Bankers on the Move:

Relationship Capital in Credit Markets

Angelo D'Andrea Bank of Italy Enrico Stivella Bocconi University

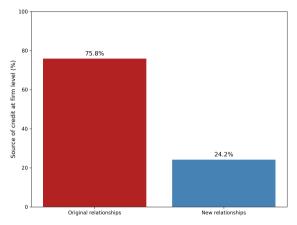
October 20, 2025

The views expressed are solely those of the authors and should not be interpreted as reflecting the view of the Bank of Italy

Financial sector workers and credit allocation

- 1. Financial sector workers hold information about borrowers (Stiglitz and Weiss 1981)
- 2. Banks design contracts to retain their managers (Bénabou and Tirole 2016)

Financial sector workers and credit allocation



- 3. 4% of bank managers have changed bank at least once in 2009-2018 Manager mobility
- 4. 1/4 of credit to Italian firms in 2018 comes from post-2009 relationships

Research Questions

1. Are capital flows influenced by worker flows in the financial sector?

- 2. What are the *efficiency* implications of this phenomenon?
 - Bright side: information diffusion
 - Dark side: suboptimal credit allocation

This Paper

- 1. Creates a novel dataset combining Italian credit and worker flow data
 - Tracks manager moves across banks in social security data
 - Constructs for each manager a *portfolio* of firms having loans with her *old* bank
- 2. Estimates probability of following the manager in an *event study*
 - Controlling for assortative matching, credit demand and supply shocks
 - Subset of *branch closure*-induced moves confirms results
- 3. Decomposes credit probability increase into application and approval
- 4. Measures loan terms and performance: interest rates and default probability

Preview of Results

- 1. 4 years after a bank manager moves to a *new* bank, portfolio *firms*:
 - Increase their probability of obtaining credit from the new bank from 1.3% to 4.5%
- 2. From loan application data, knowledge of the bank manager:
 - Increases search: portfolio firms are 3 times more likely to apply to the new bank
 - Increases application *approval* rate by 2 percentage points (from 35% to 37%)
- 3. Loans originated following the manager:
 - Have 0.5 percentage point lower interest rates w.r.t. their other loans
 - Have 4 percentage points lower *default* probability w.r.t. other loans in the *new bank*

Contribution to the Literature

1. Relationship lending:

- Amberg and Becker (2024), Bonfim, Nogueira, and Ongena (2021), Nguyen (2019), Fisman, Paravisini, and Vig (2017), Hertzberg, Liberti, and Paravisini (2010), and Stein (2002)
- Show that a portfolio of clients follows the branch manager using administrative data
- 2. Administrative data on *credit* and *workforce*:
- 3. Managerial value added:

Contribution to the Literature

1. Relationship lending:

- 2. Administrative data on *credit* and *workforce*:
 - Acabbi, Panetti, and Sforza (2024), Böhm, Metzger, and Strömberg (2023), Efing et al. (2022), Jasova et al. (2021), Philippon (2015), Bell and Van Reenen (2014), Philippon and Reshef (2012), and Panetta, Schivardi, and Shum (2009)
 - Provide stylized facts on financial labor force and link them to credit allocation
- 3. Managerial value added:

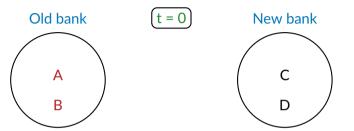
Contribution to the Literature

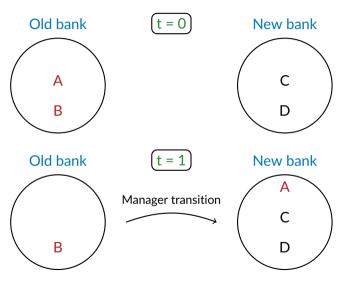
- 1. Relationship lending:
- 2. Administrative data on *credit* and *workforce*:
- 3. Managerial value added:
 - Sauvagnat and Schivardi (2024), Minni (2025), Metcalfe, Sollaci, and Syverson (2023), Fenizia (2022), Patault and Lenoir (2024), Bandiera et al. (2020), and Lazear, Shaw, and Stanton (2015)
 - Bank managers guarantee firms they know better credit access and loan conditions

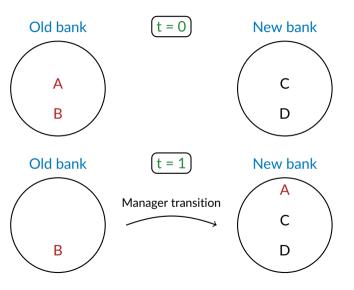
Data and sample construction

Data Sources (2009-2018)

