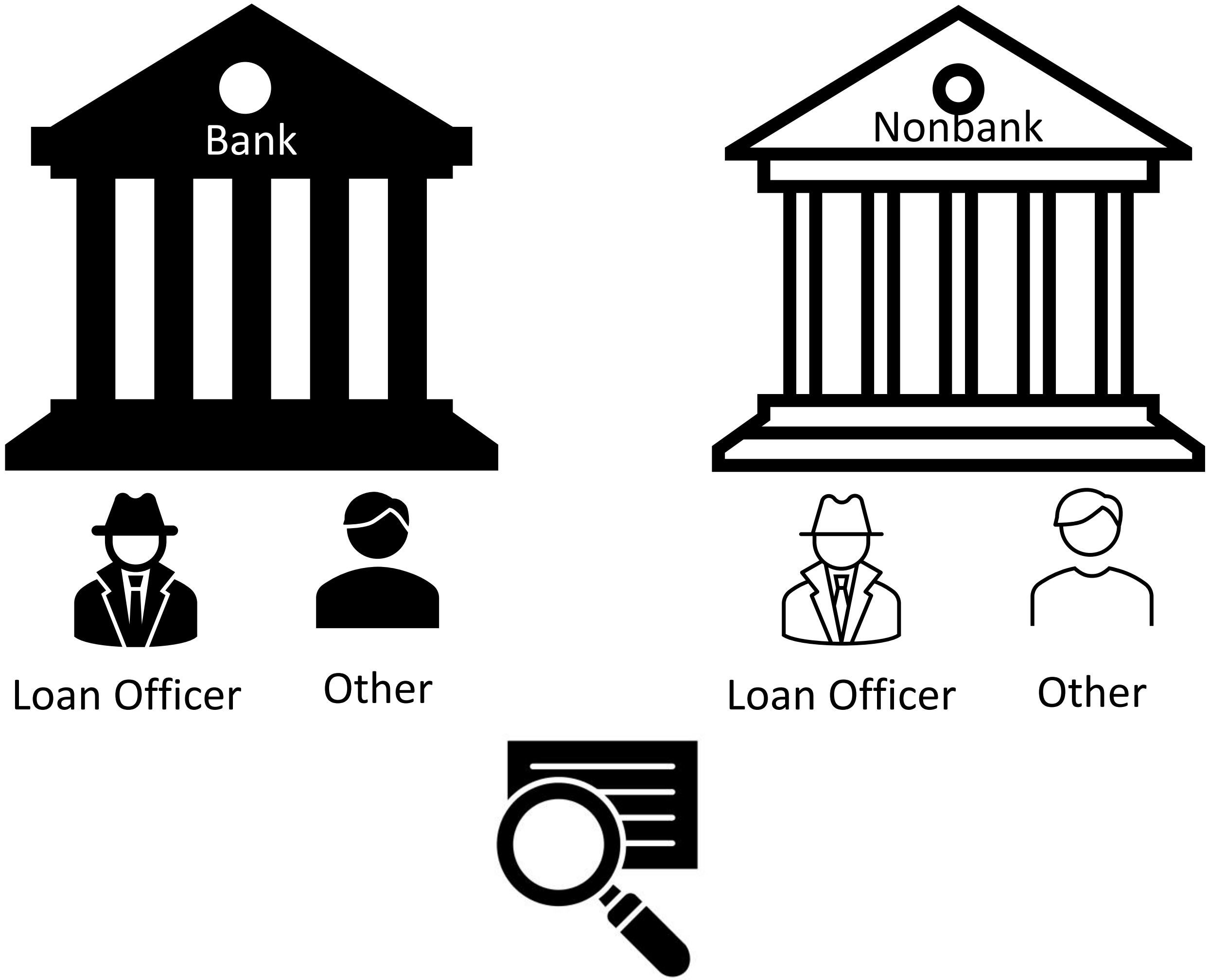
Credit Quality ↓

Opacity ↑



Pay Transparency

swiss:finance:institute

Pay transparency in the U.S.

U.S. Department of Labor:

- In the U.S. women earn 84 cent on a dollar earned by men in 2021.
- Disproportional earnings among different race and cultural background.

Wage gaps on top of policymakers' agenda (Cullen JEP 2024):

- Right of workers to talk
- Salary history bans
- **Pay transparency**
  - *Employers required to provide outright or on request salary/salary range in job postings*

Institutional setting

State-wide pay transparency policy in the U.S. introduced in:

- California – Jan 1, 2023
- Colorado – Jan 1, 2021
- Connecticut – Oct 1, 2021
- Maryland – Oct 1, 2020
- New York – Sep 17, 2023

- Nevada – Oct 1, 2021
- Rhode Island – Jan 1, 2023
- Washington – Jan 1, 2023
- Hawaii – Jan 1, 2024
- (Illinois - Jan 1, 2025)

Table 2. Implementation of the state-wide pay disclosure laws.

State	Effective date	Requirements	Coverage	Non-compliance penalty	Legal basis
California	January 1, 2023	Salary range provided in all job postings and position's salary range provided to current employees upon request.	Employers with at least 15 employees, must meet all the requirements of the law.	Civil penalty between 100 USD and 10,000 USD for each violation.	https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=202120220SB1162
Colorado	January 1, 2021	Hourly or salary compensation, or a range and a general description of all benefits and other compensation provided in all job postings (inc. promotions).	All employers with at least one employee in the State.	Civil penalty between 500 USD and 10,000 USD for each violation.	https://leg.colorado.gov/sites/default/files/2019a_085_signed.pdf
Connecticut	October 1, 2021	Salary range must be provided by employer to job candidates and current employees on request.	All employers with at least one employee in the State.	Employers may face civil action for compensatory and punitive damages, plus costs.	https://www.cga.ct.gov/2021/ACT/PA/PDF/2021PA-00030-R00HB-06380-PA.PDF
Hawaii	January 1, 2024	Salary range or hourly wage rate provided in all job postings (excl. internal transfers and promotions).	All employers with at least 50 employees (excl. public employees with compensation determined under collective bargaining agreement).	Employers may face civil action for compensatory and punitive damages, plus costs.	https://www.capitol.hawaii.gov/sessions/session2023/bills/GM1306_.PDF
Maryland	October 1, 2020	Wage scale provided to job applicants on request.	All employers active in the State.	A warning for a first violation, a 300 USD fine for a second violation, and a 600 USD fine for a third or subsequent violation	https://www.dllr.state.md.us/forms/equalpay.pdf
Nevada	October 1, 2021	Salary information provided to applicants for any role they interview for. Salary information provided to current employees seeking a promotion or internal transfer on request.	All employers active in the State.	Employers may face civil action. The Labor Commission may impose additional fine of 5,000 USD per violation	https://www.leg.state.nv.us/App/NELIS/REL/81st2021/Bill/7896/Text
New York	September 17, 2023	Salary and hourly rate ranges provided for all job adverts (inc. promotions and transfers).	All private sector employers with 4 or more employees.	Fines up to 1,000 USD for the first violation, up to 2,000 USD for the second violation, and up to 3,000 USD for the third and subsequent violations.	https://legislation.nysenate.gov/pdf/bills/2021/S9427A
Rhode Island	January 1, 2023	Pay range or rate for a given position to job applicants upon request.	All employers with at least one employee in the State.	Fine between 1,000 USD and 5,000 USD.	http://webserver.rilin.state.ri.us/BillText/BillText21/SenateText21/S0270A.pdf
Washington	January 1, 2023	Wage scale or salary range and a general description of all of the benefits and other compensation provided for all advertised positions.	All employers with 15 or more employees in the State.	Employers face paying damages to employees and fines of up to 500 USD for first violation, 1,000 USD or 10 percent of damages (whichever is greater) for repeated violations, plus fees and costs.	https://lawfilesext.leg.wa.gov/biennium/2021-22/Pdf/Bills/Session%20Laws/Senate/5761-S.SL.pdf?q=20220502103426
Not included in the treatment group					
Illinois	January 1, 2025	Salary range and benefits information provided in all job postings.	Employers with at least 15 employees.	Civil penalty between 500 USD and 10,000 USD for each violation.	https://www.ilga.gov/legislation/BillStatus.asp?DocTypeID=HB&DocNum=3129&GAID=17&SessionID=112&LegID=148283

Institutional setting

State-wide pay transparency policy in the U.S. introduced in:

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- Maryland – Oct 1, 2020
- New York – Sep 17, 2023
- Nevada – Oct 1, 2021
- Rhode Island – Jan 1, 2023
- Washington – Jan 1, 2023
- (Hawaii – Jan 1, 2024)
- (Illinois - Jan 1, 2025)

Penalties: From $100 per violation to facing civil action for compensatory and punitive damages, plus costs.

- In Colorado, **30pp** more job posts include salary information after Colorado adopted the law (Arnold, Quach & Taska 2023).
- Penalties in Colorado: $500 to $10,000 per violation.

