Gong, Di; Ongena, Steven; Qi, Shusen; Yu, Yanxin

Working Paper

Information frictions inside a bank: Evidence from borrower switching between branches

BOFIT Discussion Papers, No. 7/2025

Provided in Cooperation with:
Bank of Finland, Helsinki

BOFIT Discussion Papers
7 • 2025

Di Gong, Steven Ongena, Shusen Qi
and Yanxin Yu

Information frictions inside a bank: Evidence from borrower switching between branches

BOFIT
THE BANK OF FINLAND
INSTITUTE FOR
EMERGING ECONOMIES

BOFIT Discussion Papers
Editor-in-Chief Zuzana Fungáčová

BOFIT Discussion Papers 7/2025
29 October 2025

Di Gong, Steven Ongena, Shusen Qi and Yanxin Yu:
Information frictions inside a bank: Evidence from borrower switching between branches

ISSN 1456-5889, online

Bank of Finland
Helsinki 2025

Di Gong, Steven Ongena, Shusen Qi and Yanxin Yu

Information frictions inside a bank: Evidence from borrower switching between branches

Abstract

Banks are multidivisional organizations in which branches hold local knowledge about borrowers. Can this “soft” information be transmitted across units? Studying the population of corporate loans originated by a large commercial bank in China from 2010 to 2020, we find that when firms switch branches within bank, the switching loans carry a significantly lower spread than comparable nonswitching loans. After switching, the new branch further reduces the loan spreads initially, but ratchets it up afterwards, surprising evidence of intra-bank hold-up. By documenting how internal communication failures distort lending, we link relationship banking with delegation, coordination, and information transmission within organizations.

Keywords: organization structure, bank lending, hold-up, firm-bank relationship
JEL: G21, G32, L14

Di Gong, orcid.org/0000-0003-1197-3804. China School of Banking and Finance at University of International Business and Economics. E-mail: d.gong@uibe.edu.cn.

Steven Ongena, orcid.org/0000-0002-8381-0062. University of Zurich, Swiss Finance Institute, KU Leuven, NTNU Business School, and CEPR. E-mail: steven.ongena@df.uzh.ch.

Shusen Qi, orcid.org/0009-0009-7794-7570. School of Management at Xiamen University and the Institute of Digital Finance at Peking University. E-mail: shusenqi@xmu.edu.cn.

Yanxin Yu, China School of Banking and Finance at University of International Business and Economics. E-mail: yanxin.yu@uibe.edu.cn.

For helpful comments and discussions, we thank Felix Corell, Iftekhar Hasan, Difang Huang, Cédric Huylebroek, Sushanta Mallick, Gregor Matvos, Yun Wang, Chun Kuang, and participants at the IBEFA-FUNCAS 2025 Workshop on “Frontier Research in Financial Intermediation”, ECMI/NBS/CEPS/SUERF Research Conference, 6th Vassa Banking Research Workshop, 2025 China Financial Research Conference, CCER Summer Institute 2025, 24th China Economics Annual Conference, China Corporate Finance Summer Forum (2024), Bank of Finland, Shandong University, Xiamen University, and University of International Business and Economics. The paper was previously circulated under the title ““Time for a Change of Scenery”: Loan Conditions When Firms Switch Bank Branches.”

Non-technical summary

Focus

Banks rely heavily on information when making lending decisions, but this information—especially "soft," relationship-based knowledge—is often local and difficult to communicate across organizational units. The paper asks whether such information frictions exist within banks themselves, not just between different banks. Using the universe of over 119,000 corporate loans made by a large Chinese commercial bank from 2010 to 2020, we examine what happens when a firm changes from one branch of the same bank to another. Do the new branches fully inherit the borrower's past credit knowledge, or does the borrower experience disruptions similar to switching to a new bank?

Contribution

The study makes two key contributions. First, it provides the first empirical evidence of intra-bank "hold-up", showing that informational frictions and rent-extraction dynamics can occur even within a single financial institution. Second, it bridges relationship banking and organizational economics by demonstrating that internal communication failures between branches distort credit pricing, consistent with theories of delegation and limited information transmission inside firms.

Findings

When firms move to a new branch, their initial loans carry interest spreads about 6 basis points lower than comparable loans, but rates rise within a year as the new branch rebuilds private knowledge—clear evidence of intra-bank hold-up. The effect disappears when the original manager moves with the borrower or when FinTech and mandatory information disclosure improve data sharing. Intra-bank hold-up disproportionately harms small and private firms, raising their borrowing costs and reducing access to credit. Policy reforms that enhance information transparency and digital integration thus not only improve fairness and competition within banks but also promote more efficient credit allocation and financial inclusion.

1. Introduction

How effectively organizations collect, transmit, and act upon information lies at the heart of their performance. Banks are no exception. They are large, multi-unit organizations in which lending decisions rely on information that is often dispersed across hierarchies and geographies. A crucial insight from organizational economics is that information, particularly "soft" or qualitative information, is difficult to transmit across units. This creates a tension between local adaptation and centralized coordination (Aghion and Tirole, 1997; Garicano, 2000; Stein, 2002; Dessein, 2002; Harris and Raviv, 2005; Alonso et al., 2008). While banks operate under unified ownership and capital structures, their vast branch networks mean that the internal organization of information can resemble that of federated firms, with each branch possessing unique knowledge of local borrowers. Recent work also emphasizes that organizational design and delegation choices are deeply influenced by information frictions and the structure of decision-making authority (Romero and Freitas, 2022; Malenko, 2023; Alfaro et al., 2024).

This observation raises a fundamental question: to what extent do informational frictions exist not just across banks, but within banks themselves? The literature on relationship lending and hold-up has long emphasized the difficulties borrowers face when switching between banks (Sharpe, 1990; Rajan, 1992; Dell'Ariccia and Marquez, 2004). Because soft information is relationship-specific and context-dependent, it cannot easily be codified and transmitted to new lenders, leaving borrowers vulnerable to rent extraction (Petersen and Rajan, 1994; Berger and Udell, 1995; Liberti and Petersen, 2019). [1] Empirical contributions, such as Ioannidou and Ongena (2010), document how firms switching banks initially enjoy lower interest rates but eventually face higher rates

[1] Soft information is mostly collected in person and is often used by the same person that "the loan officer has a history with the borrower and, based on a multitude of personal contacts, has built up an impression of the borrower's honesty, creditworthiness, and likelihood of defaulting. Based on this view of the borrower and the loan officer's experience, the loan is approved or denied" (op. cit., p. 5). Uzzi and Lancaster (2003) provide a more detailed description of the interactions between borrowers and loan officers in banking.

as the new bank exploits its informational advantage.[2] This dynamic cycle of discounts followed by rent extraction has since been replicated across different settings (Barone et al., 2011; Gopalan et al., 2011; Stein, 2015; Sutherland, 2018; Bonfim et al., 2021; López-Espinosa et al., 2017; Sutherland, 2018; Kalda and Neshat, 2024).[3]

Yet this literature has overwhelmingly focused on *inter-bank* switching. Whether similar frictions arise within banks, when borrowers switch branches, remains an open question. On one hand, one might expect internal information systems, common ownership, and reputational considerations to ensure the seamless transfer of borrower information across branches. On the other hand, organizational theory suggests otherwise. Dessein (2002) demonstrates that even within firms, communication of soft information is strategic and noisy, creating a trade-off between control and effective information use. Alonso et al. (2008) show that decentralized divisions with private information may struggle to coordinate unless they credibly communicate. Applied to banking, these theories imply that branch-level incentives and organizational frictions can hinder the flow of information across branches, even within the same institution (Stein, 2002).[4] Liberti and Mian

[2] In Ioannidou and Ongena (2010), Bolivian firms initially receive an 89 basis points (bps) (≅ 7% of the average loan rate) discount when switching banks but eventually ratcheting it up sharply. This cycle explains the difference between switching and transferring loans. According to Von Thadden (2004), when firms are forced to transfer, the outside banks would pool-price the arriving firms and the rates being charged would depend on the average of firms' dynamic cycles. In contrast to switching loans, which always happen at the end of the cycle, loans could be forced to transfer at all stages of the cycle. As a result, the level of transferring cost depends on the position of the averaging cycle. For example, Bonfim et al. (2021) show that when firms are forced to transfer to other banks due to the closure of nearby branches of their current banks, they receive no discount at the time of transfer. Xu et al. (2020) find that when firms are forced to transfer from existing branches to the newly established ones, on average, they even have to pay higher interest rates. Thus, the switching discount, and the related dynamic cycle, can be more precisely identified in switching than in transferring. As a result, our paper focuses on loan switching.

[3] Barone et al. (2011) find a discount of 44 bps in Italy, Stein (2015) finds an average discount for main bank borrowers of 33 bps in Germany, while Bonfim et al. (2021) finds a 63 bps discount in Portugal. Xu et al. (2020) and Liaudinskas (2024) study loan pricing when firms are forced to transfer, while Cao et al., (2024) study pricing when firms switch banks on their deposit and/or credit relationships.

[4] If soft information cannot be communicated freely within the same bank, intra-bank competition across branches or even among loan officers may become possible (Blackwell et al., 1994; Seltzer and Frank, 2007; Xie et al., 2019). For example, loan officers might not truthfully reveal the soft information they collected to the bank (Heider and Inderst, 2012). When loan officers are on leave,

(2009) and Liberti (2017) show that organizational hierarchies and delegation of authority affect loan officers' production and usage of (soft) information in lending decisions. If so, borrowers may face hold-up not only from banks as corporate entities but also from individual branches within them.

This paper provides the first empirical evidence of such *intra-bank* hold-up. Using the complete population of 119,270 corporate loans issued by a large Chinese commercial bank between 2010 and 2020, we examine loan conditions when firms switch from one branch of the bank to another. The dataset allows us to track firms over time, identify the specific branches originating loans, and precisely compare loan terms between switching and non-switching relationships.[5] Our identification strategy follows the empirical design pioneered by Ioannidou and Ongena (2010), enabling us to isolate dynamic patterns in loan spreads while focusing on the novel margin of intra-bank switching.

Our findings reveal that when firms switch branches—moving from their incumbent "inside" branch to a new "outside" branch within the same bank—their new loans carry an average loan spread that is 6 bps lower (≅ 1% of the average loan rate, or ≅ 7% of the average loan spread) than those on comparable new loans issued to existing customers. This initial spread reduction further deepens by an additional 18 bps during the first two quarters following the switch. However, within a year, these switching firms are charged loan rates that return to the average spread and eventually exceed it. While the magnitude of this cycle is smaller than that observed in inter-bank switching studies, its very presence is striking

their related borrowers are less likely to receive new loans from the bank and are more likely to switch banks, indicating that soft information comes with the person rather than the bank (Drexler and Schoar, 2014). But the impact is less obvious when loan officers have incentives to transfer the soft information to the bank, as in the case of voluntary resignations. Goedde-Menke and Ingermann (2024) uses a wave of early loan officer retirements as a quasi-natural experiment and finds that the shock increases default rates due to an inferior production of default risk information. Loan officers are likely to adjust their behavior in response to their self-interest, such as compensation incentives and career concerns (Tzioumis and Gee, 2013; Cole, Kanz et al., 2015; Qian et al., 2015).

[5] The loan portfolio of this bank is large so that we can observe 7,628 branch-switching loans. Recall that Ioannidou and Ongena (2010) and Bonfim et al. (2021) study 1,062 and 24,292 bank-switching loans, respectively.

given that both branches operate under the same bank's ownership and information systems. These results suggest that the transmission of soft information across branches is limited, and that intra-bank organizational frictions meaningfully shape loan pricing.

We substantiate the existence of intra-bank hold-up through five key analyses. First, we explore cases where the branch manager transitions alongside the borrower to the new branch. As anticipated, we find no evidence of hold-up in these cases, implying that the manager's transfer mitigates the loss of soft information. Second, we examine the geographical proximity of switching branches and find that switching costs are economically smaller when firms switch to nearby branches, suggesting that local competition constrains the pricing power of incumbent branches. Third, we observe that switching to newly established branches results in a significantly larger spread reduction (27 bps ≅ 5% of the average loan rate, or ≅ 31% of the average loan spread), indicating that the hold-up effect intensifies when incumbent branches face minimal competitive pressure. Fourth, leveraging a natural experiment of China' Social Credit System (SCS), we provide evidence that mandatory information disclosure significantly mitigates firms' hold-up costs. By enhancing the corporate information accessible to bank branches, such disclosure policies diminish the informational advantages historically held by incumbent branches, thereby lowering switching frictions and hold-up costs. Fifth, we demonstrate that deeper FinTech adoption mitigates hold-up by transforming traditionally soft information into hard, quantifiable data. This digital transformation not only strengthens the information flow between borrowers and bank branches but also reduces the asymmetry that typically drives hold-up problems (Malenko, 2023; Alfaro et al., 2024).

Beyond pricing dynamics, we also uncover important welfare implications of intra-bank hold-up. Branches that strategically exploit their informational advantage engage in rent extraction, raising borrowing costs for smaller and more financially constrained firms. These branches benefit from improved credit portfolio quality, as higher rates screen out weaker borrowers and reduce non-performing loans, but they do so at the expense of scale, market share, and inclusivity. In effect, hold-up strategies enhance branch-level credit risk profiles while reducing allocative efficiency and access to finance. This trade-off underscores how intra-bank organizational incentives influence not only distributional outcomes across firms but also the aggregate efficiency of credit markets (Garicano, 2000; Romero and Freitas, 2022; Malenko, 2023).

While alternative mechanisms such as competition via teaser pricing, selection-on-offer, and borrower inertia could, in principle, explain some aspects of our findings, the weight of the evidence favors the organizational economics explanation of intra-bank hold-up driven by information frictions. For example, teaser pricing would predict that outside branches aggressively target larger and more transparent firms, yet we find that opaque borrowers, SMEs and private firms, experience the largest initial discounts, inconsistent with that story. Borrower-driven selection also fails to account for our findings, as it neither explains the disappearance of the discount when branch managers co-move with the borrower nor the attenuation of hold-up effects following the introduction of the SCS or FinTech adoption, both of which reduce information asymmetries. Similarly, if switching were purely driven by behavioral inertia, we would expect stable loan spreads rather than the observed overshooting above market rates over time, a pattern consistent with the gradual rebuilding of informational leverage by the new branch. Collectively, these empirical patterns align closely with the predictions of organizational economics models of hold-up under limited communication and transferability of soft information (Stein, 2002; Alonso et al., 2008), and they are difficult to reconcile with competing explanations.

Our paper makes three main contributions. First, we provide the first systematic evidence of *intra-bank* hold-up. While the classic literature emphasizes the inability to transfer relationship-specific information across banks (Sharpe, 1990; Rajan, 1992; Ioannidou and Ongena, 2010), we show that similar frictions exist even within a single institution. Borrowers switching branches face temporary discounts followed by higher spreads, revealing that hold-up dynamics arise inside banks as well as between them. In this sense, our research advances the understanding of how banks collect, process, and transmit soft information. Prior studies have established that information asymmetries can distort credit allocation, enabling banks to charge rates that exceed borrower quality (Kim et al., 2003; Ioannidou and Ongena, 2010; López-Espinosa et al., 2017; Bertrand and Burietz, 2023) or reallocate credit selectively (Dell'Ariccia and Marquez, 2004; Sette and Gobbi, 2015; Beck, et al., 2018). Our findings suggest that intra-bank hold-up may exacerbate these distortions, further questioning the efficient functioning of credit markets.

Second, we connect relationship banking to organizational economics. Banks resemble multidivisional firms in which branch managers hold critical private information. Our findings align with the theoretical predictions of Dessein (2002) and Alonso et al. (2008): communication of soft information is noisy, delegation creates informational trade-offs, and coordination failures emerge when internal incentives are misaligned. By documenting how these frictions shape credit terms, we bring organizational economics to bear on relationship lending, complementing the empirical literature on soft information (Berger et al., 2005; Liberti and Petersen, 2019).

Third, we highlight the policy and welfare implications of intra-bank frictions. We show that FinTech adoption and mandatory disclosure reforms mitigate intra-bank hold-up by transforming soft into hard information, facilitating transferability across branches. While hold-up strategies improve the credit quality of branch portfolios, they do so at the cost of higher borrowing costs for constrained firms and reduced market share. These findings underscore how organizational design, regulation, and digital transformation jointly affect credit allocation and financial efficiency (Jayaratne and Strahan, 1996; Berger et al., 1997; Jayaratne and Strahan, 1998; Black and Strahan, 2002; Morgan et al. 2004; Degryse and Ongena, 2007; Hirtle, 2007; Beck et al., 2010; Ergungor, 2010; Gilje et al., 2016; Goetz, 2018; Nguyen, 2019; Keil and Ongena, 2024).

The remainder of the paper is structured as follows: Section 2 introduces the banking system in China and its branching network. Section 3 describes the dataset and presents summary statistics. Section 4 outlines the empirical strategy and discusses the findings. Section 5 concludes.

2. Banking system and branching architecture in China

Commercial banks in China maintain extensive branch networks across the country, a structural necessity given the nation's geographic and economic scale. These branch networks make Chinese banks archetypical multidivisional organizations: branches operate within a hierarchical framework that is coordinated by the bank's headquarters, while individual branches serve as the primary interface for delivering a diverse array of banking services. In organizational economics terms, banks must resolve the classic trade-off between coordination and adaptation (Stein, 2002; Dessein, 2002; Alonso et al., 2008). Headquarters can centralize decision-making to ensure consistency, but doing so risks ignoring the rich soft information generated locally. Conversely, granting branches autonomy allows them to tailor lending to local borrower conditions but makes internal coordination and information transfer more difficult.