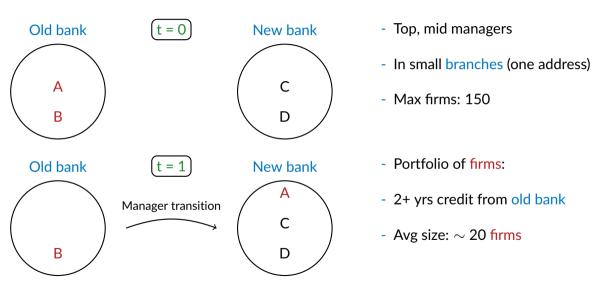
- Credit Registry (Bank of Italy):
 - All loans ≥ €30k to firms from branches, defined by bank group and municipality
 - Avoid mechanical credit relocations ⇒ bank group set at end of sample
 - 8 million obs (one per firm branch year): 440k firms, 31k branches
- Social Security (Inps):
 - All workers in the financial sector: 350k obs per year
- Firm characteristics (Cerved):
 - Legally registered firms in Italy, matched with the Credit Registry (300k matches)







- Top, mid managers
- In small branches (one address)
- Max firms: 150



Credit market: all firm - branch pairs in the same province

Branch	Firm	Status
New bank	Portfolio	Treated
New bank	In province	Control
In province	Portfolio	Control
In province	In province	Control

Treated: Portfolio firm - manager's new branch Control: all other firm - branch potential matches

- ▶ Portfolio construction
- ▶ Resulting dataset

- Province:
- admin. unit
- \sim 500k inhabitants
- 60% firms have credit in a single one ▶ Local credit
- Relevant in anti-trust cases (Crawford, Pavanini, and Schivardi 2018)

Empirical Strategy

Measuring the portability of credit relationships after a move

$$I(\text{credit})_{bft} = \sum_{\substack{\tau = -4 \\ \tau \neq -1}}^{4} \beta_{\tau} \times I\{t = t_{bf} + \tau\} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft}$$

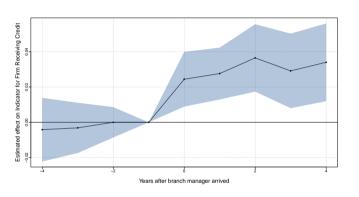
- I(credit)_{bft}: credit is granted by branch b to firm f in year t
- $I\{t = t_{bf} + \tau\}$: τ years after manager who gave credit to firm f arrives in branch b
- Control group: all firm branch potential matches within the same province Plocal credit
- Moves: branch manager moves to a different bank group

Identification discussion: fixed effects

$$I(\text{credit})_{bft} = \sum_{\substack{\tau = -4 \\ \tau \neq -1}}^{4} \beta_{\tau} \times I\{t = t_{bf} + \tau\} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft}$$

- 1. firm branch: non time-varying assortative matching characteristics (specialization)
- 2. branch time: branch-level time-varying policies, such as
 - Credit supply in branch b at time t
 - Deposit inflows, branch size, group-level policies
- 3. firm time: firm-level time-varying characteristics, such as:
 - Credit demand in firm f at time t
 - Firm size, credit score

Credit probability is 3.5 times higher 4 years after the move



Estimated via Sun and Abraham (2021). 2009–2018, N=44,681,890. SE clustered at bank-firm level. Shaded area: 95% CI.

▶ DiD estimates▶ Heterogeneity▶ Branch Closures▶ Within Bank Moves

- ATE: 0.023*** (Baseline: 0.013)
- Interpretation:
 - (i) Firm f becomes 3.5 times more likely to get credit from new branch b
 - (ii) 1 out of 30 firms follows
- Driven by:
 - (i) small, young firms
 - (ii) *older* managers
 - (iii) smaller bank groups

Decomposing the credit probability increase

$$P(credit) = P(credit|apply) \times P(apply)$$

Prediction 1:

Firm f application probability increases if it knows the manager $\Rightarrow P(apply) \uparrow$

$$I(\mathsf{apply})_{bft} = \sum_{\substack{ au = -4 \ au
eq -1}}^4 eta_ au imes I\{t = t_{bf} + au\} + lpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft}$$

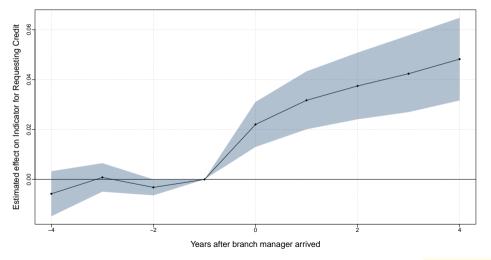
Firm f's approval probability increases if it knows the manager $\Rightarrow P(credit|apply) \uparrow$

$$I(ext{credit}| ext{apply})_{bft} = \sum_{\substack{ au=-4\\ au
eq -1}}^4 eta_ au imes I\{t=t_{bf}+ au\} + lpha_{bf} + \delta_{bt} + \gamma_{ft} + arepsilon_{bft}$$