Difference-in-differences estimations leveraging job adverts, employee- and bank-level data.

Salaries in the U.S. financial industry

- **Pay transparency**
  - Reveals gaps in pay offered by firms operating in the same sector, as well as cross-sectoral pay differences in providing a similar service.
  - American Community Survey (ACS) data 2017-2022:

Table 1	All Occupations	Loan officers	Other occupations	CEOs
Banking, saving inst., credit unions	95,446 $	81,713 $	96,913 $	164,032 $
Non-depository credit institutions	118,079 $	95,994 $	123,340 $	238,892 $

This table presents the average salaries earned by bank and non-bank employees in USD. The information is based on the data from the U.S. American Community Survey (ACS) for years 2017-2023.

Non-depository credit institutions (non-banks) includes sales financing and leasing companies, mortgage companies, personal credit institutions, or credit and charge cards issuers.

Loan officers includes also credit councillors and loan interviewers who are also involved in the loan application process.

Potential Mechanism We Now Document

Pay transparency law is passed

Pay is revealed in relatively more adverts

Experienced loan officers start to leave to nonbanks that pay more

Banks want to hire new loan officers by placing more adverts

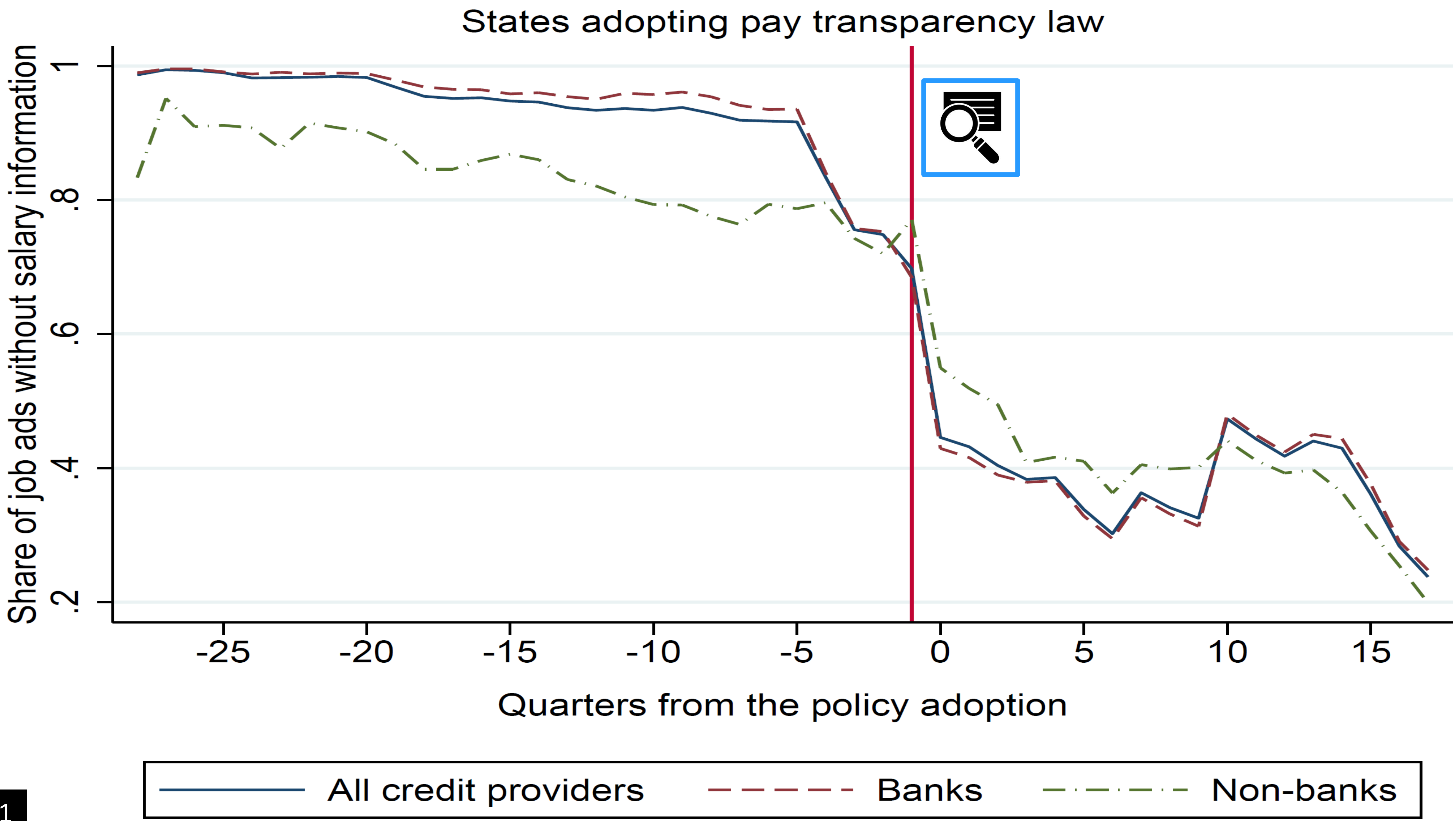
Banks have to increase wages to do so

Banks hire new loan officers, who often lack expertise

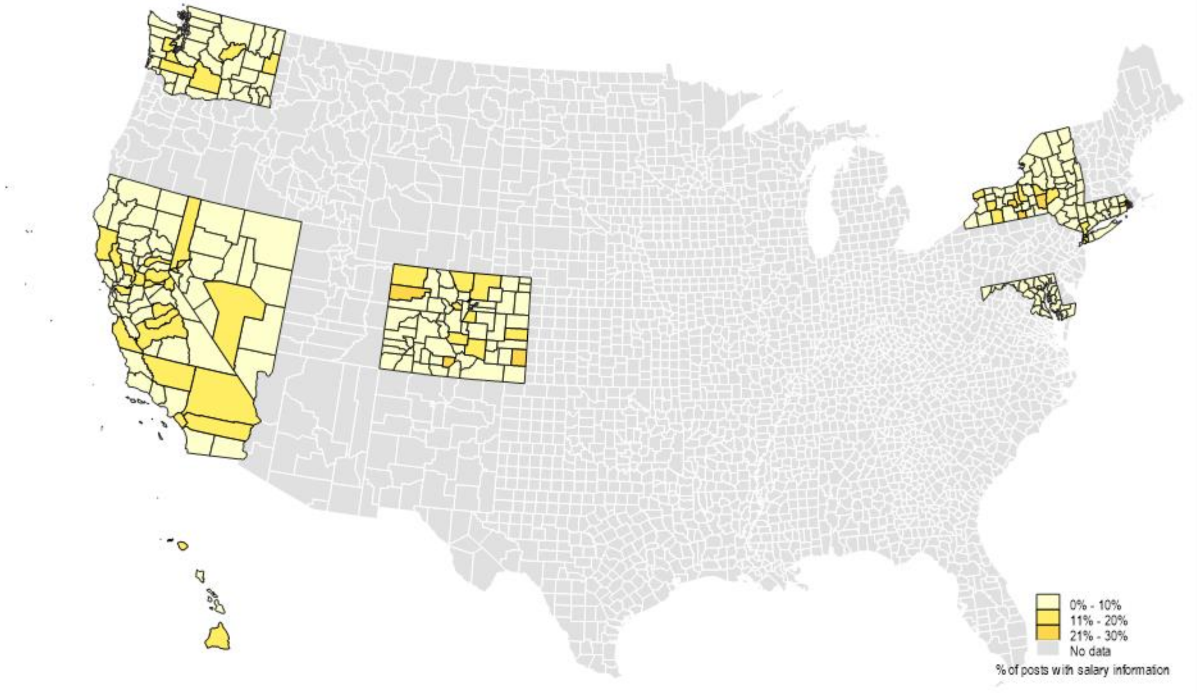
Loan quality slips, loan losses mount

Banks manage loan loss provisions more

Banks are more opaque


States adopting pay transparency law
Share of job ads without salary information
.2
.4
.6
.8
1
-25
-20
-15
-10
-5
0
5
10
15
Quarters from the policy adoption
All credit providers
Banks
Non-banks