This organizational tension is particularly relevant in the Chinese context. Regulatory reforms since the 1990s have gradually decentralized decision-making to branch-level units, allowing them to better exploit local informational advantages (Park and Shen, 2008; Qian et al., 2015). At the same time, banks rely on tournament-style performance evaluations that compare branches against each other (Xie et al., 2019). These evaluation systems strengthen incentives for branch managers to guard their informational advantage, much like divisional managers in multidivisional firms (Blackwell et al., 1994; Seltzer and Frank, 2007; Tzioumis and Gee, 2013).[6] As organizational economics predicts, this can lead to strategic communication failures: branches may not share soft information fully, and instead act as semi-autonomous units competing for clients (Dessein, 2002).

To empirically assess the prevalence and perception of such competitive dynamics and information flow barriers, we conducted an online survey targeting

[6] The tournament theory suggests that the outcome of competition within an organization is based on the relative performance evaluations, and promotions are awarded to those who achieve higher ranks (Lazear and Rosen, 1981; Connelly et al., 2014).

bank employees across China. The survey was administered in early 2024 and yielded 301 qualified responses within one week. Of these, 160 were from employees at bank headquarters and 141 from those stationed in branches. Given the study's focus on intra-bank competition and information sharing at the branch level, we restricted our analysis to the latter subgroup. Branch-level employees are more likely to possess direct insights into inter-branch dynamics and communication practices. The resulting sample comprises 141 respondents from branches located in 18 different provinces across China.[7] The original questionnaire was developed and administered in Chinese; an English translation is provided in Appendix B for reference. The survey comprises three core sections: intra-bank competition, internal information sharing, and the role of FinTech in banking operations.[8] For each question, respondents selected from a five-point Likert scale: Strongly disagree, Disagree, Neutral, Agree, and Strongly agree.

Our survey corroborates our interpretation. As shown in Figure 1, 69% of respondents reported that performance evaluations prioritize comparisons across branches within the same bank over comparisons with external institutions. Similarly, 78% noted that intra-bank rankings influence personnel assessments. Strikingly, 76% of respondents state that branches within the same bank actively compete for customers. Turning to Figure 2, while a majority of respondents recognize that their banks encourage internal information sharing, 30% report clear deficiencies in formal communication, and 22% highlight informal communication breakdowns. These patterns closely resemble the dynamics emphasized by Alonso et al. (2008): when divisions compete and incentives are not perfectly aligned, horizontal communication is limited, and the internal flow of information becomes strategically distorted.

[7] To further contextualize the responses, we distinguished between employees affiliated with the bank from which we obtained our loan-level data and those employed by other institutions. Of the 141 branch respondents, 26 were from our focal bank, while 115 represented other Chinese banks. To protect respondent confidentiality, we did not request specific institutional affiliations beyond this distinction. Notably, the responses between these two groups were largely consistent. Therefore, unless otherwise indicated, our analysis does not differentiate between them.

[8] Discussion on the application of FinTech will be presented in Section 4.6.

[Insert Figure 1 and 2 here]

The branching architecture of Chinese banks can thus be viewed through the lens of organizational economics. Banks resemble multidivisional firms in which local managers possess valuable private information but face weak incentives to communicate it. The trade-off between centralized coordination and local adaptation (Stein, 2002) is intensified by performance tournaments that heighten competition among branches. Consistent with Dessein (2002), authority is delegated to branches precisely because soft information cannot be easily codified or transmitted upwards, yet this same decentralization makes coordination across branches more difficult. Alonso et al. (2008) predict that when internal competition is strong, divisions will hold some information and under-communicate information to protect their rents, a mechanism that fits squarely with the evidence from our survey.

Framing Chinese banks in this way provides more than institutional background; it highlights a theoretical tension at the core of our analysis. If soft information does not flow seamlessly across branches, then borrowers switching branches may face informational frictions analogous to switching across banks, leading to intra-bank hold-up. Our empirical analysis leverages this organizational setting to test whether these predicted frictions manifest in loan pricing and borrower outcomes.

The setting examined is not unique to China, nor is the tension exclusively observed in Chinese banks. Utilizing data from the Argentinian branch of a major multinational U.S. bank, Hertzberg et al. (2010) demonstrate that career concerns and local control distort communication, whereas rotation helps realign incentives.

3. Data and descriptive statistics

Our empirical analysis is based on a proprietary dataset obtained from a major commercial bank in China. This institution operates nationwide, with approximately 300 branches located across more than 20 cities. Due to confidentiality agreements, we are unable to disclose the bank's identity. The dataset comprises the full population of 119,270 newly initiated corporate loans issued between 2010 and 2020, extended to 27,118 distinct firms operating in 203 cities.[9] By restricting the analysis to new loan originations, we ensure temporal alignment between loan-level contract data and firm-specific information, thereby capturing firm-branch matching dynamics at the precise moment when a firm initiates a new lending relationship. The geographical distributions of borrowers and loans in terms of value are listed in Appendix Figure A1.

For each loan, the dataset includes detailed information on contract terms, borrower characteristics, and the originating branch. The loan contract data cover origination and maturity dates, interest rates, loan amounts, collateral status (with 89% of loans secured), internal loan ratings (pass=1, special attention, sub-standard, doubtful, and write-off=5), and whether the loan is part of a credit line (which applies to 77% of cases). Borrower-level data include geographic location, industry classification, legal form (with 98% identified as corporations, and the remainder as partnerships, collectives, sole proprietorships, public institutions, and other organizational types), ownership structure (92% private firms, 8% state-owned enterprises or government-related entities), and firm size (78% small and medium-sized enterprises; 22% large firms). To protect borrower confidentiality, firm identifiers have been anonymized, preventing linkage to external financial statement databases.

A distinctive feature of the dataset is its capacity to track the issuing branch for each loan. The branch-level data include geographic location, identity codes, and establishment dates. These attributes allow us to construct novel measures of firm-branch relationship intensity. We quantify relationship duration as the number of months between a firm's first loan from a given branch and the current loan origination. Relationship density is measured as the number of loans issued by the same branch to the same firm within the preceding five years. Furthermore, we

[9] Ioannidou and Ongena (2010) observe 33,084 loan initiations to 2,805 firms between March 1999 and December 2003, while Bonfim et al. (2021) observe 1,364,250 loan initiations to 94,281 firms between June 2012 and May 2015.

construct a binary indicator for whether a firm simultaneously maintains lending relationships with multiple branches.

The institutional context of interest rate policy in China further informs our empirical framework. Since the mid-1990s, the People's Bank of China (PBoC) has gradually liberalized interest rates (Kim and Chen, 2022). The reform began with the liberalization of interbank rates, followed by the incremental expansion of the permissible range around benchmark lending and deposit rates. Key milestones occurred in 2004, 2013, and 2015, when the PBoC sequentially removed the upper and lower bounds of interest rates. These reforms culminated in the adoption of a market-oriented interest rate corridor system. Throughout this period, the policy benchmark rate remained a salient reference point for banks in pricing loans. Between 2010 and 2020, the PBoC adjusted the policy rate 21 times, with the cumulative magnitude of changes reaching up to 280 bps. Because the focal bank's pricing strategy emphasizes risk premiums rather than nominal interest rates, our primary outcome variable is the loan spread above the prevailing PBoC benchmark rate. However, our empirical findings remain robust when using nominal loan rates as an alternative specification (see columns 5-6 of Appendix Table A1).

Descriptive statistics from the dataset reveal that the average new loan carries a spread of 88 bps, has a maturity of approximately one year, and an average principal of CNY 23.7 million. Firms in the sample typically receive three loans annually from the focal bank, while an average branch originates 216 loans per year. Over the sampling period, each branch engages with an average of 507 unique borrowing firms. In terms of lending relationships, 39% of firms maintain simultaneous ties with multiple branches. Among single-branch relationships, the average duration is 32 months, with firms obtaining approximately six loans from the same branch during that period.

4. Results

4.1. Switching

Following the seminal framework of Ioannidou and Ongena (2010), we investigate the presence and implications of relationship lending within banks by examining changes in loan conditions when firms switch branches of the same bank. Specifically, we define a new loan as a "switch" (or a switching loan) when the borrowing firm receives credit from a branch with which it had no lending relationship in the preceding 12 months. We refer to such a branch as an "outside branch". This definition relies on the assumption that critical soft information from prior lending relationships deteriorates over a one-year horizon—an assumption consistent with the literature. Our findings remain robust to alternative cutoffs of 24 and 36 months (see columns 1-4 of Appendix Table A1). In line with Ioannidou and Ongena (2010), we do not distinguish between firms that "move" from one branch to another and those that "add" a new branch relationship. The rationale is that existing exposures often persist after the switch, making it difficult—both operationally and conceptually—to disentangle movers from adders. We then designate branches that extended credit to a firm within the prior 12 months as "inside branches," and define new loans issued by these branches to their existing customers as "nonswitching loans".

[Insert Figure 3 here]

Figure 3 illustrates this classification using a stylized example. Consider firm A and four bank branches (1, 2, 3, and 4). The solid lines represent ongoing loan relationships, while the dashed line denotes a newly issued loan at time t = 0. Firm A receives this new loan from branch 3, which had not engaged in lending to the firm over the prior 12 months. Branch 3 is therefore identified as an outside branch, and the loan is classified as a switching loan. In contrast, branches 1, 2, and 4 had existing relationships with the firm during the preceding year and are categorized as inside branches. Loans from these branches to firm A during the same period are classified as nonswitching loans.

Applying this definition to our dataset, we identify 7,628 switching loans, accounting for approximately 7% of all loan originations during the 2010–2020 sampling period. These loans were extended to 6,170 firms, suggesting that around 22% of firms in our sample switched branches at least once over the decade (an annual switching rate of 2.2%). This frequency is notably lower than the interbank switching rates reported in Farinha and Santos (2002) and Ioannidou and Ongena (2010), who report annual rates of 4% and 4.5%, respectively. The relative infrequency of intra-bank switching is intuitively sensible that switching within a bank is less necessary than switching across banks.

[Insert Table 1 here]

Table 1 presents descriptive statistics comparing switching and nonswitching loans. While the median loan spread is identical across groups (87 bps), switching loans exhibit a slightly higher mean spread (90 bps) than nonswitching loans (88 bps). However, this difference may reflect underlying heterogeneity between the loan types. Specifically, switching loans tend to be smaller in size, longer in maturity, more frequently collateralized, higher in internal credit ratings, and less likely to be associated with a credit line. Additionally, they are more commonly issued to SMEs and reflect weaker prior lending relationships with the originating branch. These patterns suggest that outside branches may systematically differ in both the firms they choose to finance and the contract terms they offer. Consequently, to draw valid inferences about switching costs, it is essential to control for observable firm and loan characteristics—a task we address using a rigorous matching approach.

4.2. Matching

To estimate switching costs, we ideally seek to compare the interest rate that the firm received from the outside branch with the rate it would have obtained from one of its inside branches at the same point in time. However, we do not observe counterfactual offers from the firm's incumbent branch. To approximate this unobserved benchmark, we adopt the matching strategy developed by Ioannidou and Ongena (2010). Specifically, we compare the switching loan to a set of similar loans extended by the firm's inside branches in the same month to other comparable firms. Additionally, we conduct a parallel analysis comparing the switching loan to similar loans granted by the outside branch to its existing customers at the same time. These two complementary matching strategies allow us to isolate the role of relationship history while accounting for potential branch-specific pricing behavior.

Figure 4 illustrates the first matching design. At time t = 0, the switching loan is granted by branch 3 (an outside branch). We match this loan to nonswitching loans made during the same month by the firm's inside branches—branches 1, 2, and 4—to other firms with similar observable characteristics. In the second strategy, depicted in Figure 5, we again focus on the switching loan from branch 3 at time t = 0. This time, we match it with nonswitching loans that branch 3 issued to its existing clients during the same month. This enables us to control for unobserved pricing norms or regional factors specific to the outside branch.

[Insert Figures 4 and 5 here]

Table 2 describes the variables used in the matching procedure. In both strategies, we match on the loan origination month, branch identity (inside or outside), and a rich set of borrower and contract characteristics. These include loan amount, maturity, collateral status, presence of a credit line, firm location, industry, legal form, ownership type, and firm size. To further mitigate bias from unobserved heterogeneity, we also include the bank's internal credit rating for each loan—an informative proxy for borrower risk that is observable to the bank but not externally available. As a robustness check, we also match using the borrower's most recent credit rating prior to switching, which helps address concerns regarding potential rating inconsistencies arising from information asymmetries between branches. However, since we analyze switching behavior within the same bank, such asymmetries are arguably less severe than in interbank settings. Finally, by matching on both the origination month and loan maturity, we control for temporal variation in economic conditions and interest rate expectations, ensuring that the observed differences in loan spreads are not confounded by broader macroeconomic trends.

[Insert Table 2 here]

Our estimation strategy proceeds in three steps. First, for each switching loan, we identify a set of matched nonswitching loans issued during the same month by the firm's inside or outside branches to similar borrowers.[10] Second, we compute the difference in loan spreads between the switching loan and each matched nonswitching loan. Third, we regress the differences in spreads on a constant term. A statistically significant negative constant would indicate that, on average, switching loans are priced more favorably than comparable nonswitching loans, which we interpret as evidence of switching costs due to hold-up. Importantly, any residual bias from unobservable borrower characteristics would likely attenuate our estimates, rendering them a conservative lower bound on the true magnitude of switching costs (Ioannidou and Ongena, 2010).

4.3. Switching costs

Table 3 presents the main empirical results, including the set of matching variables, the number of matched switching and nonswitching loans, the total number

[10] Our results are consistent if we employ a propensity score matching strategy.

of matched pairs, and, most importantly, the estimated coefficients on the constant term from the regression analyses. To address concerns related to potential multiplicity bias, we apply a weighting scheme in which each observation is weighted by the inverse of the number of matched nonswitching loans per switching loan. Standard errors are clustered at the level of the switching firm to further mitigate any inference distortion arising from correlated residuals within firms (our findings remain consistent when we cluster at the branch level, see columns 9-10 of Appendix Table A1).

[Insert Table 3 here]

In column 1, we follow the approach illustrated in Figure 3 by matching each switching loan to nonswitching loans issued by the same firm's inside branches within the same calendar month. This procedure yields 1,063 switching loans and 2,526 matched nonswitching loans, resulting in a total of 3,064 matched pairs. On average, each switching loan is matched to 2.4 comparable nonswitching loans. The coefficient estimate on the constant is -5.71 bps, indicating that switching loans carry a spread that is, on average, 5.71 bps lower than comparable loans issued by the firm's current inside branch in the month of switching. This effect is economically meaningful: given that the average loan spread is 88 bps and the average loan interest rate is 582 bps, the discount for switchers represents approximately 1% of the total loan rate or 6.5% of the average loan spread.

In column 2, we refine the matching strategy by comparing switching loans to nonswitching loans issued by outside branches, as depicted in Figure 3. This adjustment addresses potential concerns regarding unobserved heterogeneity across branches by ensuring that the comparison occurs within the same branch and in the same month. The key distinction in this comparison lies in the customer relationship: one loan is extended to a new client (the switcher), while the other is provided to an existing client of that branch. This approach offers a notable advantage over the inside-branch matching in column 1 or alternatives that rely on controlling for observable branch characteristics.[11] Matching on outside branches yields 2,095 switching loans and 4,949 matched nonswitching loans, resulting in 6,443 matched pairs. The estimated coefficient on the constant is -5.85 bps, which closely aligns with the result in column 1, indicating that outside branches price loans to new customers in a manner similar to how inside branches price loans to their own long-term clients.

To further assess the robustness of our findings, we conduct two additional tests. In column 3, we modify the matching procedure by substituting the credit rating assigned by the outside branch with the most recent credit rating issued by the firm's inside branch prior to the switch. This adjustment is motivated by the premise that the inside branch, having a longer-standing relationship with the firm, may provide a more accurate assessment of the firm's creditworthiness. Prior literature, notably Ioannidou and Ongena (2010), has documented that the predictive power of credit ratings increases with the duration of the lending relationship. In this context, matching on the inside branch's rating effectively imposes the requirement that the matched nonswitching loans share the same rating as the switcher, thus offering a better approximation of the inside branch's unobserved offer. This refinement modestly reduces the sample size, with the estimated spread of -3.86 bps.

In column 4, we further explore the influence of relationship strength by matching loans on several proxies that capture the depth of prior lending ties. Specifically, we include the length and density of the borrower-lender relationship as well as the existence of multiple concurrent lending relationships. This approach aims to ensure that switchers and matched nonswitchers are comparable not only in terms of observable loan and borrower characteristics but also in their relational history with the inside branch. The matching based on relationship strength reduces the number of observations to 798, with the estimated coefficient on the constant of -6.86 bps.

[11] Unless otherwise noted, we adopt the column 2 specification as our benchmark model in subsequent analyses.

Collectively, the results offer robust evidence that when firms switch branches within the same bank, the newly originated loans tend to carry spreads approximately 6 bps lower than those on comparable loans extended to existing customers. The persistence of this discount underscores that the transfer of relationship-specific soft information across branches is imperfect. In line with theories of authority and communication (Dessein, 2002; Alonso et al., 2008), these findings suggest that internal communication frictions and branch-level incentives generate an intra-bank hold-up problem, where information asymmetries are reproduced inside the organization itself.