(2)

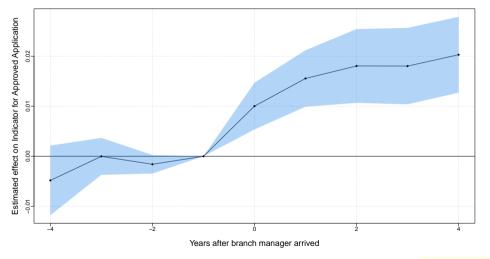
(1)

Firms are 3 times more likely to apply for credit to the new bank



Probability that a firm applies for credit to the manager's new bank. Baseline: 2% Poisson regression

Portfolio firms are 2 pp more likely to get loan applications approved



Probability of a firm being granted credit, conditional on applying. Baseline: 35% Poisson regression

Loan terms and performance

$$m{Y}_{bft} = m{eta} imes ext{Switcher}_{bft} + \gamma \log(1 + ext{credit}_{bft}) + m{X}_{bft} + m{\epsilon}_{bft}$$

- *Y*_{bft}: interest rate or non-performing loan indicator
- Switcher bft: credit relationship originated after the manager moved
- $log(1 + credit_{bft})$: loan size
- \mathbf{X}_{bft} : firm characteristics, manager, branch and year fixed effects

Loan terms and performance: comparison groups

$$m{Y}_{bft} = eta imes ext{Switcher}_{bft} + \gamma \log(1 + ext{credit}_{bft}) + m{X}_{bft} + m{\epsilon}_{bft}$$

1. Within switchers

- Are switchers paying/defaulting less when they follow their manager?

2. New relationships of the new branch

- Are switchers paying/defaulting less w.r.t. other new relationships?

Switchers pay less than their other loans

	Within switchers	
	Interest rates	Non performing loan
Switcher	-0.505* (0.264)	-0.007 (0.011)
Dependent variable mean R ² Observations	2.55 0.198 6,643	0.023 0.125 12,604

Controls: credit size, manager, bank group, year, age, size, riskiness

► Loan type breakdown

► NPL type breakdown

Switchers default less than other new relationships

	New branch	
	Interest rates	Non performing loan
Switcher	0.050 (0.144)	-0.043** (0.008)
Dependent variable mean R ² Observations	2.60 0.123 68,555	0.025 0.042 167,876

Controls: credit size, manager, bank group, year, age, size, riskiness

► Loan type breakdown

► NPL type breakdown

Conclusions and future directions

- 1. Bank managers are able to *move* their *credit relationships* to a new bank:
 - increase application and approval probabilities
 - bring their clients to banks with better loan terms
 - their clients default less often

2. Future directions:

- Firms: do firms with personal connections to the manager grow faster?
- Banks: does managers' information increase banks' profits?
- Managers: what are the incentives for managers to bring clients with them?

Research agenda: knowledge transferred by people

- 1. Is scientific human capital *portable*?
 - Scientific resilience: How Italian nuclear physics changed after the Chernobyl disaster
- 2. Can people transfer technology from large scale R&D programs?
 - Start Up Nation: Spillovers from Breakthrough Technologies (with Nicolas Serrano Velarde, Efraim Benmelech and Eran Hoffman)
- 3. Does *public demand* shape the direction of innovation?
 - Procuring Innovation: evidence fro the SBIR program

Thank you!

If you have further comments email us at

Enrico Stivella: enrico.stivella@phd.unibocconi.it

Angelo D'Andrea: angelo.dandrea@bancaditalia.it

Appendix - Table of Contents

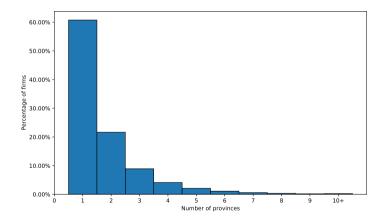
A. Descriptives

- Stylized facts
- 2. Portfolio construction details
- 3. Dataset comparison

B. Regressions

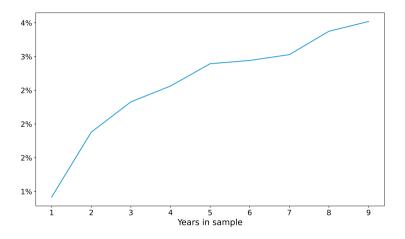
- 1. Inflow heterogeneity
- 2. Main specification alternatives
 - (i) Inflow event study within bank group
 - (ii) Identification branch closures
 - (iii) Loan applications Poisson
- 3. Loan terms and performance
 - (i) Interest rates
 - (ii) NPL

