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“TIME FOR A CHANGE OF SCENERY”: LOAN CONDITIONS WHEN FIRMS SWITCH BANK BRANCHES

Abstract

Firms switching banks initially receive a lower loan rate. But what if firms switch branches within the same bank? 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, the switching loans carry a significantly lower spread than the comparable nonswitching loans as well. After switching, the new branch further reduces the loan spreads initially, but ratchets it up afterwards, surprising evidence of the existence of intra-bank hold-up! Importantly, the deployment of FinTech within the bank first mitigates but then intensifies this hold-up.

JEL Classification: G21, G32, L14

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

DI GONG, STEVEN ONGENA, SHUSEN QI, and YANXIN YU*

January 9, 2025

Firms switching banks initially receive a lower loan rate. But what if firms switch branches within the same bank? 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, the switching loans carry a significantly lower spread than the comparable nonswitching loans as well. After switching, the new branch further reduces the loan spreads initially, but ratchets it up afterwards, surprising evidence of the existence of intra-bank hold-up! Importantly, the deployment of FinTech within the bank first mitigates but then intensifies this hold-up.

Keywords: bank lending; hold-up; firm-bank relationship
JEL codes: G21; G32; L14

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1. Introduction

Recent work documents that firms switching banks initially receive a lower loan rate. In Ioannidou and Ongena (2010) for example Bolivian firms receive an 89 basis points (bps) (≅ 7% of the average loan rate) discount when switching banks, while Portuguese firms in Bonfim, Nogueira, and Ongena (2021) obtain a 63 bps (≅ 8% of the average loan rate) discount.[1] Ioannidou and Ongena (2010) then also identify a dynamic cycle in loan rates with the new bank initially decreasing the loan rate further but eventually ratcheting it up sharply.[2]

These studies provide evidence on hold-up in relationship lending and are accompanied by other studies on the forming and switching of firm-bank relationships (Gopalan, Udell, and Yerramilli, 2011; López-Espinosa, Mayordomo, and Moreno, 2017; Sutherland, 2018; Kalda and Neshat, 2024). These studies heavily rely on the fact that relationships generate valuable private information in asymmetric information environments, and that this information is often "soft" in nature, e.g., involving a character assessment and a degree of trust (Petersen and Rajan, 1994; Berger and Udell, 1995). With soft information, the context under which the information is collected is part of the information and cannot be easily separated (Liberti and Petersen, 2019).[3] This may constrain the environments in which the information is used: the borrower cannot easily switch banks because the information cannot be transmitted without a loss, leading to the hold-up problem (Sharpe, 1990; Dell'Ariccia and Marquez, 2004).

But can soft information collected by one branch maybe be transmitted effortlessly to another branch within the same bank? To help answer this question empirically, we study the loan conditions when firms *switch branches within the same bank*. Specifically, we utilize the

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1 Barone, Felici, and Pagnini (2011) find an average discount of 44 bps in Italy, while Stein (2015) finds an average discount for main bank borrowers of 33 bps in Germany. Xu, Saunders, Xiao, and Li (2020) and Liaudinskas (2023) study loan pricing when firms are forced to transfer, while Cao, Garcia-Appendini and Huylebroek (2024) study pricing when firms switch banks on their deposit and/or credit relationships.

2 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, Nogueira, and Ongena (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, Saunders, Xiao, and Li (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 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.

population of corporate loans originated by a large commercial bank in China during 2010 and 2020. This large and novel database allows us to follow firms over an extended period,[4] to identify the branches that issue the loans, and to compare the loan conditions obtained by switching firms with comparable nonswitching loans. We apply the same matching strategy as Ioannidou and Ongena (2010) and estimate the dynamic pattern of loan conditions when firms switch branches, to investigate whether hold-up exists within the same bank.

Overall, we find that when firms switch branch, i.e., from their current "inside" branch to a new "outside" branch within the same bank, the new loan on average obtains a loan spread that is about 6 bps (≅ 1% of the average loan rate, or ≅ 7% of the average loan spread) lower than the spreads on comparable (matched) new loans originated by either their outside or inside branches to existing customers. After switching, the outside branch is willing to further reduce the loan spreads by another 18 bps within the first two quarters. However, within a year, the switchers are back to the average spread and soon start to pay higher spreads.