4.3.1. Excluding the possibility of involuntary switching

Bank policies. One potential concern is that some firms may be compelled to switch branches due to bank policies, rather than as a voluntary response to lending conditions. For instance, banks may mandate that certain loans be transferred to specialized branches tasked with handling restructuring or bankruptcy resolution. Xu et al. (2020) document a relevant example in their study of a policy implemented by a major Chinese bank, which mandated the localization of credit origination. Under this policy, the formation and maintenance of branch–borrower relationships were subject to two key restrictions: (1) within the same administrative district, a firm could not obtain loans from more than one branch of the same bank; and (2) branches were prohibited from issuing loans to firms that were not legally registered within their own district. As a result, the policy effectively forced some borrowers to switch branches to comply with these geographical lending constraints. To rule out the possibility that similar internal policies are driving the switching behavior observed in our sample, we conducted detailed discussions with senior management at our focal bank. Based on these communications, we confirm that no such branch-switching policies were in place during our study period. This assurance strengthens our interpretation that the observed switching events in our dataset reflect firms' autonomous decisions, rather than policy-induced reassignments.

Multi-market firms. Firms may also be forced to switch due to reallocation or geographic expansion of their businesses, such as the establishment of new subsidiaries or operations in different regions. In such cases, borrowers may gain access to alternative bank branches, thereby facilitating a switch in lending relationships. However, due to data limitations, we are unable to observe the precise timing of such process. But to address this concern, we conduct a robustness check by excluding firms that operate across multiple business addresses and re-estimate our baseline model on this restricted sample. The results, reported in columns 7 and 8 of Appendix Table A1, remain consistent with our main findings. This suggests that the observed discount in loan spreads for switching loans is not attributable to changes in borrower location or to different subsidiaries of the same firm applying for loans at different branches.

Branch closures. Another potential source of involuntary branch switching arises from branch closures. In studies such as Bonfim et al. (2021) and Liaudinskas (2024), firm transfers were triggered by the shutdown of local bank branches, necessitating the reassignment of existing loan relationships. However, this concern does not apply to our setting. According to internal records and confirmation from bank management, our focal bank did not undergo any branch closures during the sample period. As such, we can confidently rule out the possibility that the observed switching behavior is driven by exogenous branch shutdowns.

4.4. Heterogeneity generated by hold-up

Our findings are most consistent with an organizational economics explanation in which intra-bank information frictions generate a form of hold-up, rather than being driven by alternative mechanisms such as teaser pricing, borrower self-selection, or behavioral inertia. And such hold-up could generate the following heterogeneities.

4.4.1. Switching with (or without) branch managers

First, we investigate a unique subsample in which the borrower switches branches together with their original branch manager. Prior research emphasizes that branch managers are not passive conduits of credit policies but active holders and interpreters of soft, relationship-specific information (Aghion and Tirole, 1997; Stein, 2002; Berger and Udell, 2002; Liberti and Mian, 2009). Within the theoretical framework of relationship lending, these managers accumulate non-contractible, qualitative information that informs loan origination, renewal, renegotiation, and termination decisions. This manager-centric view of soft information is reinforced by models showing that lending discretion and local judgment are central to relationship banking (Drexler and Schoar, 2014; Canales and Greenberg, 2016).

Building on this framework, we hypothesize that when the same manager transfers to the borrower's new branch, the informational gap that typically drives initial pricing discounts should disappear. Specifically, we identify cases where the borrower switches to an outside branch within the first 12 months of a branch manager's tenure—thus minimizing potential disruption in the lending relationship. When we restrict the analysis to these "manager-continuity switches," the estimated coefficient on the spread discount becomes statistically insignificant (column 1, Table 4). In our data, managerial mobility is relatively common—46% of the 540 branch managers in the sample move at least once during the sample period—yet only 1.3% of switching loans involve a borrower moving with the original branch manager. Although this subsample is small, the result provides suggestive evidence that the presence of the same manager mitigates information loss. Conversely, when we exclude these joint-switch observations and re-estimate the baseline model, the initial discount re-emerges with virtually unchanged magnitude (column 2, Table 4).

[Insert Table 4 here]

These findings are difficult to reconcile with alternative mechanisms. Teaser pricing would not predict the elimination of the discount when managers co-move, as the initial rate reduction would reflect competitive strategies independent of managerial continuity. Likewise, a selection-on-offer explanation would imply that borrowers choose to switch based on superior terms, meaning the observed rate differential should persist regardless of managerial mobility. Finally, behavioral inertia cannot explain why the switching discount disappears when the original manager relocates with the borrower, as inertia-driven frictions are psychological and unrelated to the transfer of relationship-specific information. By contrast, the disappearance of the discount under managerial co-movement is consistent with an organizational economics interpretation of hold-up, wherein the transfer of soft information mitigates informational frictions.

4.4.2. Switching to closer (or more distant) branches

Another perspective on intra-bank hold-up comes from examining the geographic distance between a borrower's inside branch and the new (outside) branch to which it switches. From an organizational economics standpoint, geographic distance can exacerbate internal communication frictions and reduce informal monitoring, while also influencing the degree of competitive pressure across branches. Prior research highlights that proximity improves lending efficiency and strengthens competition (Degryse and Ongena, 2005). In the context of intra-bank hold-up, closer branches should face greater constraints on rent extraction, both because internal information transfer may be easier and because localized market competition limits their pricing power. Conversely, when borrowers move to more distant branches—where communication is weaker and competitive overlap is minimal—the inside branch has greater scope to exploit informational rents.

To test these predictions, we re-estimate our baseline regression on two subsamples: (i) firms switching to geographically closer branches, and (ii) firms switching to more distant branches. Distance is measured in kilometers as the straight-line distance between the borrower's previous branch and the new branch, with "closer" defined as the distance to new branch being smaller than the distance to existing branch. Roughly 54% of switches are to closer branches, while 46% are to more distant branches.

The results, presented in Table 5, align squarely with the intra-bank hold-up interpretation. For borrowers switching to closer branches (column 1), the estimated spread discount is statistically insignificant and economically small, suggesting that competitive pressure and easier internal communication mitigate the informational rents that typically drive hold-up dynamics. By contrast, when borrowers switch to more distant branches (column 2), the spread discount is larger and statistically significant, reflecting greater latitude for informational rent extraction in settings where competitive pressures are weaker and organizational frictions are greater.

[Insert Table 5 here]

These geographic patterns are inconsistent with alternative explanations such as teaser pricing and borrower selection. Teaser pricing would predict that outside branches, regardless of distance, compete aggressively to win business, particularly from high-volume or low-risk borrowers, leading to similar or even larger initial discounts in competitive, nearby markets. Selection-on-offer would similarly imply that firms switch when presented with sufficiently attractive terms, so distance should not systematically affect the magnitude of the observed discount. While behavioral inertia could, in principle, generate some geographic variation—borrowers might be more willing to switch to nearby branches where the perceived switching costs (time, administrative effort, and relational disruption) are lower—the results align most closely with an organizational economics framework: proximity enhances competitive pressure and facilitates informal information flows, constraining the incumbent branch's ability to extract informational rents.

4.4.3. Switching to newly established (or existing) branches

In a similar vein, if the hold-up mechanism underlies our findings, we would expect a more pronounced decline in loan spreads when firms switch to branches that are comparatively less informed and, consequently, less competitive. In organizational terms, incumbent (inside) branches possess superior borrower-specific informational capital, allowing them to extract informational rents from existing customers. This advantage is particularly potent when competing branches are relatively uninformed, such as newly established branches that have not yet developed the capacity to collect and interpret soft information. In such cases, the inside branch faces limited external pressure to lower spreads, and borrowers that remain are more vulnerable to rent extraction. When a borrower switches to such a nascent branch, however, the informational asymmetry between the two branches is greatest, creating an environment where the new branch must offer larger initial pricing concessions to attract the borrower, even as it gradually rebuilds its own informational advantage.

To examine this organizational dynamic, we first extend our baseline analysis to the subsample of firms switching to newly established branches.[12] These branches—defined as those within the first 12 months of operation—lack the accumulated knowledge, informal networks, and local soft-information base that seasoned branches rely on for effective screening and monitoring. As a result, they are at an informational disadvantage, both relative to incumbent branches and to more established competitors. To avoid contamination from administrative reassignments rather than true switching, we further exclude loans originated in the first three months of a branch's operation.[13]

Table 6 presents the results. Firms switching to newly established branches experience substantially larger reductions in loan spreads (26.79 bps ≅ 5% of the average loan rate or ≅ 30% of the average loan spread), compared to only 5.5 basis points (5.50 bps ≅ 1% of the average loan rate or ≅ 6% of the average loan spread)

[12] In this analysis, we match switching loans with nonswitching loans issued by the set of inside branches, as the outside branch is newly established (less than 12 months) with no existing non-switching customers. The inside matching model requires matching outside branches with inside branches in the same city. This assumes each city has at least two branches. If the outside branch is new, an established branch must already exist there. This excludes the possibility that new branches are in newly developed areas with more business opportunities and lower interest rates.
[13] Our findings are insensitive to the choice of time window.

for switches to existing branches. This striking heterogeneity reinforces the organizational economics interpretation: the magnitude of initial discounts scales with the informational disadvantage of the new branch, and the depth of the informational gap between branches dictates the intensity of the hold-up cycle.

[Insert Table 6 here]

Building on the preceding analysis, we next examine the role of managerial turnover in shaping intra-bank hold-up dynamics. From an organizational economics perspective, branch managers are the primary repositories and interpreters of soft information (Aghion and Tirole, 1997; Stein, 2002; Liberti and Mian, 2009). When a manager is newly appointed to a branch, that branch experiences a temporary informational disadvantage relative to more established incumbents. This disadvantage weakens the branch's ability to compete for borrowers and amplifies the incumbent branch's ability to extract informational rents, consistent with the internal hold-up framework.

We define a switch to a branch with a newly appointed manager as a loan originated by that branch within the first 12 months of the manager's tenure, while excluding loans granted during the initial three months to account for transitional adjustments. This exclusion mitigates noise from administrative carryovers—such as loans initiated under the previous manager but finalized under the new one—ensuring that observed dynamics reflect genuine shifts in relationship-specific information. To isolate the effect of managerial turnover from the confounding effects of branch maturity, we restrict this analysis to established branches only, excluding newly created branches where all managers are, by definition, new. This focus allows us to more cleanly assess how a loss of embedded managerial knowledge affects switching outcomes.

Table 7 presents the estimation results. Firms switching to branches with newly appointed managers receive substantially larger initial rate concessions (11.30 bps ≅ 2% of the average loan rate or ≅ 13% of the average loan spread) compared to a much smaller 3.5 basis point reduction when switching to branches with stable managerial leadership (≅ 1% of the average loan rate or ≅ 4% of the average loan spread). These findings reinforce the organizational economics interpretation of intra-bank hold-up. When a borrower switches to a branch with a manager who has not yet developed the local soft-information base, that branch is forced to compete more aggressively to attract the borrower. At the same time, the incumbent branch faces less credible competition, allowing it to extract greater informational rents from borrowers that remain.

[Insert Table 7 here]

The observed patterns when borrowers switch to newly established branches or branches with newly appointed managers could be consistent with teaser pricing or selection-on-offer mechanisms. New or transitional branches might offer temporarily lower rates to build market share, or borrowers may self-select into these branches precisely because they receive more attractive initial offers. Behavioral inertia, by contrast, offers no explanatory power in this setting, as psychological frictions do not vary systematically with the establishment age of the branch or the tenure of the branch manager. In contrast, the evidence aligns closely with an organizational economics interpretation: newly established or managed branches face acute informational disadvantages relative to incumbent branches, weakening their ability to compete on informational rents and forcing them to offer deeper initial discounts.

4.5. Mitigating hold-up

4.5.1. Social Credit System

Government-mandated information disclosure plays a critical role in reducing organizational frictions in financial markets by leveling the informational playing field between incumbents and potential competitors. By expanding the quantity, reliability, and accessibility of borrower information, such regulations constrain the ability of insiders to exploit private informational advantages (Friedman et al., 2022). They also incentivize firms to improve the quality of their financial reporting (Bertomeu et al., 2021; Bertomeu, 2023), thereby making borrower risk profiles more transparent and verifiable. Complementing these reforms, digital credit-information platforms improve the efficiency of recording, publicizing, and disseminating borrower-level credit data, reducing information asymmetries and lowering switching costs in lending markets (Ma et al., 2005; Klievink et al., 2016).

China's Social Credit System (SCS) embodies this dual function of regulatory oversight and centralized information sharing. By providing timely, comprehensive data on firms' operational performance, tax compliance, financing behavior, and credit defaults, the SCS improves transparency and strengthens lenders' ability to assess borrower quality. The institutionalization of the SCS was codified in the "Planning Outline for the Construction of the Social Credit System (2014–2020)" by the State Council in June 2014. This document laid the groundwork for the system's integration across commercial, social, and judicial domains. In response, the National Development and Reform Commission (NDRC) and the People's Bank of China (PBoC) jointly launched two waves of pilot programs in 2015 and 2016, covering 11 and 31 prefecture-level cities, respectively (see Appendix Table A2 for more details). These cities built robust online credit portals and standardized credit-sharing systems, reducing the reliance on relationship-specific soft information. Within our matched sample, 23.4% of cities participated in the pilot program, covering 3,959 loans, or 56.2% of all observed loans in the dataset.

To assess the effect of this policy on mitigating intra-bank hold-up, we estimate a difference-in-differences specification comparing loan spreads between switching and matched non-switching loans before and after SCS implementation (based on specifications in Column 2 of Table 3). The model includes policy-timing indicators, borrower and city-level controls (CV_{ft} and CV_{ct}), city fixed effects (φ_c), and province-by-year fixed effects (φ_c) to absorb unobserved heterogeneity and regional shocks. The estimating equation is as follows:

$$Spread_i = \alpha_0 + \sum_{n=1}^{4} \beta_n BEF_{ct}^{n} + \gamma CUR_{ct} + \sum_{n=1}^{4} \delta_n AFT_{ct}^{n} + \rho CV_{ft} + \theta CV_{ct} + \varphi_c + \varphi_{pt} + \varepsilon_{ifct} \quad (1)$$

where *Spread* denotes the loan spread difference between a switching loan i and its matched non-switching counterpart. The policy dummies capture the year-by-year dynamics: *BEF* equals 1 if the loan originates n years before the SCS implementation in city c; *CUR* equals 1 during the year of implementation; and *AFT* equals 1 for each of the n years following implementation.

Figure 6 visualizes the estimates, with coefficients normalized to the year before implementation and 95% confidence intervals clustered at the city level. The results provide clear evidence that mandatory disclosure reduces intra-bank hold-up. There are no statistically significant pre-trends, supporting the parallel-trends assumption. However, in the year of implementation, switching loans experience a sharp decline in spreads relative to matched non-switching loans (a significant positive estimate indicates a reduction in hold-up), an effect that persists for three years before tapering off. This temporary but economically meaningful reduction in switching costs highlights how centralized, standardized credit information systems erode the informational advantage of incumbent branches, increase internal information portability, and foster more competitive loan pricing. From an organizational economics perspective, these findings show that policy interventions that codify and share soft information can mitigate the structural frictions inherent in multi-branch banks. By reducing the opacity that fuels intra-bank hold-up, such reforms not only enhance efficiency in credit allocation but also promote broader borrower mobility and market competitiveness.

[Insert Figure 6 here]

4.5.2. Deployment of FinTech

FinTech innovations are transforming how soft information is processed, codified, and transmitted, fundamentally reshaping the organizational dynamics that give rise to intra-bank hold-up. By converting qualitative, relationship-based insights into standardized and transferable metrics, FinTech effectively "hardens" soft information (Liberti and Petersen, 2019). Technologies such as internal credit-scoring systems and machine-learning-based risk assessments make borrower information portable across branches, reducing the dependency on the subjective, context-specific knowledge of individual managers. This digitization erodes the localized informational advantages historically held by incumbent branches, thereby mitigating hold-up (Sutherland, 2018).

Our survey evidence supports this theoretical mechanism: 84% of respondents perceive significant opportunities in adopting FinTech, 89% report that banks are actively pursuing such technologies, and 79% agree that FinTech reduces information asymmetries by deepening lenders' understanding of their customers. These perceptions, summarized in Figure 7, underscore the industry-wide belief that digitalization enhances informational transparency and efficiency in lending.

[Insert Figure 7 here]

To empirically examine this channel, we re-estimate the baseline model from Column 2 of Table 3, augmenting it with a branch-level index of FinTech deployment. This measure captures both bank-wide FinTech adoption and branch-specific variation in the capacity to implement these tools. Specifically, the branch-level index is defined as:

$$Branch\ FinTech_{bt} = Scaler_{bct} \times Bank\ FinTech_t \tag{2}$$

where b indexes the bank branch, c denotes the city of the branch, and t represents the year. The term *Bank FinTech* reflects the bank-wide adoption of FinTech technologies and digitalized operations from the Digital Transformation Index of Chinese Commercial Banks developed by the Institute of Digital Finance at Peking University. This index remains uniform across all branches in a given year and it is confirmed by our bank that all branches have equal access to a centralized digital information system. While this measure captures temporal changes in FinTech usage, it does not account for spatial heterogeneity in FinTech integration across branches. In reality, the capacity of branches to effectively deploy FinTech varies significantly, influenced by regional disparities in digital infrastructure and technological adaptation. Our discussions with branch management reveal that, despite being equipped with uniform IT systems and FinTech platforms, branches exhibit varying levels of FinTech adoption and operational application. The digital awareness, literacy, and competence of branch managers, which is strongly influenced by the local FinTech penetration in their region, are primary drivers of these differences.