Credit is local: 60% of firms have credit in a single province



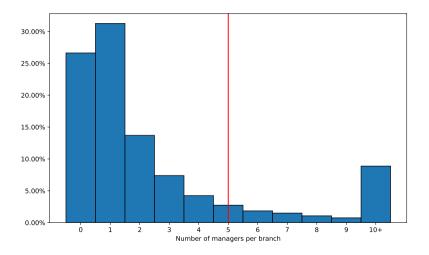
▶ Back to inflow regression

Over 9 years, 4% of branch managers have changed bank





Average branch size is 2.3 managers





A branch manager moves and brings her portfolio

Branch manager	Branch	Year	Active loans	Portfolio
L. Riva	Ubi - Crema	2009	Verdi srl	
•••	•••	•••	•••	•••
L. Riva	Ubi - Crema	2011	Verdi srl, Rossi srl	•••
L. Riva	Bper - Lodi	2012	Bianchi srl	Verdi srl, Rossi srl

- L. Riva moves from Ubi Crema to Bper Lodi in 2012
- She had active loans with Verdi srl and Rossi srl in Ubi Crema in 2011
- So they are part of her portfolio when she moves to Bper Lodi



Dyad Rossi srl - Bper - Lodi switches in 2013

Firm	Branch	Year	Credit	Branch manager in
Rossi srl	Bper - Lodi	2009	0	0
		•••		
Rossi srl	Bper - Lodi	2012	0	1
Rossi srl	Bper - Lodi	2013	1	1
		•••		
Rossi srl	Bper - Lodi	2018	1	1



Dyad Verdi srl - Bper - Lodi is only potential

Firm	Branch	Year	Credit	Branch manager in
Verdi srl	Bper - Lodi	2009	0	0
•••	•••	• • •	• • •	•••
Verdi srl	Bper - Lodi	2012	0	1
	•••	• • •	• • •	•••
Verdi srl	Bper - Lodi	2018	0	1



Dyad Bianchi srl - Bper - Lodi is out of portfolio

Firm	Branch	Year	Credit	Branch manager in
Bianchi srl	Bper - Lodi	2009	0	0
	•••	• • •	•••	
Bianchi srl	Bper - Lodi	2011	1	0
Bianchi srl	Bper - Lodi	2012	1	0
	•••	• • •	• • •	•••
Bianchi srl	Bper - Lodi	2018	1	0



Selected sample (2009-2018)

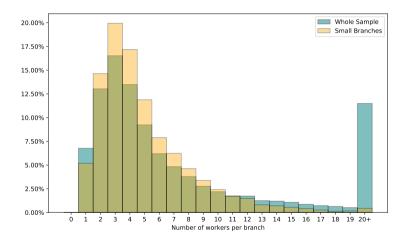
- Credit Registry (Bank of Italy):
 - Small branches (single address, less than 150 firms)
 - Goal: make sure a manager knows all the firms in the branch
 - 4 million obs (one per firm branch year): 160k firms, 14k branches
- Social Security (Inps):
 - All small-branch managers: 20k obs per year, 609 total moves
- Firm characteristics (Cerved):
 - Legally registered firms in Italy, matched with the Credit Registry (100% matches)
 - ▶ Dataset comparison slides

Comparison slides

- Credit Registry (Bank of Italy):
 - Size comparison
 - Firm comparison
 - Municipality comparison
 - ► Geographical distribution
- Firm characteristics (Cerved):
 - Features

▶ Back

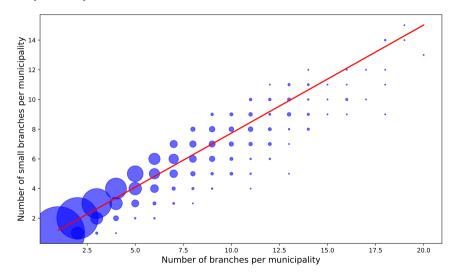
Branch size comparison



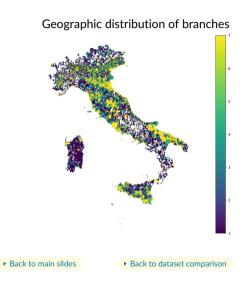
Firm comparison

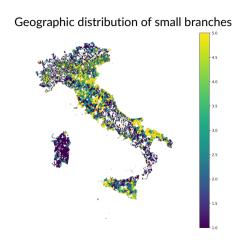
	Small branches firms	All firms
Years in sample	9.99	6.46
	0.25	3.42
Nr bank groups	4.07	2.76
	2.90	2.39
Nr branches	5.74	3.60
	4.91	3.85
Nr municipalities	3.56	2.46
	2.73	2.17
Nr provinces	2.31	1.76
	1.72	1.33
Number of firms	158,511	442,192
Percentage	35.85%	100%