A further piece of evidence is that if a firm switches to a newly established branch, the switching discount is more than four times as large (27 bps ≅ 5% of the average loan rate, or ≅ 30% of the average loan spread), as the new branch lacking any informational capital may be even less informed than existing branches. But the difference in switching discount is not driven by the distance between the borrowing firm and the branch it switches to. In other words, the larger switching discount of newly established branches is not driven by the possibility that the new branch is located further away from the borrower and consequently more severe distance related informational disadvantages (Degryse and Ongena, 2005).

It is interesting to note that these discounts and hikes are smaller and swifter than the ones documented in the empirical literature on switching bank. This is likely the case because the hold-up problem is less severe within a single bank than across different banks. Yet, we do provide pioneering evidence of its significant presence within a bank.

Importantly, we also observe that the deployment of FinTech in our bank first almost entirely mitigates hold-up but then dramatically worsens the situation (with the switching discount even dipping below 20 bps). In the initial stage, the use of FinTech is mainly aimed to transform the current information into more easily quantifiable numbers and this process could significantly reduce hold-up. But further development of FinTech such as big data technology might come with additional information advantages. In the absence of an efficiently shared information processing system, FinTech may actually intensify hold-up. These findings indicate that the hold-up problem and the resulting switching cost are still relevant in the current digitalized world.

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[4] 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, Nogueira, and Ongena (2021) study 1,062 and 24,292 bank-switching loans, respectively.

Our empirical findings speak to both salient theoretical and empirical parts of the literature. Our paper provides the first empirical evidence for the existence of an intra-bank hold-up. Stein (2002), for example, models the organizational impact of the ease and speed at which different types of information can "travel" within an organization. Hard information can be passed on easily within the organization while soft information is much harder to relay. Consequently, he derives that if the organization employs mostly soft information, a simple and flat structure, and local decision making may be optimal.[5] A corollary in this setting is that firms may be held-up by individual branches; this is the "within-bank hold-up" we document.

This interpretation is further supported by evidence from a survey we conducted among bank employees. Specifically, 76% of respondents agree that there exists intra-bank competition across branches, and 57% even clearly state that branches within the same bank are competing directly with each other for credit customers, attracting borrowers to switch from one branch to another. These ratios amount to 85% and 69% in the bank where we get our data. This is because the evaluation of performance is largely dependent on the relative comparison across branches within the same bank (85%) and sometimes performing better than other branches from the same bank is more important than outperforming other banks (69%). As a result, the communication of information among branches within the same bank is not without its barriers, 30% of the bank employees confirm that there is a clear lack of information exchange within the bank.

But the hardening of information, in our case the application of FinTech, could alter this outcome, first removing hold-up then resuscitating it up to the point that information processing may create its own new barriers *à la* Hauswald and Marquez (2003) for example. In the survey we conducted, 68% of bank employees believe that the use of FinTech actually increases their customers' reliance, especially among small-and-medium-sized enterprises (SMEs).

In general, our findings enhance our understanding of information usage by banks, especially with respect to the collection and transmission of soft information in relationship

[5] If soft information cannot be communicated easily within the same bank, intra-bank competition across branches or even among loan officers may become possible (Blackwell, Brickley, and Weisback, 1994; Seltzer and Frank, 2007; Xie, Zhang, Song, and Tong, 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, 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. Geodde-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, and Klapper, 2015; Qian, Strahan, and Yang, 2015).

lending. Even within the same bank, soft information cannot be easily separated from the context and the person. These frictions in the collection and communication of information within a bank add more challenges for an efficient allocation of credit. Extant work already has established that information asymmetries and barriers in the transmission of information across banks may distort the allocation of credit, for example, by enabling banks to charge higher loan rates than the borrower quality warrants (Kim, Kliger, and Vale, 2003; Ioannidou and Ongena, 2010; López-Espinosa, Mayordomo, and Moreno, 2017; Bertrand and Burietz, 2023) or by specifically reallocating credit to a specific group of borrowers potentially at the expense of others (Dell'Ariccia and Marquez, 2004; Sette and Gobbi, 2015; Beck, Degryse, De Haas, and Van Horen, 2018). Our findings of a hold-up problem within a bank may intensify this credit misallocation problem, potentially further questioning the efficient functioning of the banking market.