To address this limitation, we construct a MinMaxScaler that adjusts for local variations in FinTech capacity by benchmarking each city's digital financial inclusion against national levels (Clement and Tse, 2005; Do and Zhang, 2020). This scaler is derived from the Digital Financial Inclusion Index of China, developed by the Institute of Digital Finance at Peking University in partnership with Ant Group (Guo et al., 2019; Ding et al., 2022; Ling et al., 2025). This index evaluates digital financial inclusion along three dimensions: (1) breadth of coverage, reflecting accessibility to digital services; (2) depth of usage, capturing engagement with financial products such as payments and credit; and (3) degree of digitalization, measuring the integration of digital technologies into financial practices. Crucially, we utilize the third dimension of the index to highlight regional disparities in FinTech deployment, emphasizing the need for localized strategies that align with varying digital infrastructures.

To operationalize this measure, we compute the difference between the degree of digitalization of each city and the minimum degree observed across all Chinese cities for a given year t. This difference is normalized by the annual range, yielding a relative score that reflects each branch's capacity to implement FinTech solutions without altering the overall distribution of *Bank FinTech*. This adjustment allows us to effectively capture the readiness of each city to deploy FinTech solutions effectively.

Figure 8 presents the results. As FinTech penetration deepens across branches, the initial spread discounts associated with switching narrow considerably, indicating a weakening of incumbent branches' informational rents. From an organizational perspective, this reflects how digitization facilitates the internal portability of soft information, enabling outside branches to compete more effectively and eroding the structural frictions that sustain intra-bank hold-up. Borrowers benefit directly through lower switching costs and more competitive loan pricing, demonstrating that technology-driven information integration can materially improve credit market efficiency.

[Insert Figure 8 here]

The evidence from the SCS pilot program and FinTech adoption strongly supports the hold-up interpretation and is inconsistent with alternative explanations. Both teaser pricing and borrower-driven selection would predict the opposite effect: as information flows improve and borrowers become more visible to competing branches, outside branches should face stronger competitive pressure to offer even more aggressive initial pricing, thereby widening—not narrowing—the observed spread discounts. Likewise, these mechanisms cannot explain why the gap between switching and non-switching loans narrows in response to improved information sharing. Behavioral inertia, meanwhile, provides no clear prediction for how institutional reforms or digital technologies that harden soft information should affect loan spreads, since psychological frictions are unrelated to the efficiency of information transfer. By contrast, the findings align neatly with an organizational economics framework: by reducing information asymmetries between incumbent and outside branches, both SCS disclosure and FinTech adoption erode the informational rents that inside branches can extract, leading to lower hold-up costs and more competitive loan pricing.

4.6. Dynamics after switching

We further extend our analysis to explore the dynamic evolution of loan spreads following firms' transitions to outside branches. While switching may initially grant firms favorable loan terms, organizational economics suggests that these benefits may be transitory. As the outside branch gradually accumulates relationship-specific knowledge, its informational disadvantage erodes. Over time, this enables the branch to extract informational rents, replicating the hold-up behavior previously exerted by the incumbent branch.

To test this dynamic, we track each switching borrower's subsequent loans at the new branch, comparing their spreads to the initial switching loan while holding branch and firm characteristics constant. This within-branch, within-firm comparison ensures that the observed changes are driven by the evolution of the relationship rather than borrower heterogeneity or changes in branch conditions. Using our matched sample, we analyze 3,543 switching loans to 3,041 firms, alongside 12,485 subsequent loans, and group observations into quarterly intervals ranging from 1-3 months after switching to at least 13 months post-switch. For each interval, we regress loan spreads on a constant, as well as calendar-year, branch, and firm fixed effects. These fixed effects control for time-invariant characteristics and macroeconomic fluctuations, allowing for a clean identification of the temporal pattern in loan spreads.

Panel A of Table 8 reveals a clear temporal pattern. In the first six months after switching, loan spreads decline further by as much as 17.68 bps, suggesting aggressive initial competition by the outside branch. However, after roughly one year, this advantage reverses: spreads increase, eventually exceeding the initial switching loan by 18.64 bps. This rise-and-revert cycle indicates that once the outside branch develops sufficient borrower-specific knowledge, it leverages this informational advantage to extract rents, effectively becoming a new incumbent.

[Insert Table 8 here]

To further validate this observed cyclicality, we also look backward, examining historical loans from the original (inside) branch before the borrower switched. Panel B of Table 8 documents a similar trajectory: spreads initially decline as the relationship forms, then rise as the branch's informational advantage deepens. The consistency of this pattern across both forward- and backward-looking analyses, visualized in Figure 9, strengthens the evidence for endogenous informational lock-in. Relative to cross-bank switches documented in Ioannidou and Ongena (2010) and López-Espinosa et al. (2017), where spreads revert over roughly three years and 18 months respectively, the reversion here occurs more quickly—within about a year. This shorter horizon reflects the lower informational asymmetry within a single banking institution, where organizational ties and standardized procedures facilitate faster accumulation of borrower-specific information.

[Insert Figure 9 here]

We observe similar dynamics in other loan terms. As shown in Appendix Table A3, switching loans are initially associated with larger amounts and longer maturities, consistent with aggressive competition for new borrowers. Over time, however, loan amounts contract and maturities shorten, mirroring the spread cycle and reinforcing the view that branches, once informed, use their informational advantage to renegotiate terms in their favor. In contrast, collateralization requirements show little systematic variation, suggesting that collateral remains a relatively rigid feature of loan contracts, less sensitive to relational dynamics.

The temporal dynamics of loan spreads following a branch switch further reinforce the hold-up interpretation. While teaser pricing or borrower-driven selection could partially explain the initial discount, they cannot account for the rapid reversal and eventual rise in loan spreads once the outside branch establishes its own informational advantage. Under a teaser pricing framework, competitive pressures should encourage sustained or even deeper discounts to retain borrowers rather than a systematic tightening of credit terms over time. Similarly, a pure selection-on-offer mechanism predicts stable pricing consistent with the borrower's observable risk profile, not a dynamic reversion that exceeds initial levels. Behavioral inertia, by contrast, predicts relatively stable spreads over time, as borrowers remain locked into their existing relationships due to psychological frictions, offering no explanation for the observed spread cycle. By contrast, the evidence fits squarely within an organizational economics framework: informational asymmetries initially favor the borrower at the outside branch, producing a temporary reduction in spreads. As the branch accumulates borrower-specific knowledge and strengthens its informational position, it leverages this advantage to extract informational rents, leading to a gradual increase in spreads—mirroring the hold-up cycle identified in cross-bank contexts (Ioannidou and Ongena, 2010) but at a faster pace given the intra-bank setting and lower initial asymmetry.

4.7. Welfare effects

From an organizational economics perspective, certain firms are structurally more vulnerable to informational hold-up because of their limited bargaining power and reliance on relationship lending. For instance, SMEs exemplify this vulnerability. Unlike larger firms, which typically maintain diversified banking relationships and enjoy greater visibility in capital markets, SMEs often depend heavily on their local branch for credit. This dependence, combined with their informational opacity, grants incumbent branches substantial leverage to extract informational rents. Similarly, private firms are also more exposed to hold-up risks compared to State-owned enterprises (SOEs). This disparity arises from the distinct institutional advantages afforded to SOEs, who often benefit from institutional privileges—implicit government guarantees, preferential credit terms, and greater access to state-backed financing—that reduce their dependency on individual branches and make them less susceptible to rent extraction .

Table 9 empirically validates these predictions. In Columns 1 and 2, SMEs exhibit significantly higher hold-up rents than their larger counterparts, while Columns 3 and 4 show that private firms bear more of the rent burden than SOEs. These patterns suggest that branches strategically leverage their informational advantage to engage in price discrimination: extracting greater rents from firms with fewer outside options, particularly SMEs and private firms, while offering more competitive terms to large firms and SOEs.

[Insert Table 9 here]

This strategic rent extraction imposes higher switching costs on SMEs and private firms, often compelling them to seek alternative branches with more favorable loan terms. From a welfare perspective, this is particularly detrimental for these firms, as they typically have more limited access to capital markets compared to larger corporations or SOEs. The increased financing costs reduce their available capital for investment, expansion, and operational improvements, potentially stifling their growth and innovation capabilities. Higher borrowing costs can also weaken the competitive positioning of SMEs and non-SOEs in the marketplace. These firms often operate with thinner profit margins and less financial resilience, making them more vulnerable to cost fluctuations. In contrast, larger and more established firms, which are less exposed to hold-up rents, may benefit from lower financing costs and stronger credit terms, enhancing their market dominance.

This heterogeneity of hold-up effects across borrower types provides additional evidence favoring the organizational economics explanation. While borrower-driven selection and inertia could, in principle, explain why opaque firms are overrepresented among switchers, the findings run counter to the predictions of teaser pricing, which would suggest that outside branches compete more aggressively for transparent, low-risk borrowers such as large firms or SOEs.

For branches, however, these strategies create a strategic trade-off between short-term rent capture and long-term market competitiveness. Branches that aggressively extract informational rents tend to experience higher borrower attrition, particularly among SMEs and private firms that are more cost-sensitive and willing to switch for better terms. This dynamic leads to a decline in those branches' market share, both in the number of loans and in total loan volume. Yet, because the firms that switch out are typically smaller or riskier, branches that retain only larger or state-affiliated firms see an improvement in the credit quality of their remaining portfolio.

To empirically validate these theoretical predictions, we calculate the differential in loan spreads between each non-switching loan and its matched switching loan for each branch on an annual basis. The average of these differences represents the annual information rent—or hold-up rent—extracted by the branch. Following this, we compute each branch's growth rates in loan market share, both in terms of the number of loans and the total loan amount, relative to the bank's overall portfolio.

The branch-level regression results, summarized in Table 10, provide robust support for our hypotheses. We observe that higher hold-up rents are negatively associated with the growth rate of a branch's market share. Specifically, branches that prioritize rent extraction face a contraction in both the quantity and volume of loans they manage, signaling a trade-off between short-term rent capture and long-term market competitiveness. Paradoxically, however, the composition of their borrower base improves, as the higher switching costs filter out lower-quality borrowers, resulting in fewer nonperforming loans. This suggests a mixed welfare implication: while branches practicing hold-up strategies may bolster their credit portfolio's quality, they simultaneously forfeit market share and the associated scale advantages.

[Insert Table 10 here]

These results are consistent with theories of adverse selection in asymmetrically informed markets (Einav et al., 2010; Arthur and Turkson, 2021; DeFusco et al., 2022; Cahn et al., 2024). Rent extraction effectively filters out lower-quality borrowers, concentrating better credit risks in the remaining portfolio, but at the expense of scale and long-term competitiveness. This duality underscores how internal organizational frictions and informational bottlenecks shape not only borrower welfare but also branch-level performance and strategic positioning within the bank's network.

4.8. Excluding alternative explanations

Taken together, our findings present a coherent body of evidence consistent with an organizational economics framework of intra-bank hold-up. The initial loan spread discounts for switching borrowers, followed by a systematic reversion and eventual increase in spreads, highlight the dynamic process through which outside branches acquire and then leverage borrower-specific information to extract informational rents. The attenuation of the discount when branch managers move with the borrower underscores the centrality of soft information and the frictions in transferring it across organizational units. Similarly, the sharper discounts observed when borrowers switch to newly established branches or branches with newly appointed managers—units that are informationally disadvantaged—further point to the role of information asymmetry in shaping pricing dynamics. Geographic proximity amplifies this pattern: switches to nearby branches, where competitive pressure is stronger and informal information sharing is easier, show muted discounts and weaker evidence of rent extraction. Moreover, institutional and technological interventions that enhance information flows, such as the SCS and FinTech adoption, substantially erode the magnitude of hold-up, confirming that the observed dynamics are rooted in informational frictions rather than market structure alone. Finally, the disproportionate exposure of opaque borrowers, such as SMEs and private firms, to these dynamics highlights how informational disadvantages exacerbate vulnerability to rent extraction within internal banking markets.

These findings also make clear why alternative explanations fail. Teaser pricing implies that initial discounts should reflect competitive strategies independent of managerial continuity, that are more aggressive with geographic proximity or for more transparent borrowers, and increase with SCS/FinTech development, yet we observe that discounts vanish when borrowers co-move with their original branch manager, remain small when switching to nearby branches, and scale with improved information environment and among opaque borrowers—patterns that teaser strategies cannot account for. Selection-on-offer would predict that borrowers self-select into branches with superior terms, implying stable or persistent rate differentials regardless of manager mobility, branch proximity, or improvement in information envirionment; however, the discount disappears or varies systematically with managerial co-movement, branch distance, and development of SCS and FinTech. Behavioral inertia, being psychological, predicts stable borrower behavior regardless of branch-specific information, yet our data show sharp, time-varying changes in spreads that track the accumulation of relationship-specific knowledge by outside branches. It also offers no insight into the effects of manager co-movement, branch tenure, informational shocks, or technological adoption. Collectively, these inconsistencies point to organizational frictions and informational hold-up as the driving mechanism, rather than conventional competitive or behavioral explanations. More details are listed in Appendix Table A4.

5. Conclusions

This paper is motivated by a central insight from organizational economics: information within firms is costly to generate, costly to communicate, and often imperfectly transferred across units (Aghion and Tirole, 1997; Dessein, 2002; Stein, 2002). In multi-branch banks with decentralized lending decisions, these frictions create localized informational monopolies, where branches that originate and maintain lending relationships accumulate borrower-specific knowledge that is difficult to replicate elsewhere in the organization. Such structures generate scope for internal hold-up, as branches with privileged information can extract rents from borrowers, much like incumbent banks do in external markets. By contrast, a more centralized decision hierarchy could reduce such frictions by pooling borrower information, limiting the scope for branch-level rent extraction but potentially sacrificing local responsiveness and relational insight.

Using a rich dataset of 119,270 corporate loans originated by a major Chinese commercial bank between 2010 and 2020, we provide the first systematic evidence of intra-bank hold-up. When borrowers switch from their current (inside) branch to a new (outside) branch within the same bank, the new loan carries, on average, a 5.85 bps discount relative to comparable loans extended to existing customers. This discount deepens over the first two quarters post-switch, experiencing a further decline of 17.68 bps, but erodes as the outside branch gradually builds its own informational advantage. Within a year, spreads rise above the initial switching loan, illustrating how informational rents emerge and re-establish themselves over time. These dynamics mirror—but are less severe and shorter-lived than—those documented for cross-bank switching, consistent with lower informational asymmetry within a single bank but similar underlying mechanisms.

Several complementary analyses reinforce this interpretation. First, the switching discount vanishes when the borrower moves with the same branch manager, underscoring the manager-specific nature of soft information. Second, switches to geographically proximate branches exhibit smaller discounts, consistent with competitive pressure limiting rent extraction. Third, firms switching to newly established branches receive substantially larger discounts, highlighting the role of informational disadvantage in shaping initial terms. Fourth, the rollout of China's SCS, which standardized and centralized credit data, narrowed spread differentials and reduced switching costs, demonstrating that policy-driven improvements in information centralization counteract the inefficiencies of decentralized decision-making. Fifth, deeper FinTech adoption similarly mitigated hold-up by "hardening" soft information, enabling its transfer across branches and fostering more competitive pricing.

The welfare and strategic implications are substantial. SMEs and private firms, which rely more heavily on relationship lending and lack diversified financing options, bear disproportionate hold-up costs. At the branch level, aggressive rent extraction produces a trade-off between short-term rent capture and long-term competitiveness: branches extracting higher rents lose market share as cost-sensitive borrowers switch away, even as the average credit quality of their remaining portfolios improves, reducing nonperforming loan ratios. These dynamics reflect the tensions inherent in decentralized decision hierarchies, where local informational advantages can distort pricing and allocation. By contrast, more centralized lending frameworks could reduce such distortions but may limit branches' ability to tailor loans to local conditions, highlighting a fundamental policy trade-off.

Taken together, our findings show that organizational frictions in the generation and transfer of soft information can distort credit allocation, even within a single bank. By integrating organizational economics into the study of lending markets, we demonstrate that the decentralization of lending decisions and the resulting internal information bottlenecks shape pricing, allocation, and welfare outcomes in ways that are distinct from—but complementary to—external market competition. These insights carry clear policy implications: technologies and institutional frameworks that enhance the portability and centralization of information can mitigate the hold-up problem inherent in decentralized systems, promote competitive pricing, and improve both the efficiency and inclusiveness of credit markets.

References

Agarwal, S., & Hauswald, R. (2010). Distance and private information in lending. *Review of Financial Studies*, 23(7), 2757–2788.

Aghion, P., & Tirole, J. (1997). Formal and real authority in organizations. *Journal of Political Economy*, *105*(1), 1-29.

Alfaro, L., Bloom, N., Conconi, P., Fadinger, H., Legros, P., Newman, A. F., ... & Van Reenen, J. (2024). Come together: Firm boundaries and delegation. *Journal of the European Economic Association*, 22(1), 34-72.

Alonso, R., Dessein, W., & Matouschek, N. (2008). When does coordination require centralization?. *American Economic Review*, 98(1), 145-179.

Arthur, G. A., & Turkson, D. (2021). The welfare impact of household loans: An analysis for Ghana. *Journal of Finance and Economics*, *9*(2), 83-92.

Baker, M., Coval, J., & Stein, J. C. (2007). Corporate financing decisions when investors take the path of least resistance. *Journal of Financial Economics,* 84(2), 266–298.

Barone, G., Felici, R. & Pagnini, M. (2011). Switching costs in local credit markets. *International Journal of Industrial Organization,* 29(6), 694-704.

Beck, T., Degryse, H., De Haas, R., & Van Horen, N. (2018). When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics,* 127(1), 174-196.

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *Journal of Finance*, 65(5), 1637-1667.

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. *Review of Financial Studies*, *33*(7), 2845-2897.

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business,* 68(3), 351-381.