F1



Panel A: Pre-treatment period

Panel B: Post-treatment period

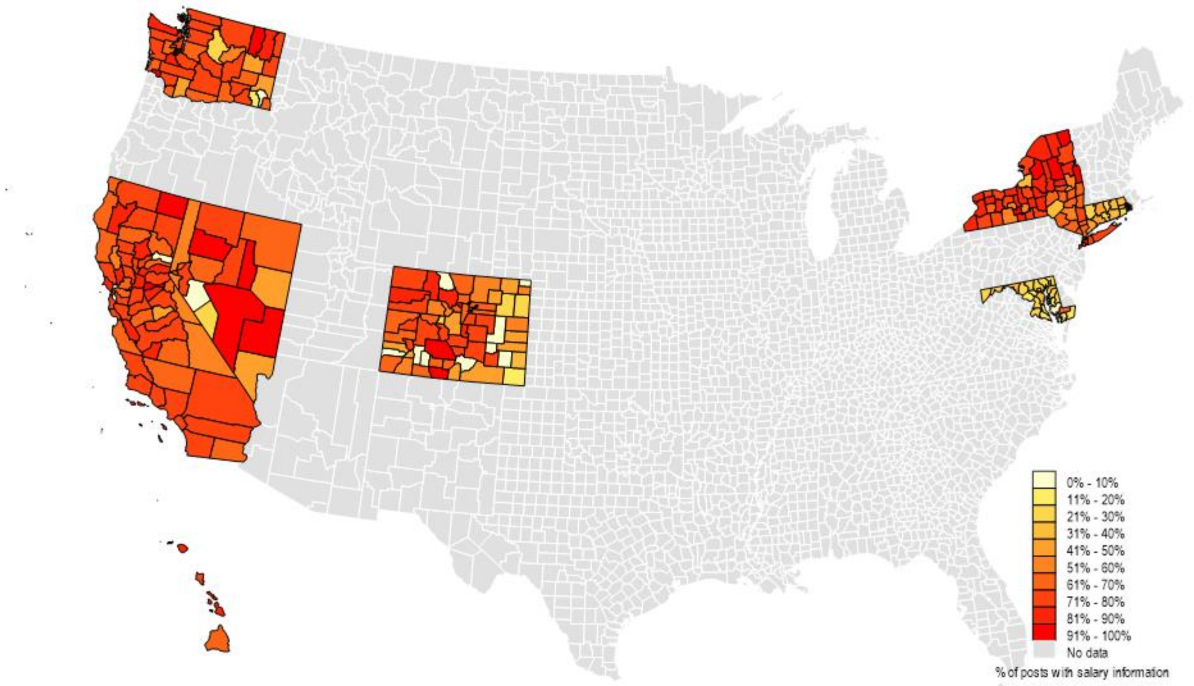
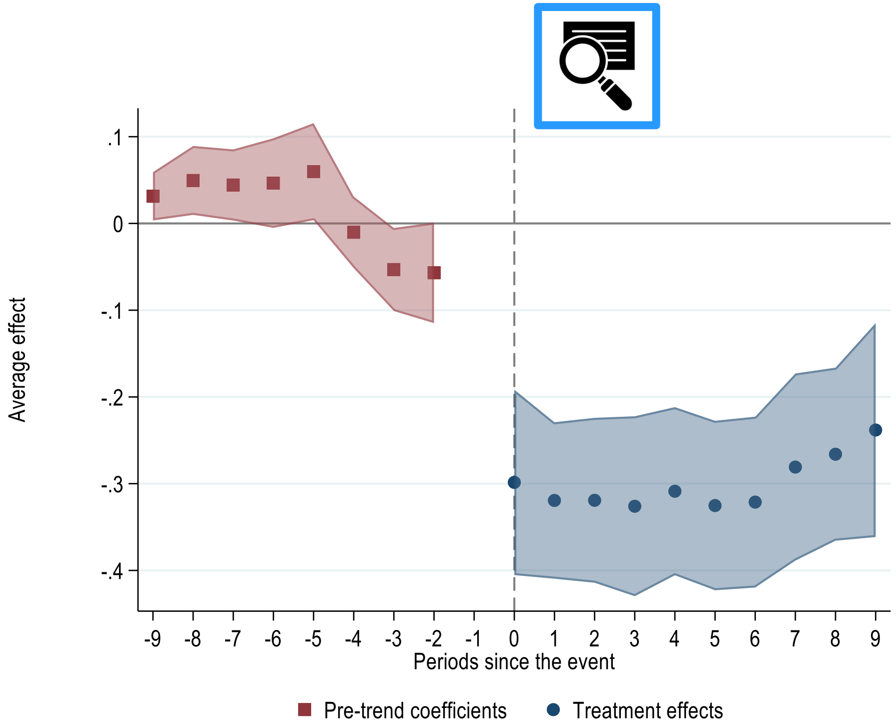
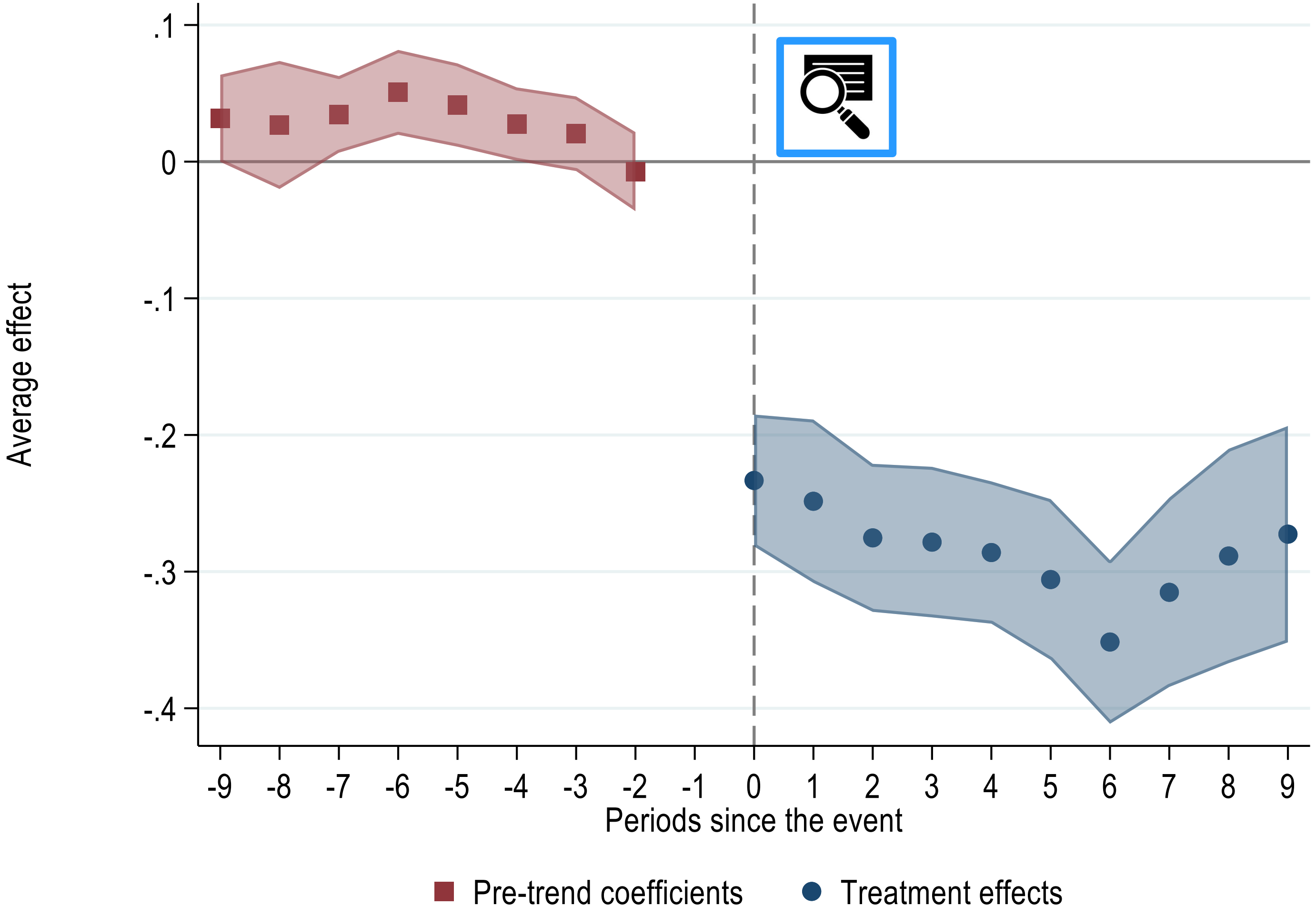


Figure 2. The effect of transparency laws on the geographical coverage of job adverts including salary information

Figure 3. The effect of transparency laws on salary disclosure in job adverts – Dynamic effects