Our paper also contributes to the economics of bank branching (see, e.g., Keil and Ongena, 2024). Prior studies focus on deregulation of bank branches, offering insights into the effects of deregulation on bank performance (Jayaratne and Strahan, 1998), bank stability (Goetz, 2018), entrepreneurship (Black and Strahan, 2002), income inequality (Beck, Levine, and Levkov, 2010), economic growth (Jayaratne and Strahan, 1996), and economic volatility (Morgan, Rime, and Strahan, 2004). Other studies examine the efficiency and performance of bank branches (Berger, Leusner, and Mingo, 1997; Hirtle, 2007), the effect of competition on bank orientation (Degryse and Ongena, 2007), the value of branches for access to finance (Ergungor, 2010; Nguyen, 2019; Bonfim, Nogueira, and Ongena, 2021), and/or the role played by branch networks in financial integration (Gilje, Loutskina, and Strahan, 2016). However, intra-bank competition and frictions have received much less or no attention so far. Our study addresses this gap by investigating switch barriers for relationship borrowers across different branches.

Our paper differs from the classic studies on hold-up problems in relationship banking (Ioannidou and Ongena, 2010, Bonfim, Nogueira, and Ongena, 2021). First, we approach the issue from the perspective of agency issues within a bank by analyzing the borrowers switching across various branches. Driven by the relative performance incentive scheme, loan officers tend to withhold some soft information rather than sharing it all to the outside branch when a borrower leaves. This moral hazard issue results in intra-bank hold-up phenomenon, which is distinct from the hold-up between different banks. Second, while Xu, Saunders, Xiao, and Li (2020) and Liaudinskas (2023) study loan pricing when firms are forced to transfer, we examine loan pricing when firms are facing newly established branches. The more aggressive discount offered by the newly established branches is in line with greater information asymmetry between the borrower and the new lender. Last, we add the discussion on the role of FinTech in the classic hold-up problem and analyze its nonlinear effect. Our analysis suggest that hold-up may exist in the digitalized world but depends on how FinTech applies in information processing.

The rest of the paper proceed as follows. Section 2 introduces the banking system in China and the branching network. Section 3 describes the data we use and provide relevant summary statistics. Section 4 presents our empirical strategy and the findings and Section 5 concludes.

2. Banking System and Branching Architecture in China

Commercial banks in China maintain extensive branch networks across the country due to its vast size. These networks operate within a hierarchical structure, with centralized control and coordination from the bank's headquarters. Branches function as frontline service providers, offering a wide range of banking services while adhering to centralized management for efficiency, compliance, and customer satisfaction. Typically, banks have multiple branches in a city, spanning downtowns, urban centers, suburban, and rural areas, providing retail banking, corporate banking, wealth management, and foreign exchange services. Branches operate under centralized management, with major decisions made at the headquarters level. While branches have some autonomy, they adhere to standardized procedures set by headquarters. Branches report to regional or district managers, who in turn report to higher-level executives. Regular communication occurs between branches and headquarters to share information and coordinate activities. However, intra-bank competition among branches may weaken communication and information sharing.

Competition in the Chinese banking sector has been becoming increasingly fierce in recent years due to market liberalization, deregulation and other regulatory reforms, entry of new banks, competition in products and services, and so forth. Most banks adopt an aggressive competition strategy to augment their market share. During this process, the performance pressure is transferred to the banks' subordinates and a multi-layered tournament system is established (Xie, Zhang, Song, and Tong, 2019). This is accompanied by China's banking reforms to decentralize the decision-making authority to branches to maximize local information advantages (Park and Shen, 2008; Qian, Strahan, and Yang, 2015). So, internal competition, or tournament, within a bank commonly exists in China. For example, branch managers compete with their peers from other branches. Inside a branch, loan officers also compete against each other for compensation and promotion (Blackwell, Brickley, and Weisback, 1994; Seltzer and Frank, 2007; Tzioumis and Gee, 2013).[6] In banks, the assessments on loan officers and branches mainly focus on their credit outcomes. To achieve and maintain an edge in the tournament, loan officers, and their branches, are incentivized to conceal information from their peers, ultimately holding up their borrowers from receiving offers from competitive branches within the same bank.

[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, Tihanyi, Crook, and Gangloff, 2014).