Municipality comparison



Geographical distribution of branches





Firm comparison (Cerved)

	Small branches firms	All firms
Age	27.07	21.00
	(12.77)	(13.15)
Log total assets	7.51	6.98
	(1.51)	(1.54)
North	0.63	0.56
	(0.48)	(0.50)
Center	0.13	0.12
	(0.34)	(0.33)
South	0.17	0.22
	(0.37)	(0.41)
Number of firms	158,511	442,190
Percentage	35.85%	100%

[▶] Back to main slides

[▶] Back to dataset comparison

Probability of relationship formation: DiD estimates

▶ Branch closures

		Credit i	ndicator	
	(1)	(2)	(3)	(4)
Inflow	0.027*** (0.007)	0.022*** (0.007)	0.026*** (0.007)	0.023*** (0.007)
Dependent variable mean	0.013	0.013	0.013	0.013
Branch-Firm fixed effects Branch-Time fixed effects Firm-Time fixed effects	\checkmark	√ ✓	√ √	✓ ✓ ✓
R ² Observations	0.772 44,681,890	0.785 44,681,890	0.773 44,681,890	0.786 44,681,890

▶ Within bank moves

Inflow heterogeneity

- 1. Structure of information:
 - Less portability to local headquarters, from small bank groups
- Headquarters
 - ▶ Bank group

- 2. Firm size and age:
 - Younger and smaller firms are more likely to follow
- ▶ Firm age ▶ Firm size

- 3. Loan size:
 - Switchers come most likely from medium-sized loans
- ▶ Loan size

Competition

- 4. Manager characteristics:
 - More likely to be followed if older or from smaller branches

- 5. Competition:
 - More portability in *more competitive* markets
- ▶ Back

Information from small banks flows less

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow	0.013***	0.023*** (0.008)	0.026*** (0.008)	0.039** (0.016)
Big to small \times Inflow	0.042* (0.022)			
Big to big \times Inflow		0.021 (0.017)		
Small to big \times Inflow			-0.029 (0.022)	
Small to small \times Inflow				-0.026* (0.015)
R^2	0.793	0.793	0.793	0.793
Observations	97,198,970	97,198,970	97,198,970	97,198,970
Firm-Time fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Branch-Time fixed effects Branch-Firm fixed effects	✓ ✓	✓ ✓	✓ ✓	✓ ✓

Young firms are more likely to follow

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow	0.023*** (0.007)	0.029*** (0.009)	0.025*** (0.007)	0.024*** (0.008)
Young \times Inflow	0.033*** (0.012)			
$Old \times Inflow$		-0.009 (0.006)		
Safe \times Inflow			-0.002 (0.004)	
$Risky \times Inflow$				-0.0006 (0.004)
R^2	0.793	0.793	0.793	0.793
Observations	97,198,970	97,198,970	97,198,970	97,198,970
Firm-Time fixed effects	✓	✓	\checkmark	\checkmark
Branch-Time fixed effects Branch-Firm fixed effects	✓ ✓	√ ✓	✓ ✓	√ ✓

Smaller firms are more likely to follow

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow	0.019***	0.021*** (0.008)	0.024*** (0.008)	0.028*** (0.008)
Micro imes Inflow	0.012 (0.008)			
Small × Inflow		0.007* (0.004)		
$Medium \times Inflow$			-0.005 (0.008)	
Big imes Inflow				-0.030*** (0.010)
R^2	0.793	0.793	0.793	0.793
Observations	97,198,970	97,198,970	97,198,970	97,198,970
Firm-Time fixed effects	✓	✓	\checkmark	\checkmark
Branch-Time fixed effects Branch-Firm fixed effects	✓ ✓	✓ ✓	✓ ✓	√ √

Switchers come most likely from medium-sized loans

	Credit indicator				
	(1)	(2)	(3)	(4)	
Former loan < 50k	0.024** (0.011)				
Former loan < 100k		0.025** (0.010)			
Former loan < 500k			0.032*** (0.010)		
Former loan \geq 500k				0.011* (0.006)	
R^2	0.793	0.793	0.793	0.793	
Observations	97,198,970	97,198,970	97,198,970	97,198,970	
Firm-Time fixed effects	\checkmark	✓	\checkmark	\checkmark	
Branch-Time fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	
Branch-Firm fixed effects	✓	✓	✓	✓	



Older managers are more likely to be followed

	Credit indicator			
	(1)	(2)	(3)	(4)
Manager younger than 45	0.022*** (0.007)			
Manager older than 45		0.026** (0.012)		
Manager younger than 55			0.022*** (0.008)	
Manager older than 55				0.043** (0.020)
R^2	0.786	0.786	0.786	0.786
Observations	44,681,890	44,681,890	44,681,890	44,681,890
Dependent variable mean	0.013	0.013	0.013	0.013
Firm-Time fixed effects	√	√	√	√
Branch-Time fixed effects Branch-Firm fixed effects	√ √	√ √	√ √	√ √