Berger, A. N., & Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *Economic Journal*, *112*(477), F32-F53.

Berger, A. N., Leusner, J. H., & Mingo, J. J. (1997). The efficiency of bank branches. *Journal of Monetary Economics*, 40(1), 141-162.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2), 237-269.

Bertomeu, J. (2023). Managers' choice of disclosure complexity. *Journal of Accounting and Economics*, *76*(2-3), 101637.

Bertomeu, J., Cheynel, E., Li, E. X., & Liang, Y. (2021). How pervasive is earnings management? Evidence from a structural model. *Management Science*, *67*(8), 5145-5162.

Bertrand, J., & Burietz, A. (2023). (Loan) price and (loan officer) prejudice. *Journal of Economic Behavior & Organization,* 210, 26-42.

Black, S. E., & Strahan, P. E. (2002). Entrepreneurship and bank credit availability. *Journal of Finance*, 57(6), 2807-2833.

Blackwell, D. W., Brickley, J. A., & Weisback, M. S. (1994). Accounting information and internal performance evaluation: Evidence from Texas banks. *Journal of Accounting and Economics,* 17(3), 331-358.

Bonfim, D., Nogueira, G., & Ongena, S. (2021). "Sorry, we're closed" bank branch closures, loan pricing, and information asymmetries. *Review of Finance*, 25(4), 1211-1259.

Cahn, C., Girotti, M., & Salvade, F. (2024). Credit ratings and the hold-up problem in the loan market. *Management Science*, 70(3), 1810-1831.

Canales, R., & Greenberg, J. (2016). A matter of (relational) style: Loan officer consistency and exchange continuity in microfinance. *Management Science*, *62*(4), 1202-1224.

Cao, J., Garcia-Appendini, E., & Huylebroek, C. (2024). Banking on Deposit Relationships: Implications for Hold-Up Problems in the Loan Market, Norges Bank, Working Paper No. 4.

Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, *60*(1), 307-341.

Cole, S., Kanz, M., & Klapper, L. (2015). Incentivizing calculated risk‐taking: Evidence from an experiment with commercial bank loan officers. *Journal of Finance,* 70(2), 537-575.

Connelly, B. L., Tihanyi, L., Crook, T. R., & Gangloff, K. A. (2014). Tournament theory: Thirty years of contests and competitions. *Journal of Management,* 40(1), 16-47.

DeFusco, A. A., Tang, H., & Yannelis, C. (2022). Measuring the welfare cost of asymmetric information in consumer credit markets. *Journal of Financial Economics*, *146*(3), 821-840.

Degryse, H., & Ongena, S. (2005). Distance, lending relationships, and competition. *Journal of Finance*, *60*(1), 231-266.

Degryse, H., & Ongena, S. (2007). The impact of competition on bank orientation. *Journal of Financial Intermediation*, 16(3), 399-424.

Dell'Ariccia, G., & Marquez, R. (2004). Information and bank credit allocation. *Journal of Financial Economics*, 72(1), 185-214.

Dessein, W. (2002). Authority and communication in organizations. *Review of Economic Studies*, 69(4), 811-838.

Ding, N., Gu, L., & Peng, Y. (2022). Fintech, financial constraints and innovation: Evidence from China. *Journal of Corporate Finance*, *73*, 102194.

Do, T. P. T., & Zhang, H. (2020). Peer effects among financial analysts. *Contemporary Accounting Research*, *37*(1), 358-391.

Drexler, A., & Schoar, A. (2014). Do relationships matter? Evidence from loan officer turnover. *Management Science*, 60(11), 2722-2736.

Einav, L., Finkelstein, A., & Cullen, M. R. (2010). Estimating welfare in insurance markets using variation in prices. *Quarterly Journal of Economics*, *125*(3), 877-921.

Ergungor, O. E. (2010). Bank branch presence and access to credit in low‐to moderate‐income neighborhoods. *Journal of Money, Credit and Banking*, 42(7), 1321-1349.

Fan, Z., Liu, Z., Peng, Y., & Wang, N. (2024). Information frictions, credit constraints, and distant borrowing. *Working Paper (December 23, 2024).*

Farinha, L. A., & Santos, J. A. (2002). Switching from single to multiple bank lending relationships: Determinants and implications. *Journal of Financial Intermediation,* 11(2), 124-151.

Friedman, H. L., Hughes, J. S., & Michaeli, B. (2022). A rationale for imperfect reporting standards. *Management Science*, *68*(3), 2028-2046.

Garicano, L. (2000). Hierarchies and the organization of knowledge in production. *Journal of Political Economy*, 108(5), 874-904.

Gilje, E. P., Loutskina, E., & Strahan, P. E. (2016). Exporting liquidity: Branch banking and financial integration. *Journal of Finance*, 71(3), 1159-1184.

Goedde-Menke, M., & Ingermann, P. H. (2024). Loan officer specialization and credit defaults. *Journal of Banking & Finance,* 161, 107077.

Goetz, M. R. (2018). Competition and bank stability. *Journal of Financial Intermediation*, 35, 57-69.

Gopalan, R., Udell, G. F., & Yerramilli, V. (2011). Why do firms form new banking relationships?. *Journal of Financial and Quantitative Analysis,* 46(5), 1335-1365.

Guo, F., Wang, J., Cheng, Z., Li, Y., Wang, F., & Wei, A. (2019). The Peking University Digital Financial Inclusion Index of China (2011-2018). *Institute of Digital Finance, Peking University, April*, 1-70.

Gustafson, M. T. (2018). Inter-market competition and bank loan spreads: Evidence from the securities offering reform. *Journal of Banking & Finance,* 94, 107–117.

Harris, M., & Raviv, A. (2005). Allocation of decision-making authority. *Review of Finance*, 9(3), 353-383.

Heider, F., & Inderst, R. (2012). Loan prospecting. *Review of Financial Studies*, 25(8), 2381-2415.

Heiss, F., McFadden, D., Winter, J., Wuppermann, A., & Zhou, B. (2021). Inattention and switching costs as sources of inertia in Medicare Part D. *American Economic Review,* 111(9), 2737–2781.

Hertzberg, A., Liberti, J. M., & Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *Journal of Finance*, 65(3), 795-828.

Hirtle, B. (2007). The impact of network size on bank branch performance. *Journal of Banking & Finance*, 31(12), 3782-3805.

Hollander, S., & Verriest, A. (2016). Bridging the gap: The design of bank loan contracts and distance. *Journal of Financial Economics*, 119(2), 399–419.

Ioannidou, V., & Ongena, S. (2010). "Time for a change": Loan conditions and bank behavior when firms switch banks. *Journal of Finance,* 65(5), 1847-1877.

Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *Quarterly Journal of Economics*, 111(3), 639-670.

Jayaratne, J., & Strahan, P. E. (1998). Entry restrictions, industry evolution, and dynamic efficiency: Evidence from commercial banking. *Journal of Law and Economics*, 41(1), 239-274.

Kalda, A. & Neshat, N. (2024). Forming banking relationships: The role of hiring bankers. *Kelley School of Business Research Paper*.

Keil, J., & Ongena, S. (2024). The demise of branch banking: Technology, consolidation, bank fragility. *Journal of Banking & Finance,* 158, 107038.

Kim, M., Kliger, D., & Vale, B. (2003). Estimating switching costs: The case of banking. *Journal of Financial Intermediation*, 12(1), 25-56.

Kim, S., & Chen, H. (2022). From a quantity to an interest rate - based framework: Multiple monetary policy instruments and their effects in China. *Journal of Money, Credit and Banking,* 54(7), 2103-2123.

Klievink, B., Bharosa, N., & Tan, Y. H. (2016). The collaborative realization of public values and business goals: Governance and infrastructure of public–private information platforms. *Government Information Quarterly*, *33*(1), 67-79.

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy,* 89(5), 841-864.

Liaudinskas, K. (2024). How forced switches reveal switching costs: Evidence from the loan market. *Journal of Financial and Quantitative Analysis*, *59*(8), 3994-4034.

Liberti, J. M. (2018). Initiative, incentives, and soft information. *Management science*, 64(8), 3714-3734.

Liberti, J. M., & Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *Review of Financial Studies*, *22*(10), 4057-4090.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies, 8*(1), 1-41.

López-Espinosa, G., Mayordomo, S., & Moreno, A. (2017). When does relationship lending start to pay?. *Journal of Financial Intermediation*, 31, 16-29.

Ma, L., Chung, J., & Thorson, S. (2005). E-government in China: Bringing economic development through administrative reform. *Government Information Quarterly*, *22*(1), 20-37.

Malenko, N. (2024). Information flows, organizational structure, and corporate governance. In *Handbook of Corporate Finance* (pp. 511-546). Edward Elgar Publishing.

Morgan, D. P., Rime, B., & Strahan, P. E. (2004). Bank integration and state business cycles. *Quarterly Journal of Economics*, 119(4), 1555-1584.

Nguyen, H. L. Q. (2019). Are credit markets still local? Evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1), 1-32.

Ornelas, J. R. H., Silva, M. S. d., & Doornik, B. F. N. V. (2022). Informational switching costs, bank competition, and the cost of finance. *Journal of Banking & Finance,* 138, 106408.

Park, A., & Shen, M. (2008). Refinancing and decentralization: Evidence from China. *Journal of Economic Behavior & Organization,* 66(3-4), 703-730.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance,* 49(1), 3-37.

Qian, J., Strahan, P. E., & Yang, Z. (2015). The impact of incentives and communication costs on information production and use: Evidence from bank lending. *Journal of Finance,* 70(4), 1457-1493.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's - length debt. *Journal of Finance*, 47(4), 1367-1400.

Romero, M. J., & Freitas, A. (2022). Microeconomic foundations of decentralised organisations. arXiv preprint arXiv:2201.07666.

Santos, J. A. C., & Winton, A. (2019). Bank capital, borrower power, and loan rates. *Review of Financial Studies*, 32(11), 4501–4541.

Seltzer, A. J., & Frank, J. (2007). Promotion tournaments and white collar careers: Evidence from Williams Deacon's Bank, 1890–1941. *Oxford Economic Papers*, 59(suppl_1), i49-i72.

Sette, E., & Gobbi, G. (2015). Relationship lending during a financial crisis. *Journal of the European Economic Association*, 13(3), 453-481.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance,* 45(4), 1069-1087.

Stein, I. (2015). The price impact of lending relationships. *German Economic Review,* 16(3), 367-89.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *Journal of Finance*, 57(5), 1891-922.

Steiner, J., Stewart, C., & Matějka, F. (2017). Rational inattention dynamics: Inertia and delay in decision-making. *Econometrica,* 85(2), 521–553.

Sutherland, A. (2018). Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. *Journal of Accounting and Economics,* 66(1), 123-141.

Tzioumis, K., & Gee, M. (2013). Nonlinear incentives and mortgage officers' decisions. *Journal of Financial Economics*, 107(2), 436-453.

Uzzi, B., & Lancaster, R. (2003). Relational embeddedness and learning: The case of bank loan managers and their clients. *Management Science*, 49(4), 383-399.

Van Leuvensteijn, M., Sørensen, C. K., Bikker, J. A., & Van Rixtel, A. A. (2013). Impact of bank competition on the interest rate pass-through in the euro area. *Applied Economics*, *45*(11), 1359-1380.

Von Thadden, E. L. (2004). Asymmetric information, bank lending and implicit contracts: The winner's curse. *Finance Research Letters, 1*(1), 11-23.

Wang, Y., & Wu, S. (2024). Impact of mobile banking on small business lending after bank branch closures. *Journal of Corporate Finance,* 87, 102593.

Xie, L., Zhang, M., Song, X., & Tong, L. (2019). Does internal competition shape bank lending behavior? Evidence from a Chinese bank. *Pacific-Basin Finance Journal*, 55, 169-181.

Xu, Y., Saunders, A., Xiao, B., & Li, X. (2020). Bank relationship loss: The moderating effect of information opacity. *Journal of Banking & Finance, 118*, 105872.

Table 1. Selected characteristics of switching loans and nonswitching loans

The table reports the descriptive statistics for selected firm and loan contract characteristics. The unit of observation in this table is the number (N) of loan initiations for switching and nonswitching loans, respectively.

	Switching Loans (N = 7,628)					Nonswitching Loans (N = 111,642)				
	Mean	SD	Median	10^{th}	90^{th}	Mean	SD	Median	10^{th}	90^{th}
Loan spread	90.20^{**}	86.23	87	0	174	88.11	88.84	87	0	174
Loan amount (in logs of CNY)	15.02^{***}	2.26	15.42	11.51	17.73	15.36	2.06	15.42	13.04	17.73
Loan maturity (in months)	13.66^{***}	11.62	12	12	12	12.29	7.46	12	11	12
Collateral	0.91^{***}	0.28	1	0	0	0.89	0.32	1	0	1
Credit rating	1.09^{***}	0.52	1	1	1	1.07	0.42	1	1	1
Credit line	0.59^{***}	0.49	1	0	1	0.79	0.41	1	0	1
Corporations	0.97^{***}	0.17	1	1	1	0.98	0.15	1	1	1
Private	0.94^{***}	0.24	1	1	1	0.93	0.26	1	1	1
SMEs	0.83^{***}	0.38	1	0	1	0.78	0.42	1	0	1
Relationship length	25.96^{***}	18.15	22^{***}	10	51	32.41	24.72	25	8	69
Relationship density	2.88^{***}	3.44	2^{***}	1	6	6.11	12.02	3	1	13
Multiple branch relationships	0.23^{***}	0.42	0	0	1	0.4	0.49	0	0	1

Table 2. Matching variables

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

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
Bank	Branch city	25	prefecture-level cities
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

Table 3. Difference in loan spreads on switching and nonswitching loans

The table assesses the difference between the loan spread on a switching loan and the loan spreads on new loans obtained (by other firms) from the switchers' set of inside bank branches in column 1 and from the switchers' outside bank branch in columns 2 to 4. In each column, we match on the indicated variables. All variables are defined in Table 2. The variables in column 4 refer to the strength of the switchers' relationships with the inside branches prior to the switch. We regress the differences on a constant and report the coefficients on the constant. We weight each observation by one over the total number of comparable nonswitching loans per switching loan. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Matched Branches	Inside	Outside		
Matching Variables	(1)	(2)	(3)	(4)
Year: month	Yes	Yes	Yes	Yes
Set of inside branches	Yes			
Set of outside branches		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
Bank branch 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	1,063	2,095	2,073	624
Number of nonswitching loans	2,526	4,949	4,896	702
Number of observations (matched pairs)	3,064	6,443	6,384	798
Spread (bps) with weighting	-5.71**	-5.85***	-3.86**	-6.86**
	(2.37)	(1.70)	(1.81)	(2.76)

Table 4. Switching with or without branch managers

The table evaluates the difference between the loan spread on a switching loan and the loan spreads on new loans obtained (by other firms) from the switchers' set of outside bank branches. A loan is considered a switching loan with branch managers if the same managers who handle the switching loan from the outside branch also approved the most recent loan prior to it from the inside branch. It is worth noting that the switching loan is approved in the first 12 months of the managers' tenure at the outside branch, which means that the loan switching is accompanied by a switching of management between bank branches. In column 1, we focus on those loans switching with branch managers. Column 2 retains only the samples that do not involve a switching of management between branches. In each column, we match on the indicated variables. All variables are defined in Table 2. We regress the differences on a constant and report the coefficients on the constant. We weight each observation by one over the total number of comparable nonswitching loans per switching loan. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Switching with branch managers	Switching without branch managers
Matching Variables	(1)	(2)
Year: month	Yes	Yes
Set of outside branches	Yes	Yes
Credit rating	Yes	Yes
Firm city	Yes	Yes
Bank Branch city	Yes	Yes
Loan amount	Yes	Yes
Loan maturity	Yes	Yes
Collateral	Yes	Yes
Credit line	Yes	Yes
Industry	Yes	Yes
Legal structure	Yes	Yes
Ownership structure	Yes	Yes
Firm size	Yes	Yes
Number of switching loans	15	2,080
Number of nonswitching loans	21	4,928
Number of observations (matched pairs)	21	6,422
Spread (bps) with weighting	-1.53	-5.88***
	(24.62)	(1.71)

Table 5. Switching to closer or more distant branches

The table displays the difference between the loan spread on a switching loan and the loan spreads on new loans obtained (by other firms) from the switchers' set of outside bank branches, considering the distance between bank branches and firms that could influence. Column 1 retains only the loan samples where firms switch the loans to a closer branch, and column 2 retains those where firms switch loans to a farther branch, both comparing with its most recent inside loan prior to the switch (if there are multiple most recent loans, we use the loan with the farthest distance). In each column, we match on the indicated variables. All variables are defined in Table 2. We regress the differences on a constant and report the coefficients on the constant. We weight each observation by one over the total number of comparable non-switching loans per switching loan. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Switch to closer branches	Switch to more distant branches
Matching Variables	(1)	(2)
Year: month	Yes	Yes
Set of outside branches	Yes	Yes
Credit rating	Yes	Yes
Firm city	Yes	Yes
Bank Branch city	Yes	Yes
Loan amount	Yes	Yes
Loan maturity	Yes	Yes
Collateral	Yes	Yes
Credit line	Yes	Yes
Industry	Yes	Yes
Legal structure	Yes	Yes
Ownership structure	Yes	Yes
Firm size	Yes	Yes
Number of switching loans	1,128	954
Number of nonswitching loans	2,871	2,414
Number of observations (matched pairs)	3,586	2,814
Spread (bps) with weighting	-3.06	-9.42***
	(2.37)	(2.47)