To formally confirm this prior, we conduct a survey among bank employees in China. In particular, the survey is conducted online and we reach to a total of 301 bank employees within a week in early 2024, and get 301 qualified feedbacks. Among these feedbacks, 160 are from the headquarters of the banks and the remaining 141 comes from employees working in bank branches. As our focus is how the intra-bank competition across branches looks like, we focus on the subsample of respondents working in bank branches. These employees are most familiar with the competition environment and have a better sense of how information flows within a bank. Thus, this selection leaves us with a final sample including 141 bank employees working in bank branches across 18 provinces in China. Among them, 53% are females and hence the gender composition seems to be quite balanced and not unlike aggregate statistics.

Moreover, we also distinguish between employees from the bank where we get our loan-level data and those from other banks. Among the final sample, 26 of them work in our sample bank and the other 115 work in other banks in China (to protect their private information, we did not ask about their specific bank names other than it is not our sample bank). The responses are mostly consistent across the two groups, so in later analysis we do not differentiate between them unless necessary.

The questionnaire is originally designed and conducted in Chinese but is translated to English in the Appendix for reference. We focus on three sections in the survey, including intra-bank competition, information communication within banks, and the application of FinTech.[7] For each question in each section, the respondent can choose from five answers: Strongly disagree, disagree, neutral, agree, and strongly agree.

[Insert Figure 1 here]

We start with intra-bank competition. There are nine questions in this section and the first five questions show the importance of meeting their performance targets in the bank. For example, 77% of the respondents confirm that banks set performance targets for the branches and 84% agree that meeting these targets are important. It is also important for personal career development (72%). Questions 6-7 continue to show that in performance evaluations, it is often the case that intra-bank comparison across branches outweighs inter-bank rankings (69%). The same applies when it comes to personnel evaluations (78%). This is shown by Panel A of Figure 1. The last two questions directly touch the heart of the intra-bank competition that branches are said to directly compete with each other for customers, within the same bank (76% agrees). This is listed in Panel B of Figure 1.

[Insert Figure 2 here]

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

We then continue with the internal sharing of information within a bank using three questions. The responses are presented in Figure 2. It is surprising that although banks usually emphasize the importance of information sharing within the bank (54% agrees), there are still 30% and 22% of the respondents think there is a lack of communication, both formally and informally. Therefore, information, especially soft information, is still hard to be transferred even within the same bank. These findings give rise to our research question and support the relevance and importance of our work.

3. Data and Descriptive Statistics

Our work utilizes data from a large commercial bank in China. This bank operates national wide with around 300 branches in more than 20 cities. For confidentiality, we are not allowed to disclose the name of the bank. Our sample covers the population of 119,270 new corporate loan initiations from this bank during 2010 and 2020 to 27,118 firms across 203 cities in China.[8] Analyzing only new loans allows us to employ up-to-date and comparable firm and contract information at the exact time when firms switch to a new branch.

For each new loan, we have information on the contract terms, the borrowing firm, and the branch that issues the loan. Contract information includes the date of origination, maturity date, loan rate, amount, collateral (of which 89% are collateralized), and rating (pass=1, special attention, substandard, doubtful, and write-off=5), and the existence of a credit line (of which 77% of loans have a credit line). For each borrowing firm, the data records its geographical location, industry, legal structure (of which 98% are corporations, with the remaining 2% includes partnerships, collective, sole proprietorships, public institutions, and other organizations), ownership structure (of which 92% are private firms and 8% are state-owned, including central SOEs, local SOEs, government financing platforms, and other government institutions), and size (of which 78% are SMEs and 22% are larger firms). Unfortunately, our data cannot be matched with firm balance-sheet information, because for confidentiality purposes the bank altered the borrower's identities before providing us the data.

Importantly, this unique database allows us to track the branch that issues each loan and contains information about the identity of the branch, the geographical location, and the establishment dates. Using the information, we could additionally construct measures to capture the intensity of firm-branch relationships. Specifically, we measure the length of the lending relationship by the number of months between the date when a firm obtained its first loan from this branch and the date when the new loan is originated. We also capture the

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

density of the relationship by the number of loans that a firm obtained from this branch within the past 5 years, before the newly issued loan. Last, we use a dummy to identify whether a firm maintains a lending relationship with multiple branches.