Managers from smaller branches are more likely to be followed

	Credit indicator			
	(1)	(2)	(3)	(4)
From \leq 3 managers branch	0.120*** (0.032)			
From > 3 managers branch		0.013** (0.006)		
From \leq 5 managers branch			0.085*** (0.024)	
From > 5 managers branch				0.012* (0.006)
R^2	0.786	0.786	0.786	0.786
Observations	44,681,890	44,681,890	44,681,890	44,681,890
Dependent variable mean	0.013	0.013	0.013	0.013
Firm-Time fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Branch-Time fixed effects	\checkmark	\checkmark	\checkmark	✓
Branch-Firm fixed effects	✓	✓	✓	✓



Firms are less likely to follow in local headquarters

	Credit indicator		
	(1)	(2)	
Inflow	0.044***	_	
	(0.016)		
Capoluogo $ imes$ Inflow	-0.035**	0.009*	
	(0.016)	(0.004)	
R^2	0.786	0.786	
Observations	44,681,890	44,681,890	
Dependent variable mean	0.013	0.013	
Firm-Time fixed effects	✓	✓	
Branch-Time fixed effects	\checkmark	\checkmark	
Branch-Firm fixed effects	✓	✓	

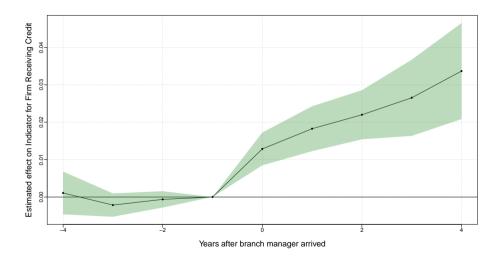


In more competitive markets (lower concentration) firms follow more

	(1)	Credit indicator (2)	. (3)
Bottom HHI quartile \times Inflow	0.100*** (0.034)		
Below median HHI $ imes$ Inflow		0.018*** (0.006)	
Below 75pct HHI × Inflow			0.023** (0.009)
R^2	0.788	0.788	0.788
Observations	27,124,990	27,124,990	27,124,990
Dependent variable mean	0.013	0.013	0.013
Firm-Time fixed effects	\checkmark	\checkmark	\checkmark
Branch-Time fixed effects	\checkmark	\checkmark	\checkmark
Branch-Firm fixed effects	✓	✓	✓



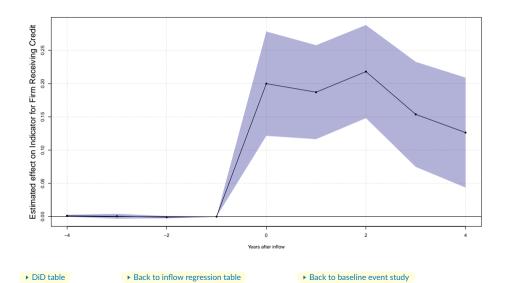
Within bank group relocations



Identification via branch closures

- Threats: variation at movement time of branch firm matching characteristics
- Two possible endogenous components of the branch manager's move:
 - 1. Separation from old branch
 - 2. Assignment to new branch
- Possible solutions:
 - 1. Branch-closure induced relocations, in different bank groups and municipalities
 - 2. Movements to the worker's birthplace, changes of marital status [TO DO]
 - ▶ Back to inflow regression table

Branch-closure induced moves



Branch-closure induced moves

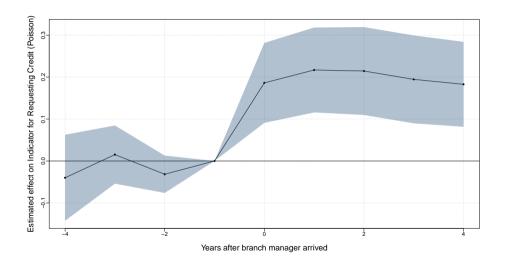
	Credit indicator				
	(1)	(2)	(3)	(4)	
Inflow from branch closure	0.184* (0.105)	0.217* (0.118)	0.183* (0.104)	0.216* (0.117)	
Dependent variable mean	0.013	0.013	0.013	0.013	
Branch-Firm-Year fixed effects Branch-Year fixed effects Firm-Year fixed effects	✓	√ ✓	✓	✓ ✓ ✓	
R ² Observations	0.772 44,681,890	0.785 44,681,890	0.773 44,681,890	0.786 44,681,890	