Panel A: All job posts



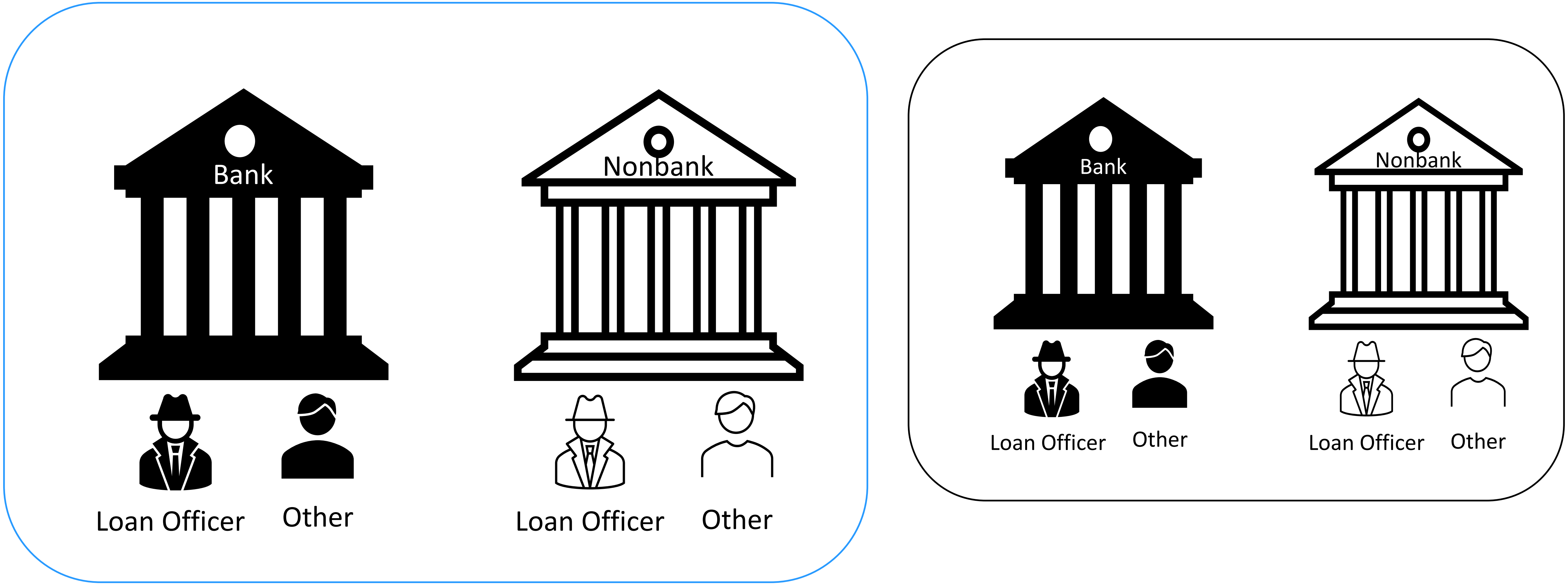
Panel B: Loan officer posts

Notes. This figure presents the dynamic effects of pay transparency laws on salary disclosure in job adverts using Sun and Abraham (2021) IW estimator. The dependent variable is a dummy variable equal to 1 for job posts excluding salary information, and zero otherwise.

Table 3. Salary information in finance industry job adverts

Panel A: All credit intermediation firms - Banks and Non-banks			
Institution type	All	Banks	Non-banks
# of adverts	5,252,710	4,488,797	763,913
# no salary information	4,388,146	3,843,848	544,298
% no salary information	83.5%	85.6%	71.3%
# of adverts – loan officer	401,657	312,916	88,741
# no salary information – loan officer	346,304	276,095	70,209
% no salary information – loan officer	86.2%	88.2%	79.1%
Panel B: Institutions in states introducing pay transparency: Pre-introduction			
Institution type	All	Banks	Non-banks
# of adverts	962,673	850,618	112,055
# no salary information	883,482	792,356	91,126
% no salary information	91.8%	93.2%	81.3%
# of adverts – loan officer	78,995	57,057	21,938
# no salary information – loan officer	71,542	53,309	18,233
% no salary information – loan officer	90.6%	93.4%	83.1%
Panel C: Institutions in states introducing pay transparency: Post-introduction			
Institution type	All	Banks	Non-banks
# of adverts	348,157	298,974	49,183
# no salary information	130,850	109,829	21,021
% no salary information	37.5%	36.7%	42.7%
# of adverts – loan officer	22,782	17,918	4,864
# no salary information – loan officer	10,315	7,657	2,658
% no salary information – loan officer	45.3%	42.7%	54.6%
Panel D: Institutions in states not introducing pay transparency			
Institution type	All	Banks	Non-banks
# of adverts	3,941,880	3,339,205	602,675
# no salary information	3,373,814	2,941,663	432,151
% no salary information	85.6%	88.1%	71.7%
# of adverts – loan officer	299,880	237,941	61,939
# no salary information – loan officer	264,447	215,129	49,318
% no salary information – loan officer	88.2%	90.4%	79.6%

Difference-in-differences estimations: Employee- and bank-level



Pay Transparency

Diff-in-Diff Estimations: **Employee-level**

- **Employee-level data – American Community Survey (ACS):**
  - Salary information for 8,040,200 individuals employed in the U.S. between 2017-2023.
  - Hours worked in a week and weeks worked per year - part-time and full-time employees.
  - Information on occupation, sector, industry, location (state), demographic characteristics (gender, age, race, marital status).
  - We compare wages and full-time employment status of individuals in affected vs. unaffected states (before and after law adoption):

$$ln(Y_{ist}) = \beta(State_s * Lawt) + \gamma X_{ist} + \delta_i + \varphi_t + \varepsilon_{it}$$

i – individual; s – state of employment; t – year

Y – log of wages, dummy = 1 for full-time employment (= 0 for part-time)
State = 1 for States adopting pay transparency (= 0 otherwise)
Law = 1 for years following adoption (= 0 otherwise)
X – age, education, year-by-NAICS 3-digit industry, year-by-SOC 3-digit occupation

(Cullen and Pakzad-Hurson ECMA 2023)

Results: **Employee-level**

Table 5. The effect of transparency laws on employment

Industry:	Commercial and savings banks, credit unions ("banks")			Non-depository credit institutions ("non-banks")		
Occupation	All employees	Loan officers	Other employees	All employees	Loan officers	Other employees
State*Law	-0.012	-0.078**	-0.006	0.012	0.070***	-0.004
	(0.013)	(0.030)	(0.013)	(0.013)	(0.020)	(0.017)
Observations	94,452	8,473	85,965	51,984	9,921	42,046
R-squared	0.046	0.042	0.048	0.034	0.044	0.039
Controls	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

The number of loan officers employed in banks decreases by 8% while the number of loan officers employed by non-bank credit institutions increases by 7% in states adopting pay transparency. Employment in the private sector overall increases by 0.5% (not displayed here)

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Results: Employee-level

Table 6. The effect of transparency laws on salaries

Industry:	Commercial and savings banks, credit unions ("banks")			Non-depository credit institutions ("non-banks")		
Occupation:	All employees	Loan officers	Other employees	All employees	Loan officers	Other employees
State*Law	-0.004	0.107*	-0.012	0.008	-0.042	0.017
	(0.021)	(0.060)	(0.022)	(0.017)	(0.054)	(0.021)
Observations	79,204	7,634	71,556	41,339	7,941	33,381
R-squared	0.415	0.322	0.426	0.379	0.250	0.410
Controls	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

- Banks respond by increasing loan officers' salaries by 11%.
- No economically or statistically significant salary increase among bank executives and non-bank employees.

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Diff-in-Diff Estimations: **Bank-level**

- **Bank-level data – Federal Financial Institutions Examination Council (EFFIEC):**
  - Quarterly call reports of all commercial and savings banks in the U.S. between 2017q1-2024q4.
  - Information on salary expenses, the number of full-time employees, loans outstanding and non-performing loans.
  - We compare salaries, employment, non-performing loans of banks affected vs. unaffected by transparency laws (before and after law adoption):

$$Y_{ist} = \beta(State_s * Lawt) + \delta_i + \varphi_t + \varepsilon_{it}$$

i – bank; s – state of operation; t – year-quarter

Y – average salary, salary, employees, non-performing loans/total loans
State = 1 for States adopting pay transparency (= 0 otherwise)
Law = 1 for quarters following adoption (= 0 otherwise)

Only institutions operating in one State included.