In China, the People's Bank of China (PBoC), the central bank of China, has gradually liberalized interest rates since 1996 (Kim and Chen, 2022). The interbank rate was first liberalized and for the next 8 years, the PBoC gradually expanded the interest rate range based on benchmark lending and deposit rates. In 2004, 2013, and 2015, the PBoC removed the upper and lower bounds of lending and deposit rates. This last step completed the interest rate liberalization of retail lending and deposit, and subsequently, the benchmark rate serves as a reference for retail lending and deposit. Fully liberalized interest rates have led the PBoC to establish an interest rate corridor system. Overall, the policy rate, both before and after the interest rate liberalization, plays an important role when banks determine their loan rates in China. During our sampling period of 2010-2020, the policy rate has been adjusted for 21 times, with a maximum of deviation amounts to 280 bps. As the bank obviously cares more about the risk premium than about the nominal interest rate, we focus on the loan spread above the PBoC's monetary policy rate. But our results are robust if we directly use the nominal loan rates.

An average loan initiated in our sample carries a loan spread of 88 bps with about 1 year of maturity, and amounts to CNY 23.7 million. A typical firm obtains 3 loans per year from our bank and a typical branch originates about 216 loans on an annual basis. During the whole sampling period, an average branch grants loans to 507 different firms. Regarding the lending relationships, 39% of firms maintain relationships with multiple branches and a typical relationship lasts for 32 months with 6 prior loans within the same branch.

4. Results

In light of Ioannidou and Ongena (2010), we examine the differences in loan conditions when firms switch branches within the same bank to first document that relationship lending exists even within the same bank, and then investigate how the use of fintech in banking affects the relationship.

4.1. Switching

We strictly follow Ioannidou and Ongena (2010) to define a new loan as a switch (or a switching loan) when a firm obtains a new loan from a branch with which it did not have a lending relationship during the prior 12 months.[9] We call such branches "outside" branches. In this case, we make the same assumption that the key inside information can get stale within 1 year. But our results remain consistent when we use 24- or 36-month cut-offs.

[9] Unlike the case of forced loan "transferring" in Xu, Saunders, Xiao, and Li (2020) (by the "localization of credit issuance" policy) and Bonfim, Nogueira, and Ongena (2021) (by branch closure), our paper captures "switching", as in Ioannidou and Ongena (2010).

Similar to Ioannidou and Ongena (2010), our definition of switching does not differentiate between those firms that "move" across branches and those firms that "add" a relationship with a branch. Ioannidou and Ongena (2010) provides a solid explanation on why distinguishing between "movers" and "adders" is not necessary in this setting as extant exposures may be built down only after the firm switches (and operationally this is what we observe). We then define "inside" branches as those branches with a lending relationship with the firm during the prior 12 months. Accordingly, we label new loans that the inside branch originates to its existing customers as nonswitching loans.

[Insert Figure 3 here]

Figure 3 presents such classification. There is one firm A and four bank branches 1, 2, 3, and 4. A line represents an outstanding loan and the dots indicate the starting and ending dates of this loan. 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, 2, and 4 are the switcher's inside branches, as in the last 12 months firm A had at least one loan outstanding with these branches. Thus, focusing on time t=0, the switching loan is represented by the dashed line and the nonswitching loan is indicated by the solid line.

Given our definition of switching, our data contains 7,628 switching loans, accounting to approximately 7% of the loan originations during our sampling period. These switching loans were granted to 6,170 firms, indicating that about 22% of firms in our sample switch branches at some point during 2010-2020 (2.2% per year). These percentages are lower than the switching between banks in Farinha and Santos (2002) (4% per year) and Ioannidou and Ongena (2010) (4.5% per year), suggesting that switching branches within the same bank is less frequent than switching banks. This is intuitively sensible that switching within a bank is less necessary than switching across banks.

[Insert Table 1 here]

Table 1 provides the descriptive statistics for switching and nonswitching loans. In general, the loan spreads are comparable between the two groups with the medians both equal to 87 bps. But the average loan spread is a bit higher among switching loans (90 bps) compared to the nonswitching ones (88 bps). This could be explained by other differences between the two groups. For instance, switching loans are often smaller, longer in maturity, more often to be collateralized, higher in credit rating, less likely to have a credit line, more likely to be granted to SMEs, and having less intense lending relationships with the branch. These differences suggest that outside branches may behave differently compared to the inside branch, in terms of the group of firms to lend and the contract terms to offer. As a result, when comparing the loan spreads at the time when firms switch, it is essential to properly control for the various firm and contract characteristics, and this triggers us to utilize a matching methodology to address this challenge.