[▶] Event study

[▶] Back to inflow regression table

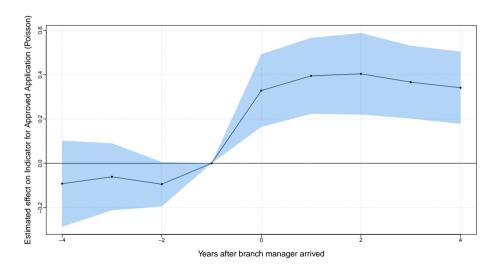
[▶] Back to baseline event study

Probability of requesting, Poisson



[▶] Back to request probability table

Approval probability, Poisson



[▶] Back to approval probability table

Effects on interest rate based on loan type

- 1. Comparing switchers to their other relationships:
 - Decrease driven by credit lines

 Within switchers
- 2. Comparing switchers to new relationships of portfolio members:
 - Decrease driven by credit lines, increase in int. rate for term loans
- ► Switchers vs new portfolio

- 3. Comparing switchers to old relationships of portfolio members:
 - Decrease mostly in credit lines Switchers vs old portfolio
- 4. Comparing switchers to new relationships of their new branch:
 - Almost zero effect ► Switchers vs new branch
- 5. Comparing switchers to their old relationships:
 - Generalized decrease, mostly in credit lines

 ► Switchers vs old branch

Comparing switchers to their other relationships

	Average rate (2y) (1)	Average self-liquidating rate (2y) (2)	Average credit line rate (2y) (3)	Average rate, term loans (2y) (4)
Manager inflow	-0.505* (0.264)	0.069 (0.582)	-0.641 (1.87)	0.111 (0.188)
Log. average credit (2y)	-0.555*** (0.019)			
Log. average self-liquidating credit (2y)		-0.302*** (0.008)		
Log. average credit line credit (2y)		(====,	-1.00*** (0.036)	
Log. average credit, term loans (2y)			(-1)	-0.117*** (0.006)
R^2	0.198	0.249	0.161	0.313
Observations Dependent variable mean	6,643 2.55	4,562 4.93	4,559 11.5	4,420 3.07



Comparing switchers to new relationship of portfolio members

	Average rate (2y) (1)	Average self-liquidating rate (2y) (2)	Average credit line rate (2y) (3)	Average rate, term loans (2y) (4)
Manager inflow	-0.657 (0.699)	0.956 (0.733)	-6.34*** (2.30)	0.529*** (0.151)
Log. average credit (2y)	-0.669*** (0.004)			
Log. average self-liquidating credit (2y)		-0.366*** (0.002)		
Log. average credit line credit (2y)		,	-0.896*** (0.014)	
Log. average credit, term loans (2y)			,,	-0.130*** (0.002)
R ²	0.197	0.221	0.090	0.334
Observations Dependent variable mean	23,609 2.53	15,355 4.88	14,654 11.6	15,955 2.72



Comparing switchers to old relationship of portfolio members

	Average rate (2y) (1)	Average self-liquidating rate (2y) (2)	Average credit line rate (2y) (3)	Average rate, term loans (2y) (4)
Manager inflow	-0.289* (0.172)	-0.063 (0.320)	-0.145 (0.788)	0.088 (0.143)
Log. average credit (2y)	-0.716*** (0.003)			
Log. average self-liquidating credit (2y)		-0.348*** (0.002)		
Log. average credit line credit (2y)		,,	-0.940*** (0.005)	
Log. average credit, term loans (2y)			(-1,	-0.096*** (0.001)
R^2	0.188	0.222	0.112	0.187
Observations Dependent variable mean	35,585 2.92	24,317 5.21	26,483 11.6	22,209 3.43



Comparing switchers to new relationships of their branch

	Average rate (2y) (1)	Average self-liquidating rate (2y) (2)	Average credit line rate (2y) (3)	Average rate, term loans (2y) (4)
Manager inflow	0.050 (0.144)	-0.148 (0.269)	-0.171 (0.594)	0.065 (0.125)
Log. average credit (2y)	-0.268*** (0.004)			
Log. average self-liquidating credit (2y)		-0.037*** (0.0004)		
Log. average credit line credit (2y)		,,	-0.152*** (0.002)	
Log. average credit, term loans (2y)			, , , ,	-0.065*** (0.0003)
R ²	0.123	0.166	0.042	0.271
Observations Dependent variable mean	68,555 2.60	43,288 5.34	41,535 12.2	49,168 3.15