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Table 7. The effect of transparency laws on Salary and Employment

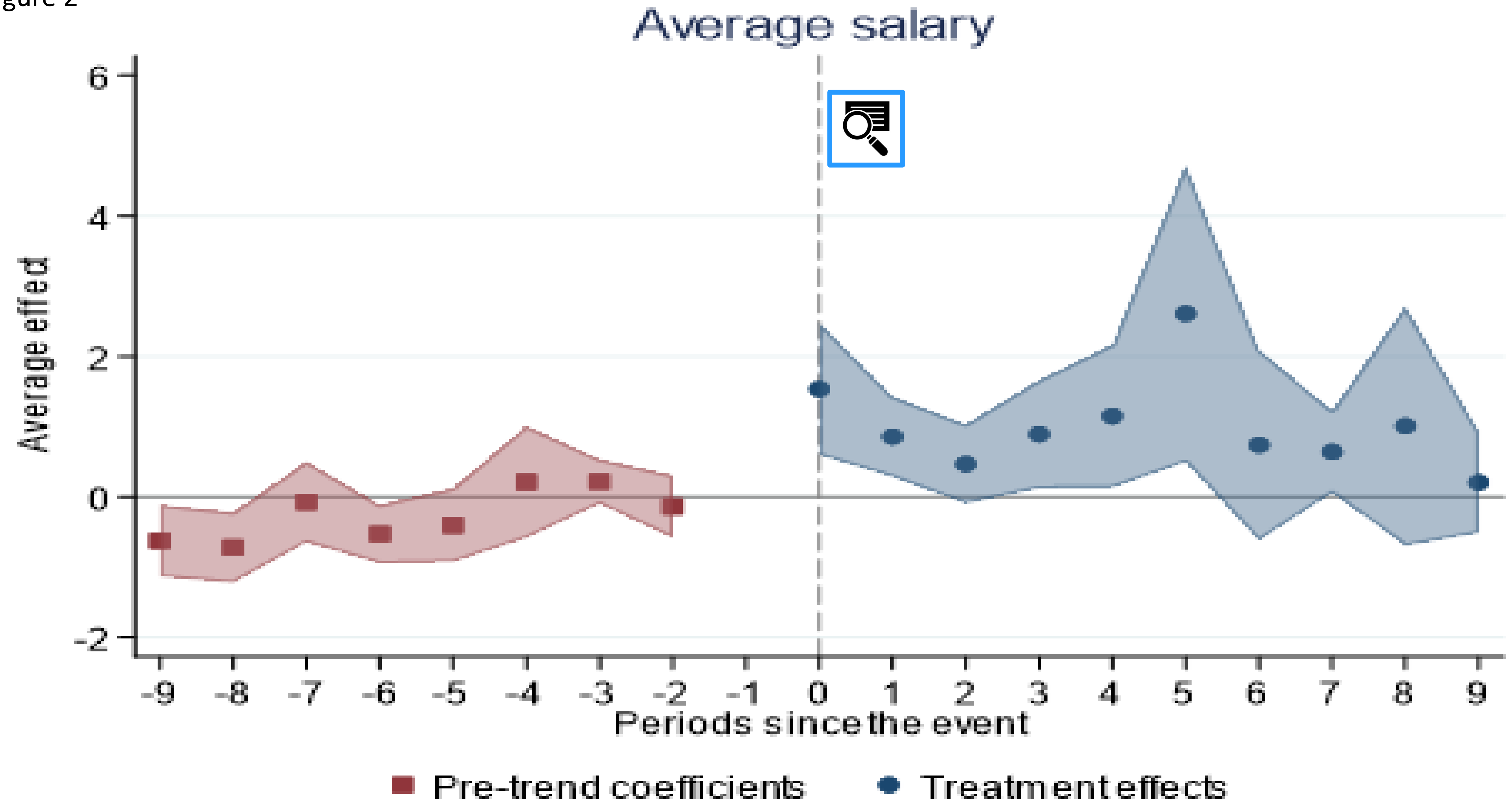
Dependent variable	AVERAGE SALARY			SALARY			EMPLOYMENT		
Specification	Standard DID	Gormley-Matsa Stack DID	Sun-Abraham IW Estimator	Standard DID	Gormley-Matsa Stack DID	Sun-Abraham IW Estimator	Standard DID	Gormley-Matsa Stack DID	Sun-Abraham IW Estimator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State*Law	1.800**	1.437**		0.481	0.343*		2.317	0.917	
	(0.773)	(0.603)		(0.300)	(0.182)		(3.653)	(2.111)	
Dynamic Post-Treatment Estimates									
t = 0			1.537***			0.161***			-1.946***
			(0.366)			(0.049)			(0.638)
t = 1			0.856***			0.037			-2.785***
			(0.222)			(0.036)			(0.613)
t = 2			0.468**			-0.016			-1.516***
			(0.218)			(0.047)			(0.532)
t = 3			0.892***			-0.003			-1.408***
			(0.299)			(0.043)			(0.480)
t = 4			1.150***			0.225***			-0.580
			(0.395)			(0.047)			(0.508)
t = 5			2.610***			0.301***			-0.184
			(0.821)			(0.051)			(0.695)
t = 6			0.739			0.187***			1.421
			(0.528)			(0.072)			(1.566)
t = 7			0.640***			0.258***			2.987*
			(0.226)			(0.089)			(1.615)
t = 8			1.009			0.261***			2.308
			(0.662)			(0.093)			(1.709)
t = 9			0.207			0.085			0.559
			(0.280)			(0.183)			(2.921)
Observations	140,007	435,656	140,007	140,007	435,656	140,007	140,007	435,656	140,007
R-squared	0.739	0.771	0.740	0.934	0.964	0.934	0.977	0.987	0.977
Bank FE	YES	NO	YES	YES	NO	YES	YES	NO	YES
Quarter FE	YES	NO	YES	YES	NO	YES	YES	NO	YES
Bank-cohort FE	NO	YES	NO	NO	YES	NO	NO	YES	NO
Quarter-cohort FE	NO	YES	NO	NO	YES	NO	NO	YES	NO

Average salaries increase by 6% (1,437 USD).

Driven by salaries (343,000 USD).

Employment contracts early-on.

Figure 2

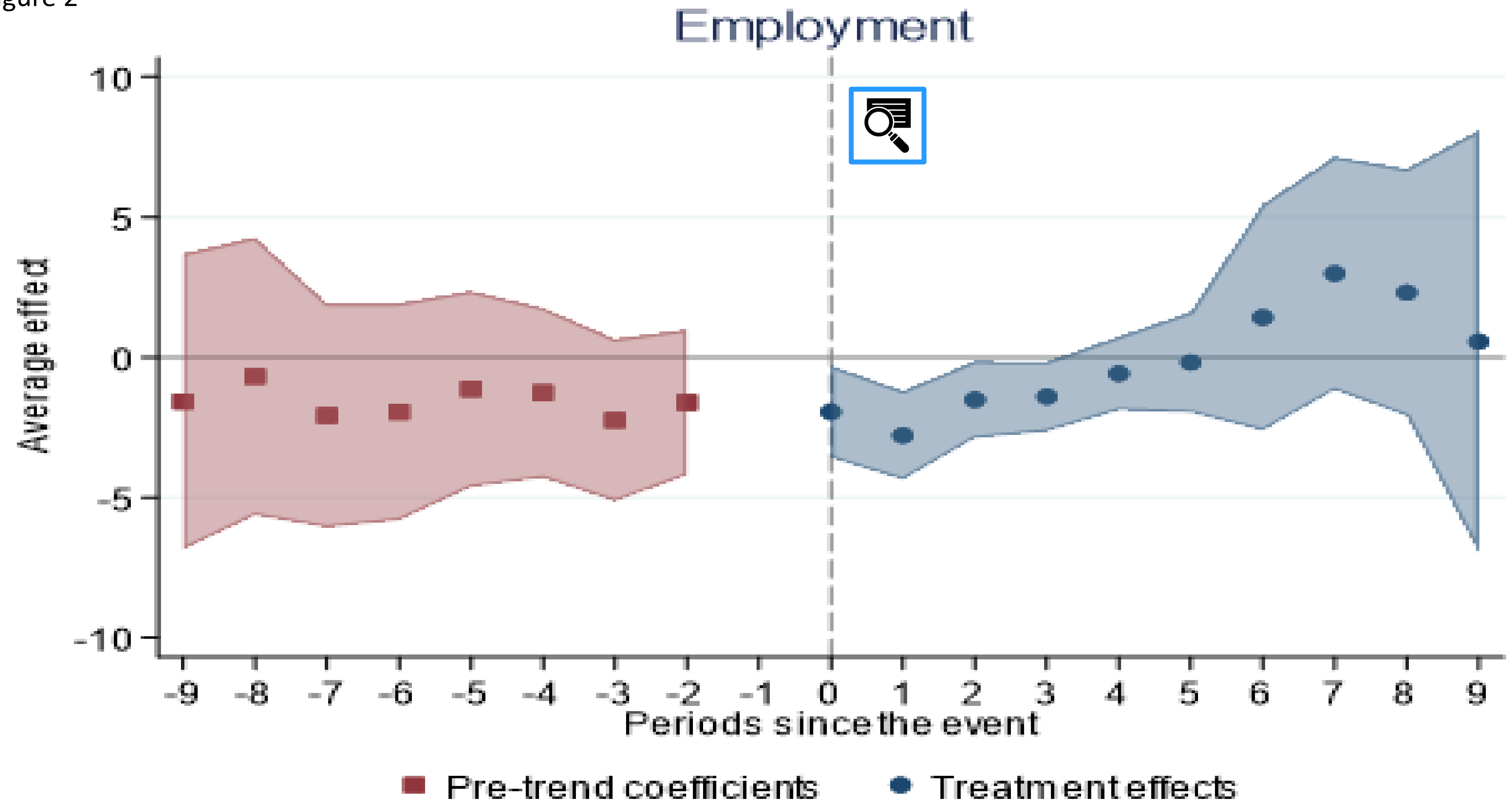


Average salary
6
4
2
0
-2
Average effect
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
Periods since the event
Pre-trend coefficients
Treatment effects