Table 6. Switching to newly established branches V.S. existing branches

The table assesses the difference between the loan spread on a switching loan and the loan spreads on new loans obtained (by other firms) from the switchers' set of inside bank branches. A branch is defined as a new branch if the switching loan is issued by this branch within the first 12 months (but excluding the first three month) since its establishment. Column 1 focuses on the switching to existing branches and column 2 focuses on the switching to newly established branches. In each column, we match on the indicated variables. All variables are defined in Table 2. We regress the differences on a constant and report the coefficients on the constant. We weight each observation by one over the total number of comparable nonswitching loans per switching loan. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Switching to Existing Branches	Switching to Newly Established Branches
Matching Variables	(1)	(2)
Year: month	Yes	Yes
Set of inside branches	Yes	Yes
Credit rating	Yes	Yes
Firm city	Yes	Yes
Bank Branch city	Yes	Yes
Loan amount	Yes	Yes
Loan maturity	Yes	Yes
Collateral	Yes	Yes
Credit line	Yes	Yes
Industry	Yes	Yes
Legal structure	Yes	Yes
Ownership structure	Yes	Yes
Firm size	Yes	Yes
Number of switching loans	961	42
Number of nonswitching loans	2,295	108
Number of observations (matched pairs)	2,735	123
Spread (bps) with weighting	-5.50**	-26.79**
	(2.54)	(10.90)

Table 7. Switching to branches with V.S. without newly appointed managers

The table shows the difference between the loan spread on a switching loan and the loan spreads on new loans obtained (by other firms) from the switchers' set of outside bank branches. An outside branch with newly appointed managers is defined as one where the switching loan is issued by this branch within the first 12 months (but excluding the first three month) of the managers' tenure. Column 1 focuses on switching to branches without newly appointed managers, while column 2 focuses on switching to branches with newly appointed managers. In each column, we match on the indicated variables. All variables are defined in Table 2. We regress the differences on a constant and report the coefficients on the constant. We weight each observation by one over the total number of comparable nonswitching loans per switching loan. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Existing Branches	Outside branch without newly appointed managers	Outside branch with newly appointed managers
Matching Variables	(1)	(2)
Year: month	Yes	Yes
Set of outside branches	Yes	Yes
Credit rating	Yes	Yes
Firm city	Yes	Yes
Bank Branch city	Yes	Yes
Loan amount	Yes	Yes
Loan maturity	Yes	Yes
Collateral	Yes	Yes
Credit line	Yes	Yes
Industry	Yes	Yes
Legal structure	Yes	Yes
Ownership structure	Yes	Yes
Firm size	Yes	Yes
Number of switching loans	1,383	602
Number of nonswitching loans	3,206	1,621
Number of observations (matched pairs)	4,154	2,092
Spread (bps) with weighting	-3.51^{*}	-11.30^{***}
	(1.96)	(3.72)

Table 8. Differences in loan spreads before and after switching

In Panel A, we calculate the difference in loan spreads between new loans obtained by the switcher from the outside branch and the switching loan. In Panel B, we calculate the difference in loan spreads between the past loans obtained by the switcher from the inside branch and the first loan that the switcher obtained from this inside branch. Apart from matching on firm and branch identity, we also match on the relevant variables from our benchmark model in column 2 of Table 3. All variables are defined in Table 2. We group the corresponding matches in five quarters ("1-3" to "at least 13" months) since the switching loan. For each quarter, we regress the loan spreads on a constant, calendar-year dummies, branch dummies, and firm dummies. We report the coefficients of the constant and standard errors are clustered at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: Difference in loan spreads between new loans from outside branch and switching loan

Periods (in months) since the switching loan	1-3	4-6	7-9	10-12	>=13
Firm identity	Yes	Yes	Yes	Yes	Yes
Branch identity	Yes	Yes	Yes	Yes	Yes
Loan matching variables	Yes	Yes	Yes	Yes	Yes
Number of observations (matched pairs)	293	165	231	1,247	6,906
Spread (bps) with weighting	-3.02***	-17.68***	-5.68***	7.30***	18.46***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Difference in loan spreads between past loans from inside branch and first loan

Periods (in months) since the first loan	1-3	4-6	7-9	10-12	>=13
Firm identity	Yes	Yes	Yes	Yes	Yes
Branch identity	Yes	Yes	Yes	Yes	Yes
Loan matching variables	Yes	Yes	Yes	Yes	Yes
Number of observations (matched pairs)	9,829	1,618	505	2,424	26,276
Spread (bps) with weighting	-0.48***	-4.02***	4.54***	9.33***	10.60***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 9. Heterogeneity across firm types

This table presents the heterogeneous effects across firm types. Based on the results from the outside matching model, we have grouped the samples in the outside branches as follows: First, since SMEs generally face higher information asymmetry compared to medium and large enterprises, we divide the sample into non-SMEs (column 1) and SMEs (column 2). Similarly, given that private firms generally experience higher information asymmetry than SOEs, we classify the sample into SOEs (column 3) and private firms (column 4). In each column, we match on the indicated variables. All variables are defined in Table 2. Standard errors are clustered at the switching-firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Non-SME	SME	SOE	Private firm
Matching Variables	(1)	(2)	(3)	(4)
Year: month	Yes	Yes	Yes	Yes
Set of outside branches	Yes	Yes	Yes	Yes
Credit rating	Yes	Yes	Yes	Yes
Firm city	Yes	Yes	Yes	Yes
Bank Branch 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	212	1,883	45	2,050
Number of nonswitching loans	268	4,681	59	4,890
Number of observations (matched pairs)	318	6,125	62	6,381
Spread (bps) with weighting	0.79	-6.59***	2.90	-6.04***
	(4.12)	(1.84)	(11.07)	(1.72)

Table 10. Welfare effects

This table illustrates how hold-up problems affect the welfares of bank branches. The explanatory variable, *Hold-up rent*, is the average difference of interest rate spread between non-switching and switching loans at the bank branch level (based on the outside/inside matching model), reflecting the information rent charged by the branch in the hold-up problem. The branch-level dependent variables include: the growth rate of the branch's market share measured by total number of loans (column 1), the growth rate of the branch's loan share measured by aggregate amount of loans (column 2), the proportion of defaulted loans at the branch level, weighted by loan amount each year, relative to the total defaulted loans of the entire bank (column 3); the growth rate of the proportion of defaulted loans at the branch level (column 4). We control for city × year and bank branch fixed effects. Standard errors clustered at the city level are reported in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Market Share Growth (Loan Count)	Market Share Growth (Loan Amount)	Nonperformance Loan Proportion	Nonperformance Loan Proportion Growth
	(1)	(2)	(3)	(4)
Hold-up rent	-0.21*	-0.52***	-19.82*	-0.07***
	(0.10)	(0.15)	(10.16)	(0.02)
City×Year FE	Yes	Yes	Yes	Yes
Bank Branch FE	Yes	Yes	Yes	Yes
Observations	732	732	732	732
R^2	0.524	0.484	0.382	0.220

Panel A: Intra-Bank Ranking		Panel B: Intra-Bank Competition	
Q6	Q7	Q8	Q9

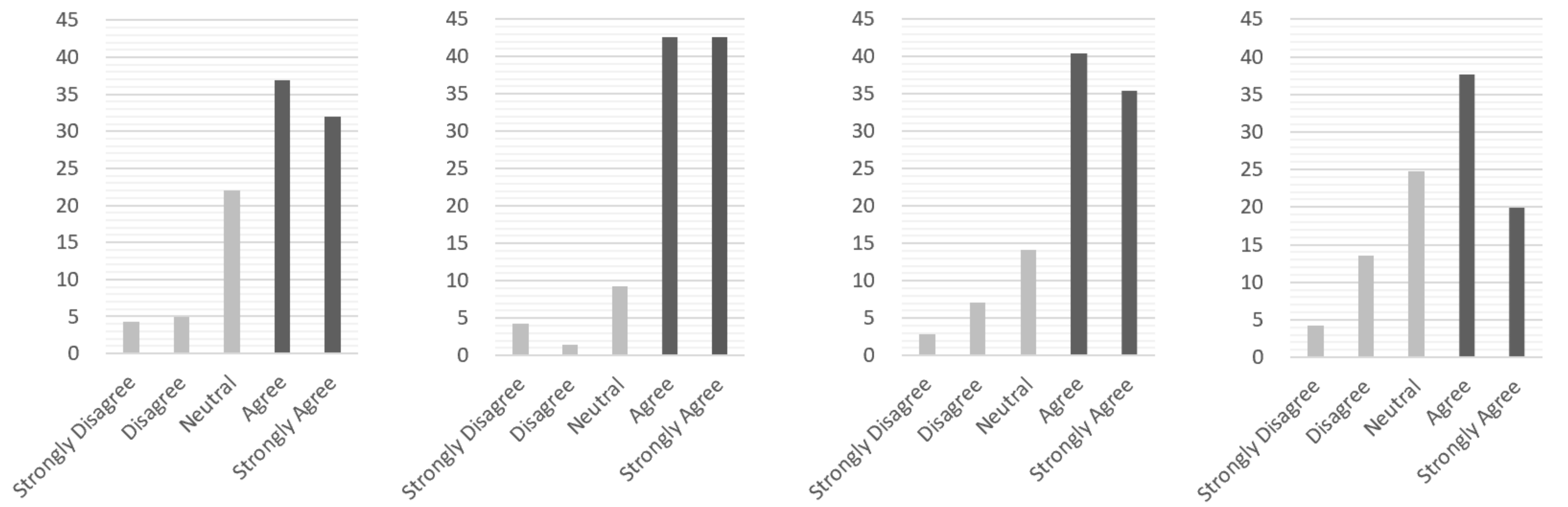


Figure 1. Intra-bank competition

This figure presents the responses in percentages for each of the questions in the survey. Black indicates the responses that we are interested in and grey indicates other responses to the question.

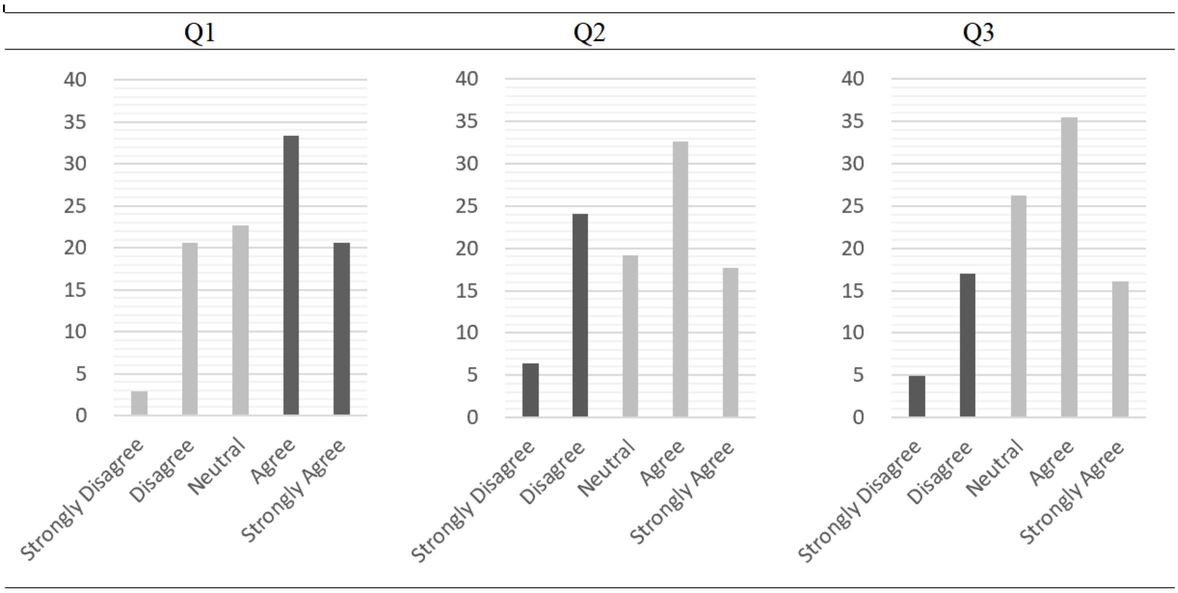


Figure 2. Information communication

This figure presents the responses in percentages for each of the questions in the survey. Black indicates the responses that we are interested in and grey indicates other responses to the question.

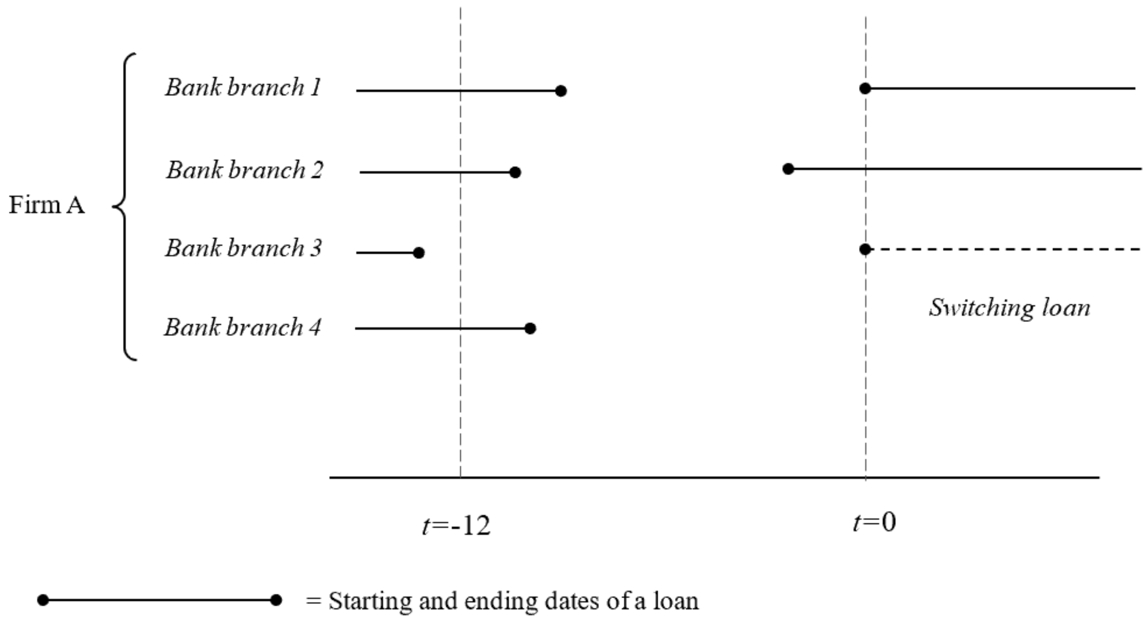


Figure 3. Switchers, inside branches, and outside branches

The figure depicts the definition of switchers, inside branches, and outside branches. We call firm A the switcher and branch 3 the outside branch for firm A, as branch 3 did not lend to firm A during the last 12 months. Branches 1 and 2 are the switcher's inside branches, as in the last 12 months firm A had at least one loan outstanding with these branches.

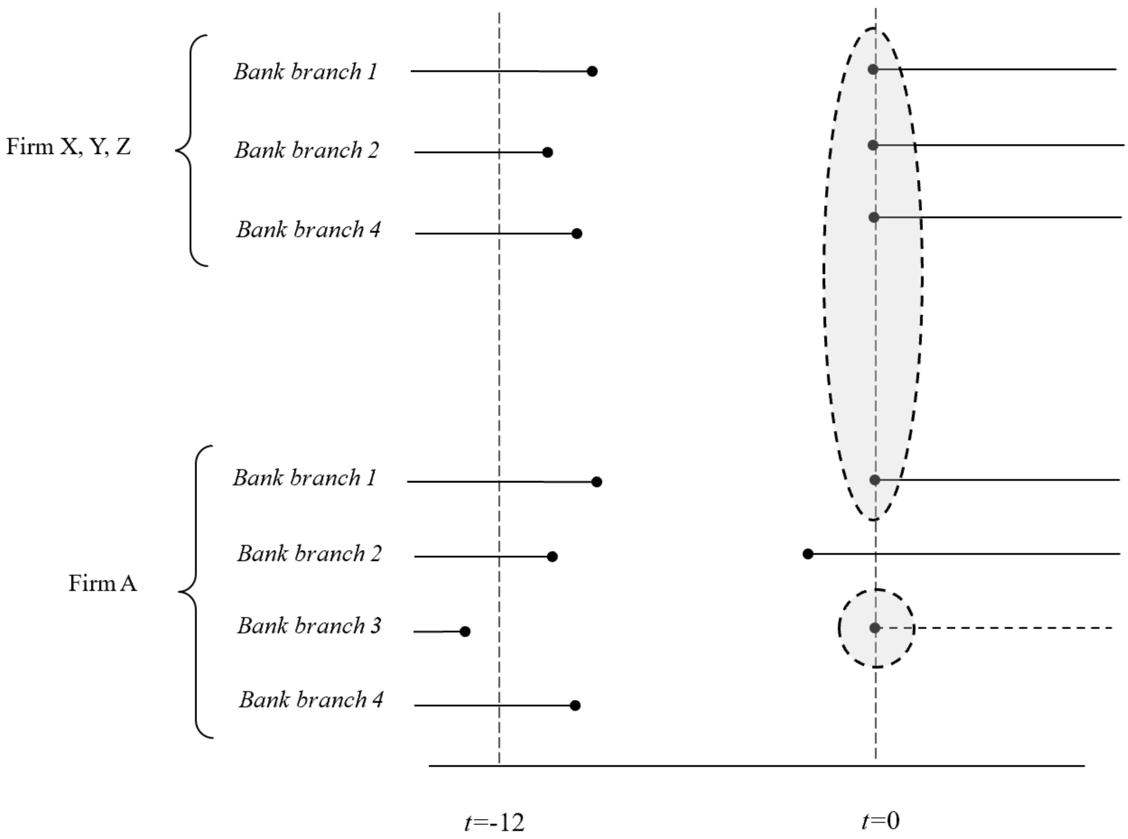


Figure 4. Switching versus nonswitching loans at the switcher's inside branch

The figure displays the analysis in column 1 of Table 3, where we compare the rate of the switching loan with the rate of comparable nonswitching loans from the switcher's inside branches at the time of the switch.