Comparing switchers to their old relationships

	Average rate (2y) (1)	Average self-liquidating rate (2y) (2)	Average credit line rate (2y) (3)	Average rate, term loans (2y) (4)
Manager inflow	-0.926*** (0.195)	-0.780** (0.339)	-3.85* (2.28)	-0.024 (0.289)
Log. average credit (2y)	-0.773*** (0.097)			
Log. average self-liquidating credit (2y)		-0.213*** (0.025)		
Log. average credit line credit (2y)		(,	-1.13*** (0.224)	
Log. average credit, term loans (2y)			, <i>,</i>	-0.053 (0.043)
R ²	0.311	0.408	0.281	0.386
Observations Dependent variable mean	1,387 2.93	930 5.44	1,008 11.9	906 3.34



Npl probability for risky firms

Non-perform	ming loan
-------------	-----------

	Within switchers	Portfolio new	Portfolio old	New branch
Switcher	-0.015**	-0.008	-0.021**	-0.043**
	(0.006)	(0.007)	(0.011)	(0.019)
Switcher \times Risky	0.011	-0.037**	0.012	-0.0007
	(0.015)	(0.017)	(0.014)	(0.011)
R^2	0.115	0.101	0.055	0.048
Observations	13,320	45,700	65,195	187,389
Dependent variable mean	0.017	0.027	0.015	0.016

Npl regressions: full tables

- 1. Comparing switchers to their other relationships:
 - Most effects in the first year Within switchers
- 2. Comparing switchers to new relationships of portfolio members:
 - Almost no effect Switchers vs new portfolio
- 3. Comparing switchers to old relationships of portfolio members:
 - Effect is consistent in time Switchers vs old portfolio
- 4. Comparing switchers to new relationships of their new branch:
 - Strongest and most persistent effect Switchers vs new branch



Comparing switchers to their other relationships

	Npl probability (0 years)	Npl probability (1 year)	Npl probability (2 years)
	(1)	(2)	(3)
Manager inflow	-0.014**	-0.007	0.016
	(0.006)	(0.011)	(0.020)
Log. average self-liquidating credit (2y)	-0.0009***	-0.0006**	-0.0006
	(0.0003)	(0.0003)	(0.0004)
Log. average credit line credit (2y)	8.82×10^{-5} (0.0004)	0.0002 (0.0005)	0.0005 (0.0005)
Log. average credit, term loans (2y)	0.0007***	0.001***	0.002***
	(0.0002)	(0.0003)	(0.0004)
R^2	0.115	0.125	0.128
Observations	13,320	12,604	11,413
Dependent variable mean	0.017	0.023	0.030



Comparing switchers to new relationship of portfolio members

	Npl probability (0 years) (1)	Npl probability (1 year) (2)	Npl probability (2 years) (3)
Manager inflow	-0.011 (0.007)	-0.003 (0.008)	0.012 (0.014)
Log. average self-liquidating credit (2y)	-0.001*** (0.0003)	-0.001*** (0.0003)	-0.0009* (0.0005)
Log. average credit line credit (2y)	-0.0002 (0.0005)	3.98×10^{-5} (0.0005)	0.0006
Log. average credit, term loans (2y)	0.0009*** (0.0001)	0.001*** (0.0002)	0.002*** (0.0003)
R^2	0.101	0.109	0.117
Observations	45,700	40,370	30,536
Dependent variable mean	0.027	0.035	0.043



Comparing switchers to old relationship of portfolio members

	Npl probability (0 years) (1)	Npl probability (1 year) (2)	Npl probability (2 years) (3)
Manager inflow	-0.020*	-0.017	-0.015
	(0.011)	(0.011)	(0.015)
Log. average self-liquidating credit (2y)	-0.0003**	-0.0003	-0.0002
, , , , ,	(0.0002)	(0.0002)	(0.0003)
Log. average credit line credit (2y)	-0.0002	6.14×10^{-5}	0.0003
	(0.0003)	(0.0003)	(0.0004)
Log. average credit, term loans (2y)	0.0005***	0.0008***	0.001***
, ,	(0.0001)	(0.0002)	(0.0002)
R^2	0.055	0.061	0.066
Observations	65.195	65.140	64,991
Dependent variable mean	0.015	0.023	0.032



Comparing switchers to new relationships of their branch

	Npl probability (0 years) (1)	Npl probability (1 year) (2)	Npl probability (2 years) (3)
Manager inflow	-0.043** (0.019)	-0.043*** (0.008)	-0.030*** (0.008)
Log. average self-liquidating credit (2y)	-0.001***	-0.0005***	0.0001
	(0.0001)	(4.88×10^{-5})	(0.0001)
Log. average credit line credit (2y)	0.0005** (0.0002)	0.0006** (0.0002)	0.001*** (0.0002)
Log. average credit, term loans (2y)	0.0003**	0.0008***	0.001***
	(0.0001)	(5.37×10^{-5})	(4.37×10^{-5})
R^2	0.048	0.042	0.041
Observations	187,389	167,876	142,976
Dependent variable mean	0.016	0.025	0.032