Figure 2

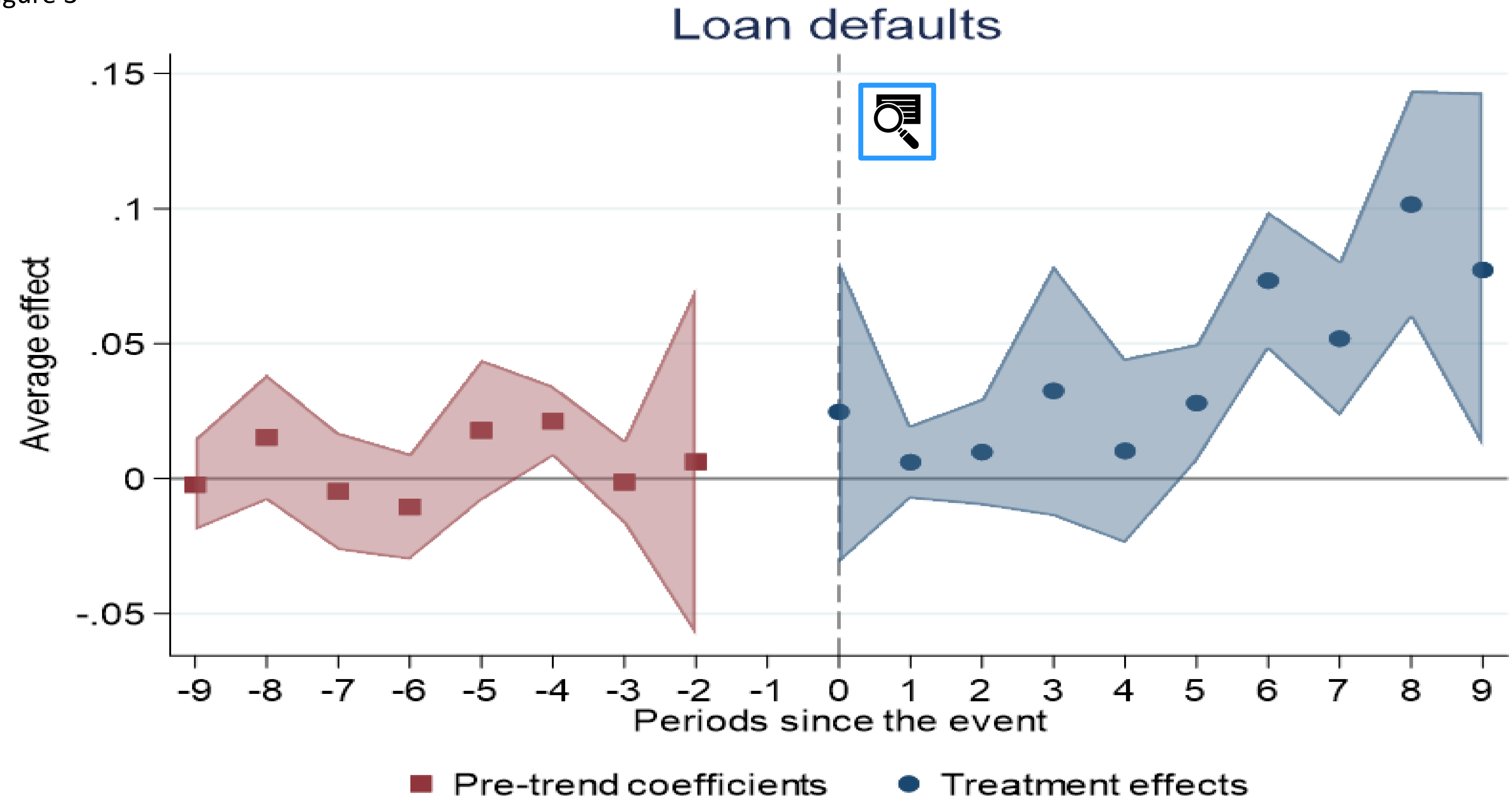
Salary
.5
0
-.5
Average effect
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
Periods since the event
Pre-trend coefficients
Treatment effects

Figure 2



Employment
Average effect
10
5
0
-5
-10
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
Periods since the event
Pre-trend coefficients
Treatment effects

Figure 3


Loan defaults
.15
.1
.05
0
-.05
Average effect
-9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9
Periods since the event
Pre-trend coefficients
Treatment effects

Diff-in-Diff Estimations: **Bank-level**

$$LLP_{ist} = \alpha_0 + \alpha_1 \Delta NPA_{ist+1} + \alpha_2 \Delta NPA_{ist} + \alpha_3 \Delta NPA_{ist-1} + \alpha_4 \Delta NPA_{ist-2} + \alpha_5 SIZE_{ist-1} + \alpha_6 \Delta LOAN_{ist} + \alpha_7 \Delta GSP_{st} + \alpha_8 \Delta HPI_{st} + \alpha_9 \Delta UNEMP_{st} + \alpha_{10} State_{sc} * Law_{tc} * \Delta NPA_{ist+1} + \alpha_{11} State_{sc} * Law_{tc} * \Delta NPA_{ist} + \alpha_{12} State_{sc} * Law_{tc} * \Delta NPA_{ist-1} + \alpha_{13} State_{sc} * Law_{tc} * \Delta NPA_{ist-2} + \alpha_{14} State_{sc} * Law_{tc} * SIZE_{ist-1} + \alpha_{15} State_{sc} * Law_{tc} * \Delta LOAN_{ist} + \alpha_{16} State_{sc} * Law_{tc} * \Delta GSP_{st} + \alpha_{17} State_{sc} * Law_{tc} * \Delta HPI_{st} + \alpha_{18} State_{sc} * Law_{tc} * \Delta UNEMP_{st} + \varepsilon_{ist},$$

Calculate: ln|residual$_{ist}$|

i – bank; s – state of operation; t – year-quarter

LLP = loan loss provisions
NPA = non-performing assets
State = 1 for States adopting pay transparency (= 0 otherwise)
Law = 1 for quarters following adoption (= 0 otherwise)

Jiang, Levine and Lin (RFS 2016); Beatty and Liao (JAE 2014)

swiss:finance:institute

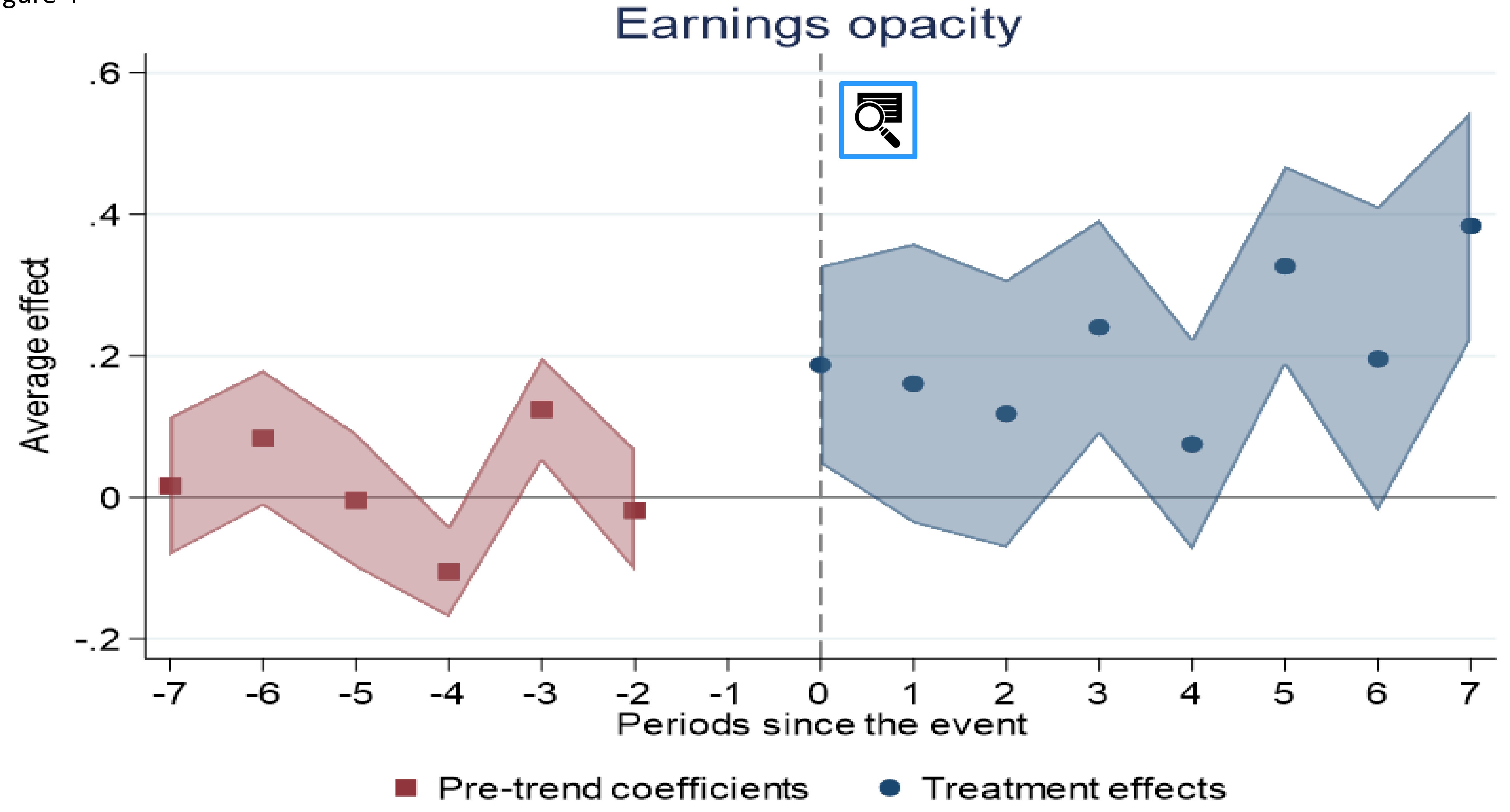
Table 9. The effect of transparency laws on bank earnings opacity