4.2. Matching

Ideally, we would like to compare the loan rate that the switcher receives from the outside branch with the rate its inside branch offered. But we are not able to observe the inside branch's unsuccessful offer. To proxy for this counterfactual, we follow Ioannidou and Ongena (2010) to utilize similar loans that the inside branch granted in the same month to other comparable firms (Figure 4). To address the potential impact of branch characteristics on the inside and outside offers, in a similar matching exercise we also compare the rates on the switching loans to the rates of similar loans that the switcher's outside branch granted in the same month to other comparable existing customers (Figure 5).

[Insert Figure 4 here]

For example, in Figure 4, the dashed line represents the switching loan and branch 3 is the firm's outside branch and branches 1, 2, and 4 are the inside branches. In this case, we match the switching loan issued at time t=0 with the other four nonswitching loans from the switcher's inside branches (branches 1, 2, and 4) at the same time of the switch. In Figure 5, the dashed line is the same switching loan occurring at time t=0. Now we match this switching loan with the nonswitching loans originated by the firm's outside branch (branch 3) at the same time of the switch.

[Insert Figure 5 here]

Table 2 provides a description of the variables we match on. Apart from matching on the month of loan origination and the identity of the switcher's inside or outside branches, we also match on a set of firm and loan contract characteristics, including loan amount, maturity, collateral, and credit line, as well as the firm city, industry, legal and ownership structure, and size. These matching variables tend to minimize the observable differences between the switching and nonswitching loans, and also the corresponding firms. In our case, as suggested by Ioannidou and Ongena (2010), any unobservable heterogeneity would work against our hypothesis so that what we find here would be a lower bound of the switching cost. However, we do try to minimize the impact from potential unobservables by also matching on the bank's internal credit rating for each new loan. This matching would reduce bias from the unobservable-to-us but observable-to-bank characteristics. In a sensitivity analysis, we also match using the switcher's most recent credit rating prior to the switch from the inside branch. This could further address concerns of rating bias due to information asymmetries between a firm's inside and outside branches. Having said that, in our setting of switching branches within the same bank, this asymmetry in information is less of a concern compared to the case in Ioannidou and Ongena (2010) when firms switch banks. Last, matching on both the month of loan origination and loan maturity allows us to control for unobservable economic environment and expectations that could affect the loan spread.

[Insert Table 2 here]

Overall, our testing strategy has three steps: (1) we match each switching loan with all similar nonswitching loans to other comparable firms granted by the switcher's inside or outside branches at the time of the switch;[10] (2) we calculate the difference between the loan spreads on the switching loan and each matched nonswitching loan; and (3) we regress the difference in loan spreads on a constant. A statistically significantly negative constant term indicates that the loan spreads on the switching loans are on average lower than the rates on comparable nonswitching loans, and we classify as estimates of the switching costs.

4.3. Switching Costs

The results are presented in Table 3, including the matching variables, the number of matched switching and nonswitching loans, the number of observations in matched pairs, and most importantly the coefficient estimates on the constant term in the regression. The weighting system and the clustering of the standard errors at the switching firm level are to address for the potential multiplicity concern. Specifically, we adjust the coefficient estimates by weighting each observation by one over the total number of matched nonswitching loans per switching loan.

[Insert Table 3 here]

In column 1, we match switching loans with comparable nonswitching loans issued at the same month by its inside branches, as suggested by Figure 2. In this matching, we are left with 1,063 switching loans and 2,526 nonswitching loans, and together results in 3,064 matched pairs. So, on average, each switching loan is matched with 2.4 comparable nonswitching loans. The coefficient estimates on the constant equals -5.71 with weighting, suggesting that the loan spreads on the switching loans are on average 5.71 bps lower than the spreads on comparable nonswitching loans, or in other words, comparable loans issued by its inside branches at the same month of switch. Economically, this number is sizable given the fact that the average loan spread is 88 bps and average loan rate is 582 bps. In other words, switchers can obtain a loan spread that is 1% of the loan rate or 6.5% of the loan spread below a normal loan that their current inside branches could offer.