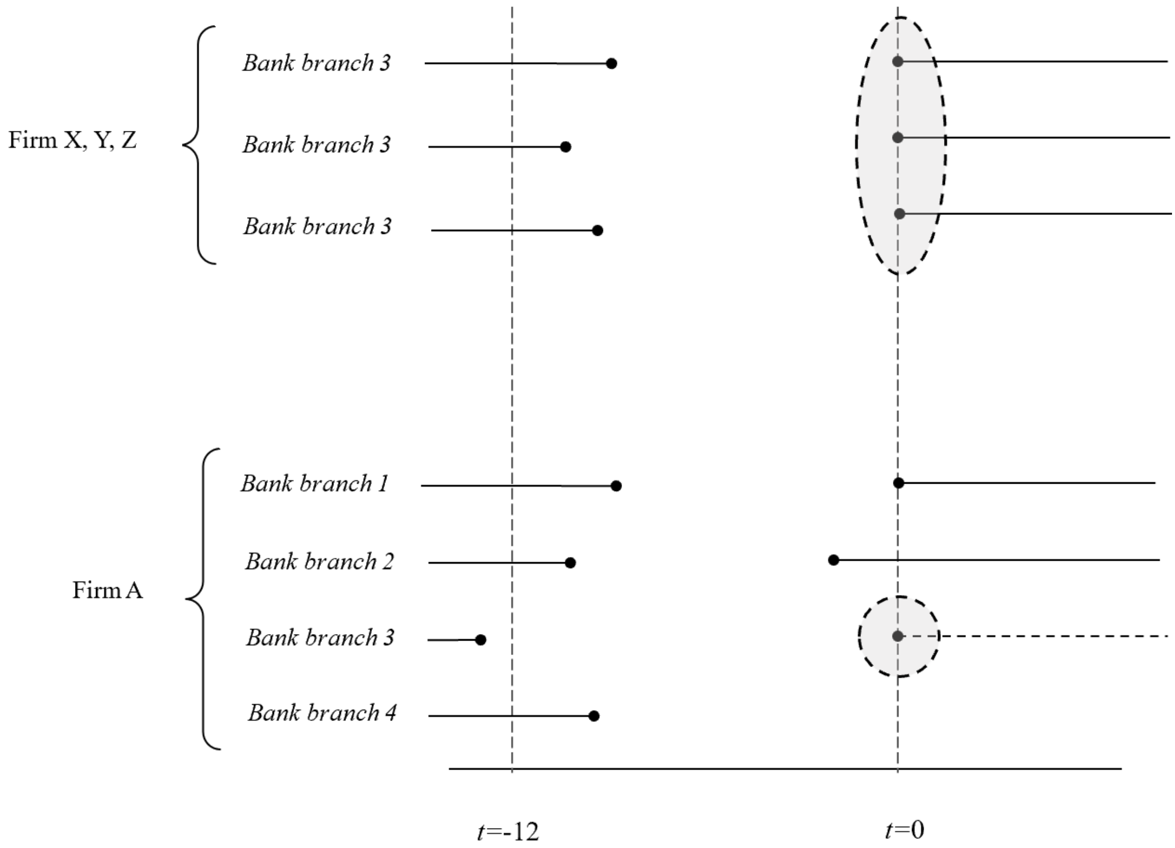


Figure 5. Switching versus nonswitching loans at the switcher's outside branch

The figure displays the analysis in column 2 of Table 3, where we compare the rate of the switching loan with the rate of comparable nonswitching loans that the switcher's outside branch at the time of the switch.

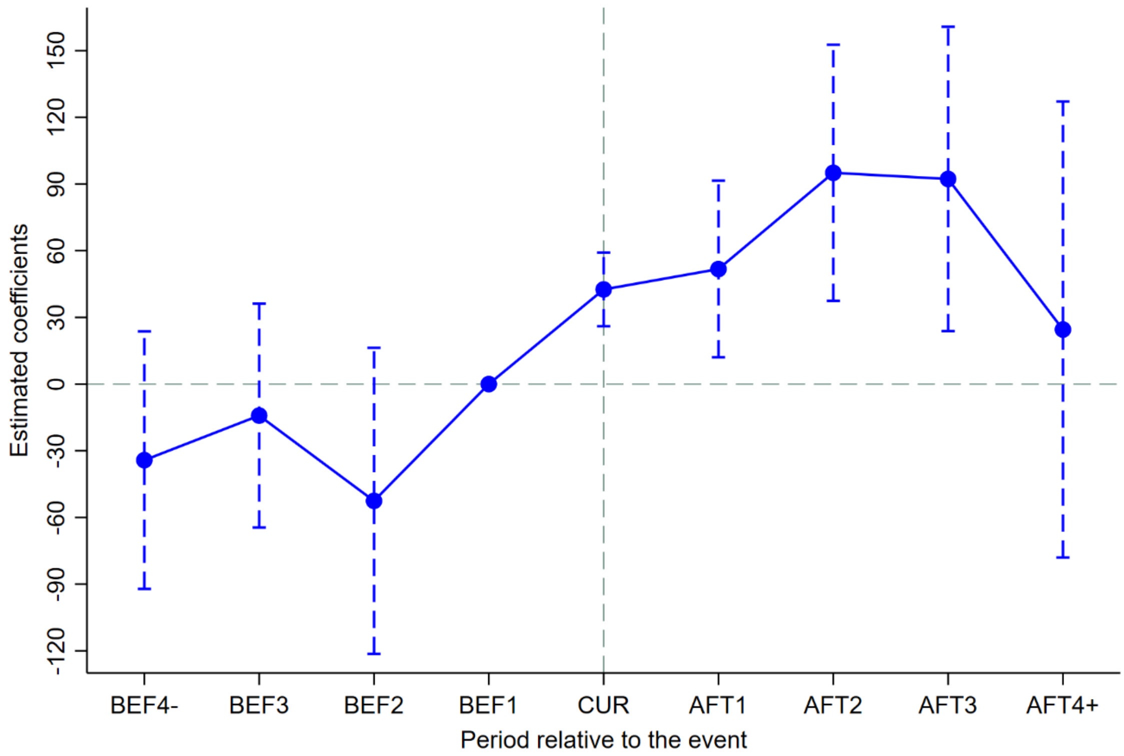


Figure 6. Implementation of SCS

This figure plots the impact of SCS polit policy on the difference in loan spreads. We consider a time window of 9 years, spanning from 4 years before the event until 4 years after the event. The dashed lines represent 95% confidence intervals, adjusted for city-level clustering. Specifically, we report estimated coefficients from the regression of model (1).

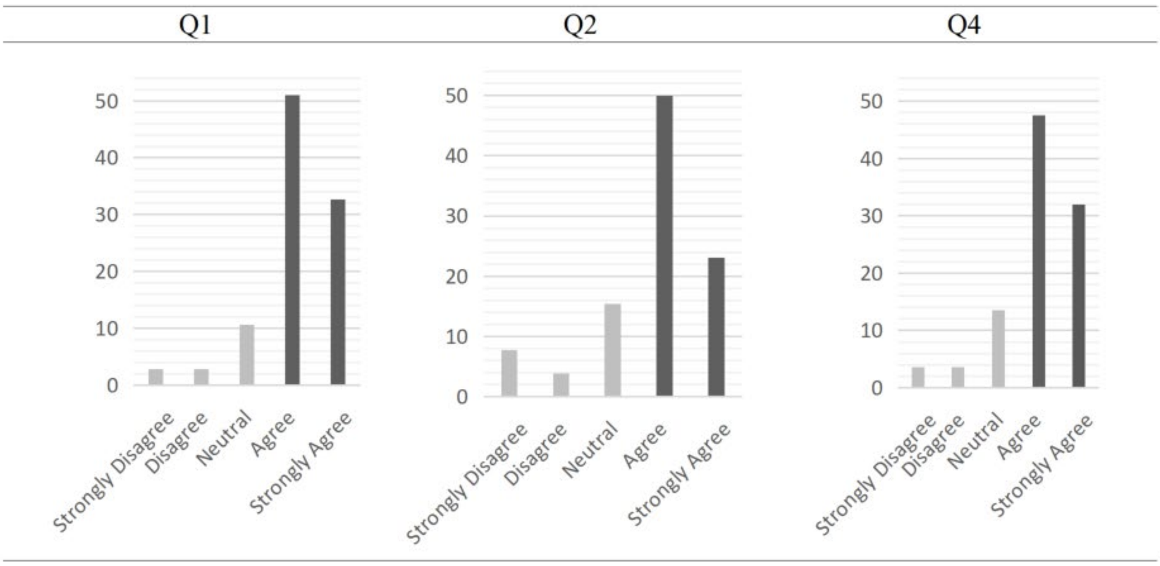


Figure 7. Application of FinTech

This figure presents the responses in percentages for each of the questions in the survey. Black indicates the responses that we are interested in and grey indicates other responses to the question.

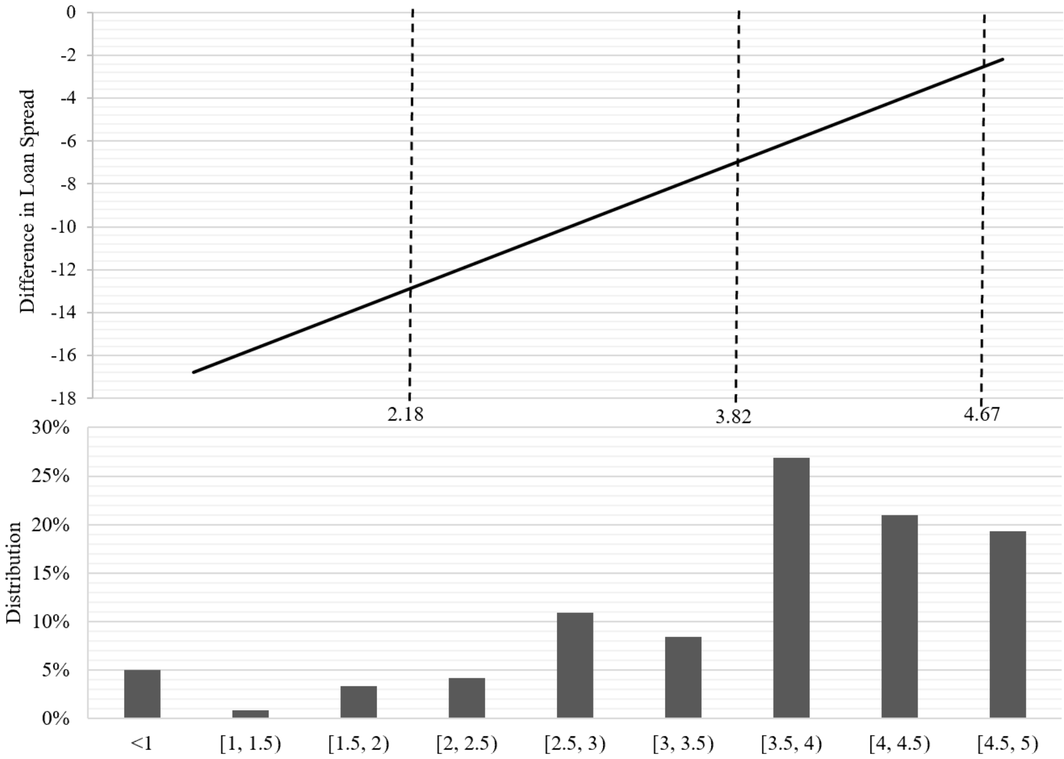


Figure 8. Deployment of FinTech

The figure illustrates the relationship between the FinTech index of our bank's branches and the estimated hold-up cost (in basis points), as well as the probability distribution of the FinTech index. The upper graph shows the FinTech index of our bank's branches on the horizontal axis and the difference between the loan spreads on the vertical axis. we estimate $Spread_{ibfct} = \alpha + \beta FinTech_{bt} + FE + \varepsilon_{ibfct}$, where $FinTech_{bt}$ is the FinTech application across various branch b in t year. The estimated parameters are $\hat{\alpha}$= -20.43*** and $\hat{\beta}$=3.65**. Using these estimates, we fit an upward-sloping line with a slope of 3.65. This fitted line shows that as FinTech advances, the loan spread discount steadily declines, reflecting a reduction in hold-up costs. The analysis controls for year and branch fixed effects to address any potential endogeneity concerns. The three vertical dashed lines represent the 10th percentile (2.18), median (3.82), and 90th percentile (4.67) of the FinTech index (log). The lower graph shows the probability distribution of the FinTech index across branches, with the horizontal axis representing different log-transformed groups of the FinTech index and the vertical axis representing the probability distribution of the number of branches corresponding to each group.

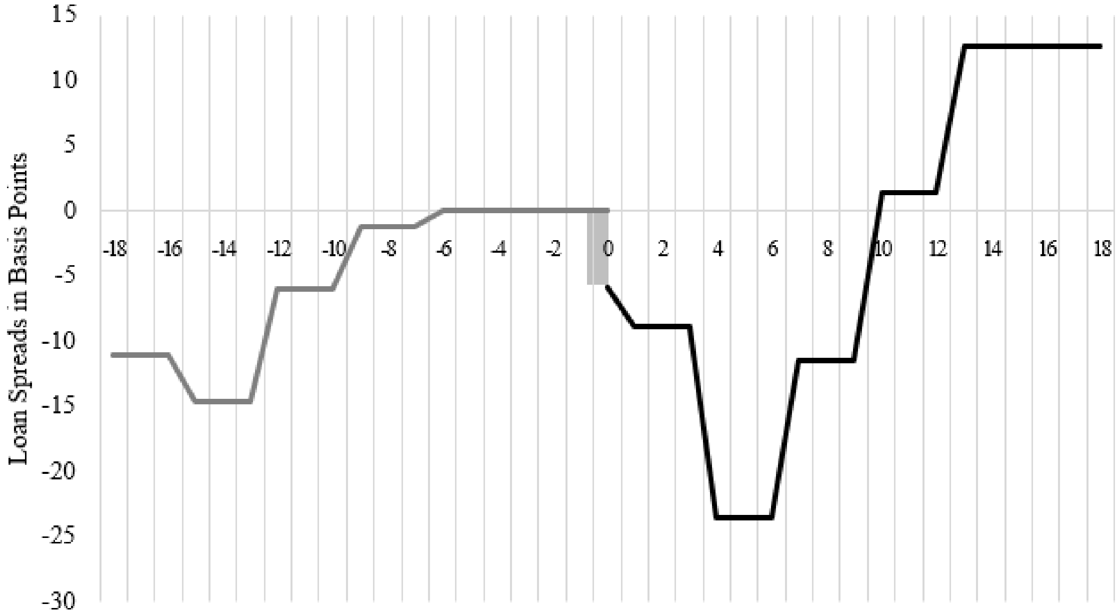


Figure 9. Loan spread differences before and after switching

The figure displays the differences in loan spreads in basis points between the new loans obtained by the switcher and the loans obtained by matched firms from their inside or outside branches before, around, and after the switch. The lines are the coefficient estimates from Tables 3 (column 2) and Table 8. The estimates of Table 8 (Panel A) are anchored at the −5.85 basis points spread from Table 3 (column 2). The estimates of Table 8 (Panel B) are anchored at zero.

Appendix A

Table A1. Robustness checks

In columns 1-4, we show that our main results are robust to using 24- and 36-month cut-offs, whatever in outside branch matching groups (columns 1 and 3) or inside branch groups (columns 2 and 4). In columns 5-6, our findings remain robust when using the differences in loan rates between switching and nonswitching loans. Additionally, in columns 7-8, the results hold when excluding geographic expansion or the establishment of new subsidiaries in other regions. Furthermore, in columns 9-10, standard errors clustered at the outside-branch level are shown in parentheses. In other columns, we report the firm-level clustered standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	24 months		36 months		Loan rate		Without multi-market firms		Branch-clustered standard errors	
Matched Branches	Outside	Inside	Outside	Inside	Outside	Inside	Outside	Inside	Outside	Inside
Matching Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year: month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Set of inside branches		Yes		Yes		Yes		Yes		Yes
Set of outside branches	Yes		Yes		Yes		Yes		Yes	
Credit rating	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prior credit rating from inside branch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank branch city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan amount	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit line	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Ownership structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of switching loans	2,301	1,177	2,444	1,251	2,095	1,063	1,557	1,055	2,095	1,063
Number of nonswitching loans	5,291	2,890	5,673	3,110	4,949	2,526	3,492	2,403	4,949	2,526
Number of observations (matched pairs)	7,115	3,469	7,649	3848	6,443	3,064	4,516	2,945	6,443	3,064
Spread (bps) with weighting	-5.50***	-5.92***	-6.54***	-6.32***	-5.27***	-5.52**	-4.28**	-3.43***	-5.85***	-5.71**
	(1.66)	(2.29)	(1.67)	(2.19)	(1.10)	(2.36)	(1.77)	(1.01)	(1.56)	(2.33)

Table A2. Lists of SCS Pilot Cities

This table shows the list of two rounds of SCS pilot cities in China and when each city's SCS was launched. From 2015 to 2016, the construction of SCS pilot cities involved 15 provinces (including the Inner Mongolia Autonomous Region) and a total of 42 cities (including Beijing and Shanghai).