Dependent variable	EARNINGS OPACITY		
Specification	Standard DID	Gormley-Matsa Stack DID	Sun-Abraham IW Estimator
	(1)	(2)	(3)
State*Law	0.173***	0.183***	
	(0.048)	(0.048)	
Dynamic Post-Treatment Estimates			
t = 0			0.188***
			(0.054)
t = 1			0.159**
			(0.076)
t = 2			0.116
			(0.073)
t = 3			0.238***
			(0.058)
t = 4			0.072
			(0.059)
t = 5			0.325***
			(0.055)
t = 6			0.194**
			(0.084)
t = 7			0.381***
			(0.063)
Observations	124,665	346,479	124,665
R-squared	0.262	0.324	0.263
Bank FE	YES	NO	YES
Quarter FE	YES	NO	YES
Bank-cohort FE	NO	YES	NO
Quarter-cohort FE	NO	YES	NO

Opacity increases by 18%

Notes. This table reports the coefficients and standard errors clustered at the state level (in parentheses) obtained using equation 2, documenting the effect of introducing pay transparency laws on salaries and employment in t banking sector. The dependent variable is average salary expenses (Columns 1-3), salary expenses (Column 4-6), and the number of full time employees (Column 7-9). The main explanatory variable is an interaction term between t variable State (equal to 1 for banks headquartered and operating only in states adopting the pay transparency law, and zero otherwise) and Law (equal to 1 for quarters following the adoption of the pay transparency law, and ze otherwise). ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent statistical level, respectively.

Figure 4



Earnings opacity
.6
.4
.2
0
-.2
Average effect
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
Periods since the event
Pre-trend coefficients
Treatment effects

Table 10. Pay transparency, bank loan defaults, and earnings opacity – Mechanism and additional results

Dependent variable	LOAN DEFAULTS			EARNINGS OPACITY	
Specification	Standard DID	Gormley-Matsa Stack DID		Standard DID	Gormley-Matsa Stack DID
	(1)	(2)		(3)	(4)
PANEL A: BANK EMPLOYEE MOBILITY					
State*Law*IDD	-0.032	-0.047		-0.121	-0.186*
	(0.032)	(0.031)		(0.119)	(0.094)
State*Law	0.064***	0.048***		0.214***	0.252***
	(0.020)	(0.013)		(0.025)	(0.065)
State*Law+ State*Law*IDD	0.033	0.001		0.093	0.066
	(0.025)	(0.028)		(0.116)	(0.068)
Observations	140,007	435,656		124,665	346,479
R-squared	0.502	0.590		0.262	0.324
PANEL B: BANK EMPLOYEE QUALITY					
State*Law*Sanctions	-0.162	-0.070		-0.166	-0.014
	(0.106)	(0.071)		(0.288)	(0.292)
State*Law	0.054***	0.031*		0.176***	0.184***
	(0.016)	(0.016)		(0.044)	(0.050)
State*Law+State*Law*Sanctions	-0.108	-0.039		0.010	0.169
	(0.103)	(0.067)		(0.314)	(0.286)
Observations	140,007	435,656		124,665	346,479
R-squared	0.502	0.590		0.262	0.325

Notes. This table reports the coefficients and standard errors clustered at the state level (in parentheses) documenting the effect of introducing pay transparency laws on banks' asset portfolio quality. The dependent variable is the ratio of loans past due 90+ days to total loans, a measure of loan defaults. The main explanatory variables are an interaction term between the variable State (equal to 1 for banks headquartered and operating only in states adopting the pay transparency law, and zero otherwise) and Law (equal to 1 for quarters following the adoption of the pay transparency law, and zero otherwise), and triple interaction term between State, Law and *IDD* equal to 1 for banks operating in states with the Inevitable Disclosure Doctrine, and zero otherwise (Panel A); *Sanctions*, equal to 1 for banks repeatedly sanctioned with a regulatory enforcement actions between years 2011-2019, and zero otherwise (Panel B). ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent statistical level, respectively.

Dependent variable	LOAN DEFAULTS			EARNINGS OPACITY	
Specification	Standard DID	Gormley-Matsa Stack DID		Standard DID	Gormley-Matsa Stack DID
	(1)	(2)		(3)	(4)
PANEL C: BANKS EMPLOYING LOAN OFFICERS					
State*Law*Advert	-0.079*	-0.036***		-0.121	-0.118
	(0.042)	(0.013)		(0.141)	(0.128)
State*Law	0.090***	0.046***		0.226***	0.250***
	(0.022)	(0.010)		(0.082)	(0.076)
State*Law+State*Law*Advert	0.011	0.009		0.104	0.131*
	(0.026)	(0.017)		(0.082)	(0.076)
Observations	140,007	435,656		124,665	346,479
R-squared	0.502	0.590		0.265	0.327
PANEL D: BANKS EMPLOYING LOAN OFFICERS WITH PRIOR JOB EXPERIENCE					
State*Law* ExpAdvert	-0.111***	-0.070***		-0.090	-0.087
	(0.034)	(0.019)		(0.122)	(0.119)
State*Law	0.104***	0.064***		0.205***	0.229***
	(0.020)	(0.019)		(0.066)	(0.064)
State*Law+State*Law* ExpAdvert	-0.008	-0.006		0.115	0.142*
	(0.027)	(0.015)		(0.083)	(0.081)
Observations	140,007	435,656		124,665	346,479
R-squared	0.502	0.590		0.264	0.326

Alternative explanations

- Merger banks removed
- Failed banks removed
  - Consolidation affects loan pricing (Sapienza JF 2002) and borrower screening efforts (Panetta, Schivardi & Shum JMCB 2009)
  - Significant reduction in banks' personnel expenses around mergers (Cornett, McNutt and Tehranian JMCB 2006)
- States adopting transparency laws during COVID removed
  - Banks more geographically exposed to COVID-19 lockdown measures and the pandemic experience an increase in nonperforming loans (Beck and Keil JCF 2022).
  - Earnings shocks during pandemic (Larrimore, Mortenson & Splinter JPubE 2022) .