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

In column 2, instead of matching on the set of inside branches, we match each switching loan with comparable nonswitching loans issued by the outside branches, as depicted by Figure 3. Such a matching strategy could alleviate concerns regarding any difference in characteristics between the inside and outside branches, because the comparison is now made within the same branch in the same month. The only difference is that one is a switching loan (the firm just switched to the branch) and the other is a nonswitching loan from an existing customer. This is an important advantage over the matching exercise in column 1 or an alternative exercise whereby some branch characteristics are added to the set of matching variables. Matching on the outside branches leaves 6,443 matched pairs with 2,095 switching loans and 4,949 comparable nonswitching loans. The estimated spread is equal to -5.85 bps, which is very similar to the number in column 1. In the follow-up research, except for Section 4.4, which is based on column 1 for analysis, we consider column 2 as our benchmark model for other sections.

We also conduct two robustness tests to validate our findings. First, in column 3, we replace the credit rating that the switchers obtain from the outside branch with the most recent credit rating they obtained from their inside branch prior to the switch. The inside branch's ratings might be more informative because the inside branches may know the firm better. Ioannidou and Ongena (2010) suggests that ratings become better predictors of ex post performance as the length of a lending relationship increases. In addition, matching on the inside branch's rating is equivalent to requiring the matched nonswitching loans to have the same credit rating as the switcher from the same inside branch. This could help better approximate the inside branch's unobserved offer to the switcher. This matching slightly reduces the number of observations with an estimated spread of -3.86 bps. Second, in column 4, we try to control for the effect of the strength of the switchers' lending relationships with the inside branches by matching on a set of measures to capture the relationship strength, including the length and the density of the lending relationship, as well as the existence of multiple relationships. With this matching methodology, we require that the strength of switchers' relationships with their inside branches prior to the switch be comparable with the relationship strength of the matched nonswitchers. Matching on these three relationship proxies reduces the number of observations to 798 with an estimate of -6.86 bps.

Taken together, the results, especially the ones in columns 1 and 2, suggest that outside branches are similar from the switcher's inside branches in their pricing behavior vis-a-vis their existing customers.[11]

4.4. Switching to Newly Established Branches vs Existing Branches

If hold-up and the resulted switching discounts could explain our findings, we would expect

[11] Our results are robust if we use 24- and 36-month cut-offs, as well as directly using loan rates rather than loan spreads. The results are presented in Appendix Table A1.

the discount to be larger when a firm switches to branches that are less informed yet more in need of credit business. So, in a further analysis, we focus on switching to newly established branches.[12] When being set up, new branches have no informational capital to speak of yet are usually more active in attracting customers and building up their credit business. Loan prospecting incentives are usually strong among newly established branches (Heider and Inderst, 2012, Agarwal and Ben-David, 2018), where the internal agency problem may distort decision-making. Switching to a newly established branch is defined if the switching loan is issued by this branch within the first 12 months since its establishment. Here we exclude switching loans granted in the first three months of the branch's opening to avoid any potential bias, as the process of loan application and granting takes a certain amount of time.[13] Some of the loans that were issued by the new branch in its opening month might be the ones that already started the process in other branches, so technically might not be switching loans in the first place. The results are presented in Table 4. We indeed find that switching to newly established branches lead to a larger switching discount (26.79 bps ≅ 5% of the average loan rate or ≅ 30% of the average loan spread), compared to the switching to existing branches (5.50 bps ≅ 1% of the average loan rate or ≅ 6% of the average loan spread).

[Insert Table 4 here]

One potential concern is that the switching benefits we find might be driven by switchers that switch to branches closer by, which allows them to borrow at lower loan rates due to lower screening and monitoring costs (as a result of the shorter distance between the branch and the borrower). In our sample, about 70% of the borrowing firms switch to closer branches, among which 6% switches to closer branches that are newly established. To address this concern, we re-estimate our baseline model in column 1 of Table 3 by introducing various distance related proxies:[14]

$$r_{switch} - r_{nonswitch} = \beta_0 + \beta_1 \, Firm\text{-}Branch\ Distance + \varepsilon \tag{1}$$

where β_0 and β_1 are the coefficients to be estimated, and ε is the error term. We measure the *Firm-Branch Distance* between the borrowing firm and its corresponding branch by

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[12] In this analysis, we only 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 nonswitching customers.

[13] In the robustness check, we also adjusted this time window for testing, and the results remained robust. Due to space constraints, we do not present the details here.