Launch year	Province	Prefecture-level city
2015	Liaoning	Shenyang
	Shandong	Qingdao
	Jiangsu	Nanjing
		Wuxi
		Suqian
	Zhejiang	Hangzhou
		Wenzhou
		Yiwu
	Anhui	Hefei
		Wuhu
	Sichuan	Chengdu
2016	Beijing	Beijing
	Inner Mongolia	Hohhot
		Wuhai
	Liaoning	Dalian
		Anshan
		Liaoyang
	Heilongjiang	Suifenhe
	Shanghai	Shanghai
	Jiangsu	Suzhou
	Zhejiang	Taizhou
	Anhui	Anqing
		Huaibei
	Fujian	Fuzhou
		Xiamen
		Putian
	Shandong	Weifang
		Weihai
		Dezhou
		Rongcheng
	Henan	Zhengzhou
		Nanyang
	Hubei	Wuhan
		Xianning
		Yichang
		Huangshi
	Guangdong	Guangzhou
		Shenzhen

		Zhuhai
		Shantou
		Huizhou
	Sichuan	Luzhou

Table A3. Differences in other loan conditions before and after switching

The table calculates the difference in other loan conditions between new loans obtained by the switcher from the outside branch and the switching loan. All variables are defined in Table 2. We group the corresponding matches in five quarters ("1-3" to "at least 13" months) since the switching loan. For each quarter, we regress the loan spreads on a constant, calendar-year dummies, branch dummies, and firm dummies. We report the coefficients of the constant. Standard errors are clustered at the firm level. *, **, and***indicate significance at the 10%, 5%, and 1% levels.

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			
1-3	0.26***	-0.09***	-0.0009***
4-6	0.17***	0.25***	-0.0005***
7-9	-0.09***	0.31***	0.01***
10-12	-0.09***	-0.02***	-0.01***
>= 13	-0.02***	-0.24***	0.01***

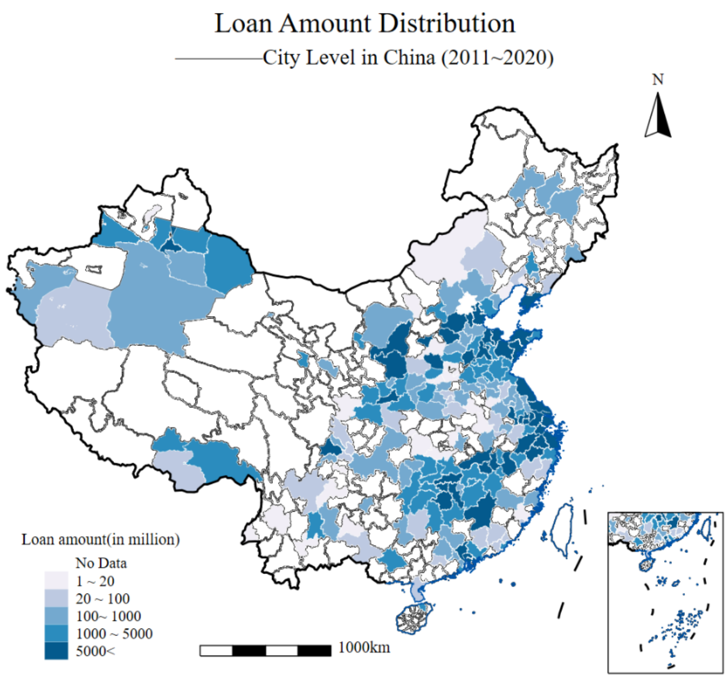
Table A4. Alternative explanations for switching-loan pricing

This table presents findings from seven analytical dimensions, comparing our explanations based on hold-up due to information frictions against three alternative explanations: competition via teaser pricing, selection-on-offer, and borrower inertia.

Our analyses	Our findings	Our explanation	Alternative explanations		
		Hold-up due to information frictions (Alonso et al., 2008; Ioannidou and Ongena, 2010; Agarwal and Hauswald, 2010)	**Competition vis teaser pricing** (Van Leuvensteijn, Sørensen, Bikker and Van Rixtel, 2013; Hollander and Verriest, 2016; Ornelas, Silva, and Doornik, 2022)	**Selection-on-offer** (Gustafson, 2018; Santos and Winton, 2019; Berg et al., 2020; Fan, Liu, Peng and Wang, 2024)	**Borrower inertia** (Baker, Coval and Stein, 2007; Steiner, Stewart, and Matějka, 2017; Heiss, McFadden, Winter, Wuppermann and Zhou, 2021)
Initial loan rate at switching	**Lower initial rates at switching**	**Prediction: Lower initial rates at switching** (organizational frictions hinder the flow of information, representing hold-up costs) **✓ Consistent**	**Prediction: Lower initial rates at switching** (outside branches offer lower initial rates to attract the borrower) **✓ Consistent**	**Prediction: Lower initial rates at switching** (switch only occurs when the outside offer is better enough) **✓ Consistent**	**Prediction: Lower initial rates at switching** (only large perceived gains overcome inertia) **✓ Consistent**
Subsequent loan rate path	**Reversal above the market average**	**Prediction: Reversal above the market average** (as outside branch accumulates soft information, it regains informational leverage and begins to extract rents) **✓ Consistent**	**Prediction: Remain stable or revert to the market average** (no reason for spreads to overshoot) **✓ Partially Consistent**	**Prediction: Remain stable or revert to the market average** (no reason for spreads to overshoot) **✓ Partially Consistent**	**Prediction: Remain stable** (inertia is about reluctance to move, not about pricing dynamics once moved) **✗ Inconsistent**

Branch manager Co-movement	**Discount disappears when switch with managers**	**Prediction: Discount disappears when switch with managers** (soft information transfers seamlessly, eliminating informational frictions) ✓ Consistent	**Prediction: No difference** (teaser pricing is a market-based strategy unrelated to who the manager is) ✗ Inconsistent	**Prediction: No difference** (selection is driven by borrower behavior, not internal information flows) ✗ Inconsistent	**Prediction: No difference** (inertia is behavioral, unrelated to soft information transfer) ✗ Inconsistent
Lender-borrower geographic proximity	**Smaller initial discounts**	**Prediction: Smaller initial discounts** (nearby branches exert greater competitive pressure, constraining the incumbent's ability to extract rents) ✓ Consistent	**Prediction: Larger initial discounts** (greater proximity leads to more intense competition and deeper discounts) ✗ Inconsistent	**Prediction: No difference** (selection should depend on better offers, not distance) ✗ Inconsistent	**Prediction: Smaller initial discounts** (inertia is weaker when outside option is nearby and samll discount can overcome it) ✓ Consistent
Newly established branches	**Larger initial discounts**	**Prediction: Larger initial discounts** (new branches with less informational capital pose incumbents with less competitive pressure and can extract larger rents) ✓ Consistent	**Prediction: Larger initial discounts** (new branches use aggressive teaser pricing to build loan portfolios) ✓ Consistent	**Prediction: Larger initial discounts** (borrowers might select new branches offering aggressive rates) ✓ Consistent	**Prediction: No difference** (both newly established and existing branches can lead to inertia) ✗ Inconsistent
SCS/FinTech reducing information frictions	**Smaller initial discounts**	**Prediction: Smaller initial discounts** (better information flows reduce asymmetry and weaken	**Prediction: Larger initial discounts**	**Prediction: Larger initial discounts** (better information environment leads to better offers)	**Prediction: No difference** (inertia is psychological, should not be affected by information envirionment)

		incumbents' ability to hold up borrowers) ✓ Consistent	(better information environment leads to more severe competition) ✗ Inconsistent	✗ Inconsistent	✗ Inconsistent
Borrower opacity (SMEs/private firms)	**Larger initial discounts**	**Prediction: Larger initial discounts** (opaque borrowers are more dependent on relationship lending and thus more vulnerable to rent extraction) ✓ Consistent	**Prediction: Smaller initial discounts** (competitive teaser pricing should target larger, safer, and more visible firms) ✗ Inconsistent	**Prediction: Larger initial discounts** (opaque firms should switch only when rates are very favorable) ✓ Consistent	**Prediction: Larger initial discounts** (opaque borrowers exhibit more inertia, staying put despite worse terms) ✓ Consistent



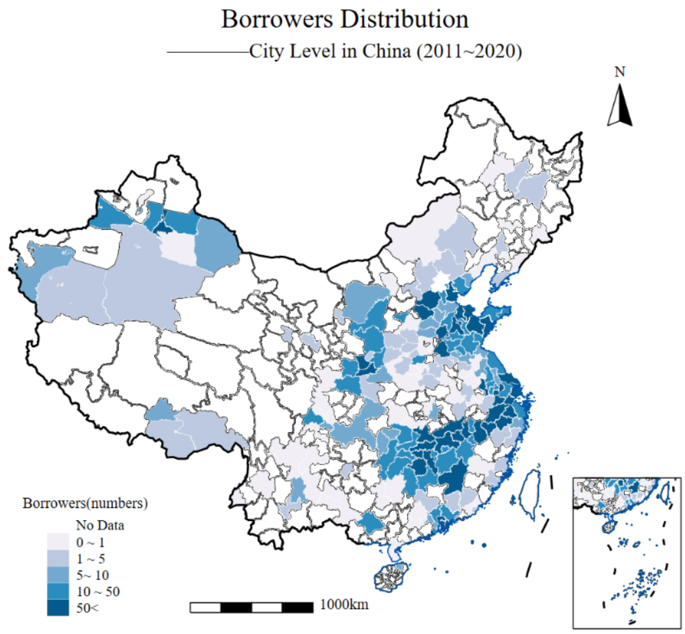


Figure A1. Sample Distribution

These figures present the distribution of loan amounts and the distribution of lending firms at the city level.

Appendix B: Questionnaire

Basic Information
Please provide the following information. Please note that your confidentiality and the sensitive information you provided will be strictly enforced.

1. What is your gender?
   A. Male
   B. Female
2. Which type of bank are you affiliated with?
   A. State-owned commercial banks
   B. Joint-stock commercial banks
   C. City commercial banks
   D. Rural commercial banks
   E. Rural credit cooperatives
   F. Village banks
   G. Private-owned commercial banks
   H. Foreign banks
   I. Others
3. Where is your place of work?
4. What level of branch hierarchy are you employed in?
   A. Headquarter
   B. First-tier Branch
   C. Second-tier Branch
   D. First-tier Sub-branch
   E. Second-tier Sub-branch
   F. Others

Survey Questions
Kindly assess your bank based on the following descriptions according to your genuine feelings and experiences. Indicate the most appropriate category based on the following criteria.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

Section 1. Intra-Bank Competition
1. The bank sets high performance targets for the branch.
2. The bank emphasizes on whether the branch could meet the targets.
3. The branch can only get recognition from the bank if the branch performs well.
4. The branch is responsible to meet the targets and satisfy the bank.
5. The employee's promotion prospects are highly dependent on her performance.
6. The bank evaluates the performance of the branch based more on the comparison across branches within the bank than the comparison to other banks.
7. The branch managers evaluate the performance of employees based on the comparison with other branches within the bank.
8. There exist intra-bank competition among branches to attract customers.
9. The branch tries to attract credit customers from other branches within the bank.

Section 2. Information Communication
1. The branches within the bank emphasize on the communication and sharing of information.
2. Different branches within the bank regularly arrange meeting or other formal occasions to discuss strategic decisions.
3. Different branches within the bank regularly communicate informally and exchange opinions on strategic decisions.

Section 3. Application of FinTech
1. The application of FinTech provides great opportunities for the bank.
2. The bank has continued to emphasize the importance of FinTech.
3. The bank has encountered some challenges in the application of FinTech.
4. The application of FinTech enriches the bank's information about the customers.
5. The application of FinTech increases the customers' reliance on the bank.
6. The application of FinTech increases SMEs reliance on the branch.

BOFIT Discussion Papers

A series devoted to academic studies by BOFIT economists and guest researchers. The focus is on works relevant for economic policy and economic developments in transition / emerging economies.

2022	No 1	Michael Funke and Adrian Wende: The US–China phase one trade deal: An economic analysis of the managed trade agreement
	No 2	Michael Alexeev and Nikita Zakharov: Who profits from windfalls in oil tax revenue? Inequality, protests, and the role of corruption
	No 3	Florian Léon and Laurent Weill: Elections hinder firms' access to credit
	No 4	Alistair Dieppe and Hideaki Matsuoka: Sectoral decomposition of convergence in labor productivity: A re-examination from a new dataset
	No 5	David P. Newton, Steven Ongena, Ru Xie and Binru Zhao: Banks vs. markets: Are banks more effective in facilitating sustainability?
	No 6	Tat-kei Lai and Luhang Wang: Spatial disparity of skill premium in China: The role of financial intermediation development
	No 7	Zuzana Fungáčová, Alexei Karas, Laura Solanko and Laurent Weill: The politics of bank failures in Russia
	No 8	Jin Cao, Valeriya Dinger, Ragnar E. Juelsrud and Karolis Liaudinskas: Trade conflicts and credit supply spillovers: Evidence from the Nobel Peace Prize trade shock
	No 9	Nils Steiner, Ruxanda Berlinschi, Etienne Farvaque, Jan Fidrmuc, Philipp Harms, Alexander Mihailov, Michael Neugart and Piotr Stanek: Rallying around the EU flag: Russia's invasion of Ukraine and attitudes toward European integration
	No 10	Andrey Tkachenko: State-business relations and access to external financing
	No 11	Denis Davydov, Tatiana Garanina and Laurent Weill: Managing bank liquidity hoarding during uncertain times: The role of board gender diversity
	No 12	Timur Natkhov and William Pyle: Revealed in transition: The political effect of planning's legacy
	No 13	Michael Funke and Adrian Wende: Modeling semiconductor export restrictions and the US-China trade conflict
	No 14	David Finck and Peter Tillmann: The macroeconomic effects of global supply chain disruptions
2023	No 1	Francis Osei and Laurent Weill: Regional favoritism in access to credit: just believe it
	No 2	Yiping Huang, Xiang Li, Han Qiu and Changhua Yu: BigTech Credit and Monetary Policy Transmission: Micro-Level Evidence from China
	No 3	Günther G. Schulze and Nikita Zakharov: Political cycles of media repression
	No 4	Anna Di Gong, Jin Wu and Jigao Zhu: When banks' shadow fades and shadow banking rises: Securitization and loan performance in China
	No 5	Julia Niemeläinen: China's macroeconomic policies and spillover effects
	No 6	Loren Brandt, Johannes Van Biesebroeck, Luhang Wang and Yifan Zhang: Where has all the dynamism gone? Productivity growth in China's manufacturing sector, 1998-2013
	No 7	Xiaoshan Hu, Guanghua Wan and Congmin Zuo: Education expansion and income inequality: Empirical evidence from China
	No 8	Tuuli McCully: Drivers of portfolio flows into Chinese debt securities amidst China's bond market development
	No 9	Iftekhar Hasan, Xiang Li and Tuomas Takalo: Technological innovation and the bank lending channel of monetary policy transmission
2024	No 1	David Lodge, Ana-Simona Manu and Ine Van Robays: China's footprint in global financial markets
	No 2	Mustafa Özer, Jan Fidrmuc, Emmanouil Mentzakis and Özcan Özkan: Does education affect religiosity? Causal evidence from a conservative emerging economy
	No 3	Iikka Korhonen and Heli Simola: High-priority battlefield items and television sets – How sanctions reduced Russians' access to goods
	No 4	Zuzana Fungáčová, Eeva Kerola and Laurent Weill: European banks are not immune to national elections
	No 5	Kari Heimonen and Risto Rönkkö: The RMB's global role as an anchor currency: no evidence
	No 6	Biswajit Banerjee and Risto Herrala: Testing the impact of liquidation speed on leverage using Indian data
	No 7	Madhav S. Aney and Sanjay Banerji: Forgery, market liquidity, and demat trading: Evidence from the national stock exchange in India
	No 8	Eeva Kerola, Tuuli McCully and Riikka Nuutilainen: Trade with Chinese characteristics – economics versus politics
	No 9	Martin Hodula, Jan Janků, Simona Malovaná and Ngoc Anh Ngo: Geopolitical risks and their impact on global macro-financial stability: Literature and measurements
	No 10	Lea Borchert, Ralph De Haas, Karolin Kirschenmann and Alison Schultz: Broken relationships: De-risking by correspondent banks and international trade
	No 11	Liyuan Liu, Xianshuang Wang and Zhen Zhou: Let a small bank fail: Implicit non-guarantee and financial contagion
2025	No 1	Hans Degryse, Cédric Huylebroek and Bernardus Van Doornik: The disciplining effect of bank supervision: Evidence from SupTech
	No 2	Richard C. K. Burdekin and Pierre L. Siklos: Combating crises and deflation in China's central bank: Modeling post-pandemic monetary policymaking
	No 3	Mika Nieminen and Anni Norring: What motives and conditions drive countries to adopt macroprudential and capital management measures?
	No 4	Michael Funke and Adrian Wende: The limited effectiveness of sanctions on Russia: Modeling loopholes and workarounds
	No 5	Tural Yusifzada, Hasan Comert and Vugar Ahmadov: A composite approach to nonlinear inflation dynamics in BRICS countries and Türkiye
	No 6	Biswajit Banerjee and Risto Herrala: An agency cost channel from creditor rights reforms to leverage
	No 7	Di Gong, Steven Ongena, Shusen Qi and Yanxin Yu: Information frictions inside a bank: Evidence from borrower switching between branches

BOFIT Discussion Papers
http://www.bofit.fi/en • email: bofit@bof.fi
ISSN 1456-5889 (online)