Table 12. Pay transparency and bank loan defaults – Sensitivity tests

Dependent variable	BANK LOAN DEFAULTS		BANK EARNINGS OPACITY	
Specification	Standard DID	Gormley-Matsa Stack DID	Standard DID	Gormley-Matsa Stack DID
	(1)	(2)	(3)	(4)
PANEL A: JANUARY 2023 PAY TRANSPARENCY LAWS				
State*Law	0.073***	0.045***	0.221***	0.140***
	(0.014)	(0.010)	(0.018)	(0.046)
Observations	133,213	71,289	118,628	58,889
R-squared	0.513	0.567	0.262	0.340
PANEL B: STATES ADOPTING LAWS IN CITIES EXCLUDED				
State*Law	0.060***	0.046***	0.173***	0.194***
	(0.015)	(0.009)	(0.058)	(0.060)
Observations	130,801	351,756	116,502	279,888
R-squared	0.500	0.590	0.258	0.317
PANEL C: BANKS CHANGING STATE OF HEADQUARTER EXCLUDED				
State*Law	0.051***	0.030**	0.173***	0.183***
	(0.015)	(0.014)	(0.047)	(0.047)
Observations	139,606	434,367	124,349	345,614
R-squared	0.502	0.591	0.261	0.323
PANEL D: ONLY CONTIGUOUS STATES IN THE CONTROL GROUP				
State*Law	0.054**	0.037**	0.152**	0.174***
	(0.022)	(0.015)	(0.058)	(0.051)
Observations	42,570	124,670	37,852	99,097
R-squared	0.577	0.680	0.315	0.382
PANEL E: NO CONTIGUOUS STATES IN THE CONTROL GROUP				
State*Law	0.047***	0.026*	0.177***	0.183***
	(0.016)	(0.015)	(0.048)	(0.049)
Observations	108,554	335,818	96,740	267,290
R-squared	0.405	0.475	0.237	0.299

Table 12. Pay transparency and bank loan defaults – Sensitivity tests

Dependent variable	BANK LOAN DEFAULTS		BANK EARNINGS OPACITY	
Specification	Standard DID	Gormley-Matsa Stack DID	Standard DID	Gormley-Matsa Stack DID
	(1)	(2)	(3)	(4)
PANEL F: CROSS-STATE SPILLOVER EFFECTS				
State*Law	-0.007	-0.007	-0.009	-0.039
	(0.017)	(0.018)	(0.044)	(0.035)
Observations	128,880	410,003	114,727	222,741
R-squared	0.517	0.562	0.259	0.315
PANEL G: STANDARD ERRORS CLUSTERED AT THE BANK LEVEL				
State*Law	0.051**	0.030*	0.173***	0.182***
	(0.024)	(0.016)	(0.036)	(0.040)
Observations	140,007	435,626	124,665	346,470
R-squared	0.502	0.590	0.262	0.324
PANEL H: CONTROL GROUP BANKS MATCHED ON PRE-TREATMENT SIZE (4 MATCHES)				
State*Law	0.055**	0.042**	0.138**	0.168***
	(0.022)	(0.018)	(0.052)	(0.047)
Observations	42,832	125,287	38,222	100,070
R-squared	0.544	0.687	0.282	0.344
PANEL I: ADDITIONAL CONTROL VARIABLES INCLUDED				
State*Law	0.052***	0.034***	0.172***	0.179***
	(0.014)	(0.013)	(0.049)	(0.049)
Observations	136,220	425,026	124,665	346,479
R-squared	0.510	0.597	0.262	0.325
PANEL J: BANK HOLDING COMPANY BANKS REMOVED				
State*Law	0.051***	0.029**	0.199***	0.203***
	(0.016)	(0.015)	(0.053)	(0.049)
Observations	121,212	378,191	108,179	364,782
R-squared	0.504	0.593	0.257	0.302

Tentative Conclusions

Pay transparency laws gain traction in the U.S. and around the world:

- Outside the U.S., pay transparency laws recently introduced in: Austria, Canada (Ontario), Latvia, Lithuania, Slovakia.

- Several U.S. states consider introducing such measures in the future: *Alaska, District of Columbia, Kentucky, Maine, Massachusetts, Michigan, Missouri, Montana, New Jersey, Oregon, South Dakota, Vermont, Virginia, West Virginia.*

Policy seems to have a *positive* effect on salaries in the private sector.

Our study highlights potential *adverse effect* of pay transparency laws on banks' risk and opacity.

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Potential Mechanism Documented

Pay transparency law is passed

Pay is revealed in relatively more adverts

Experienced loan officers start to leave to nonbanks that pay more

Banks want to hire new loan officers by placing more adverts

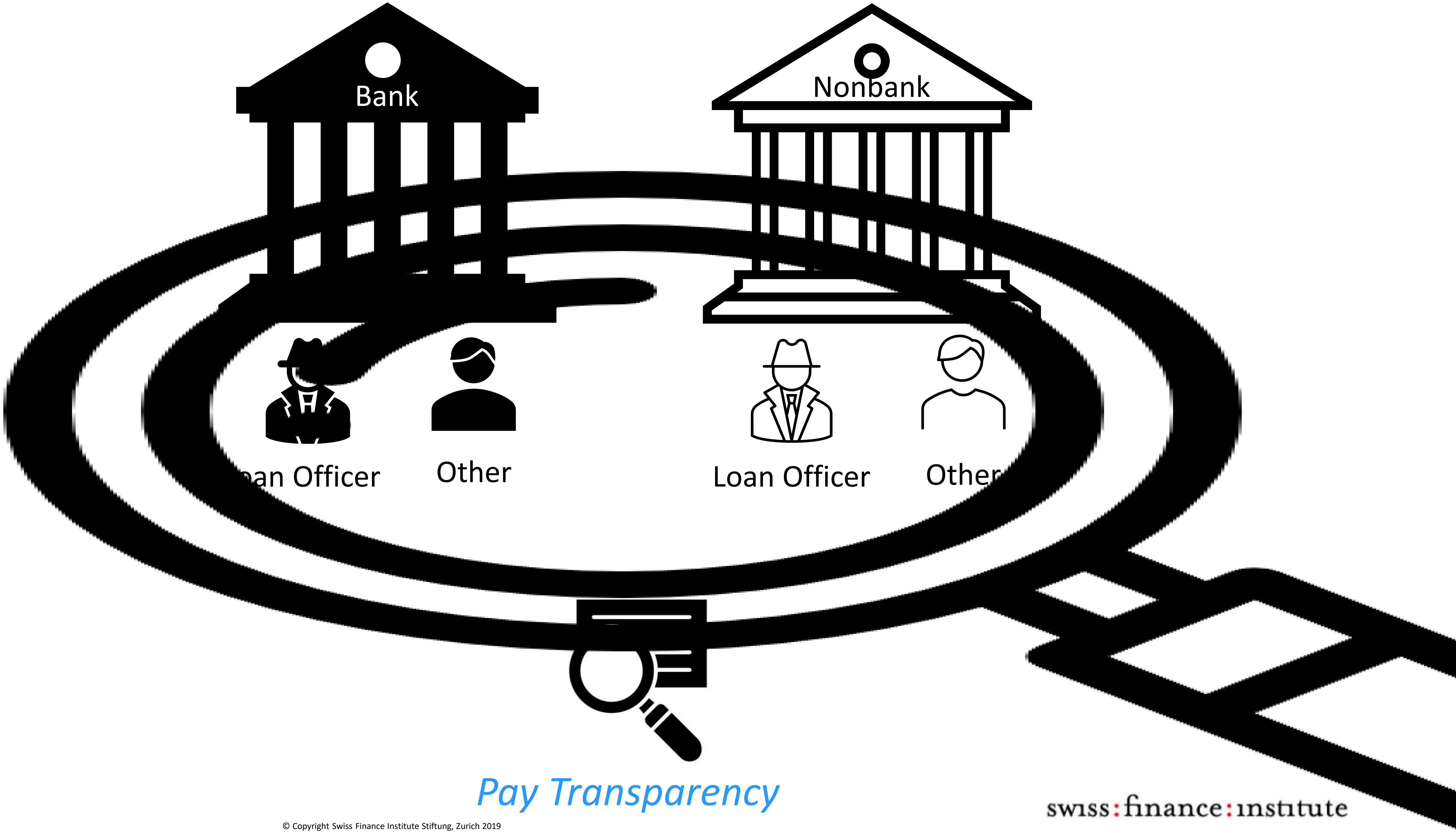
Banks have to increase wages to do so

Banks hire new loan officers, who often lack expertise

Loan quality slips, loan losses mount

Banks manage loan loss provisions more

Banks are more opaque



Pay Transparency

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Occupational Heterogeneity and the Distributional Impact of Inflation

Ahya Eyvazi (*Allameh Tabataba'i University*)

Majid Einian (*Arcada University of Applied Sciences*)

Steven Ongena *(Zurich, SFI, KU Leuven, NTNU, CEPR)*

Naser Amanzadeh (*Sharif University of Technology*)

One-Page Summary

Inflation can redistribute real wealth from lenders to borrowers by altering the value of nominal assets and liabilities

Iranian Household Income and Expenditure Survey, 2010-2023, 20K Households

compare households with access to credit to those without

Household heads employed in the banking sector receive, on average 38 million rials (900 US dollars), or 30% of durable goods expenditures, more in credit than comparable households not employed there.

The negative effect of inflation on durable expenditure growth is **4.3 percentage points weaker for bank households** compared to non-bank households.

Bank households are relatively insulated from inflationary pressures, due to better access to credit.

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Banks collate *information*

Banks use *information*

Banks compartmentalize *information*

Banks manage *information display*

Bankers use *information*

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Much more to be discovered ...

Maybe Interesting Margins to Push Research?

- More on nonbanks, fintech and banks and their differential access, processing and use of information?

- Substitutability and complementarity of Artificial Intelligence and loan officer expertise?

- Internal (within bank) access to information collected by loan officers?

- Social media and societal loss of privacy, access to credit and societal outcomes in terms of income, wealth and political affiliation.