[14] Under the assumption of not distinguishing between newly established branches and existing branches, we also re-estimate our model in column 2 of Table 3, and the results remain robust. Due to space constraints, we do not present the details here.

Difference in Firm-Branch Distance. It represents the change in distance (in log of kilometers) when the firm switches from its inside branch (the inside branch with the most recent loan prior to switching) to the outside branch. So larger numbers indicate switching to further away branches. We further construct a dummy for *Switch to Further Away Branch*, taking the value of 1 when *Difference in Firm-Branch Distance* exceeds 0, and 0 otherwise. The results are presented in Table A2 of the appendix. All two distance proxies enter insignificantly, indicating that the switching discount is not driven by the distance between the borrowing firm and the branch it switches to.

4.5. Dynamics after Switching

Switching might give a firm an initial advantage that fades over time, as the existing customers of outside branches have to pay more. In other words, if the cut in loan spreads were permanent, we would find no systematic differences in spreads between similar loans from switching and existing customers of the outside branches. Intuitively, our findings suggest that after winning the firm with an attractive offer, the outside branch starts behaving like an inside branch and extracts rents from these firms. To test this hypothesis more directly, we examine the evolvement of loan spreads by tracing the dynamic path of switchers in their outside branch after switching.

Specifically, we trace each switcher over time in its new outside branch, and calculate the difference in loan spreads between the switching loan and the new loans that the switcher obtained from the outside branch after the switch. The comparison is now within the same branch and within the same borrowing firm. Moreover, we also match on the relevant variables from our benchmark model in column 2 of Table 3. This implies that we compare only the loans to switchers that remained with the new outside branch and whose contract terms did not change after the switch, especially the credit rating. This matching exercise yields 3,543 switching loans to 3,041 firms and 10,243 comparable future loans. More than 99% of these loans have the best rating and these are the firms that the outside branch originally rated highly, and that maintained their high ratings throughout. In effect, as suggested by Ioannidou and Ongena (2010), these are the good firms that are potentially exposed to hold-up.

Using this sample, we group the corresponding matches in quarters ("1 to 3 months" to "at least 12 months") after the switch. For each quarter, we regress the loan spreads on a constant, calendar-year dummies, branch dummies, and firm dummies. These dummies eliminate the impact of time-invariant firm and branch characteristics, and the overall impact of macroeconomic conditions. We report the coefficient estimates of the constant and standard errors are clustered at the firm level. The results are presented in Panel A and B of Table 5. We find that in the first 9 months after the switch, the loan spreads drop further by up to 52.34 bps in newly established branches and in the first 6 months after the switch, the loan spreads drop further by up to 18.38 bps in existing branches, and start increasing thereafter.

This is due to the potential concern of losing this customer from the outside branch, especially among the newly established branches. In order to keep the customer, the outside branch has to give additional discounts for the upcoming loans after the initial switch. However, once this initial period is passed, the switcher starts to pay more. For example, one year after the switch, the loan spread on new loans is 26.22 (17.00) bps higher than the switching loan.

[Insert Table 5 here]

As a robustness check, rather than looking forward, we also look backward and check whether a similar loan spread cycle can also be traced in the past loans that the switchers obtained from their inside branches before the switch. We, therefore, identify all loans that a switcher obtained from its inside branch before the switch and compare the loan spreads with the first recorded loan from this inside branch using the same specifications as in the previous exercise. Panel C of Table 5 reports the estimated coefficients. The resulting loan spread pattern is similar to the one identified in Panel A and B, with slightly different lengths of reversion.

[Insert Figure 6 here]

This dynamic is presented intuitively in Figure 6. Note that the act of switching involves a loan spread reduction of 5.50 (26.79) bps (estimates from column 1 and 2 of Table 4) and the estimates in Table 5 are anchored to this initial decrease. Therefore, after firms' switch to the new branch, the maximum of reduction in loan spread could be 52.34 (18.38) bps, which amounts to almost 60% of the average spread. This reduction returns back to zero in the third quarter after the switch. This reversal is shorter than the one observed when firms switch banks: 3 years in Ioannidou and Ongena (2010) and 18 months in López-Espinosa, Mayordomo, and Moreno (2017), possibly due to the lower level of information asymmetries within a single bank rather than across banks. As the estimated median length of an observed relationship is 32 months, 2 years after the median firm starts paying "hold-up rents," it switches again to another branch. Such a pattern suggests that branches would recoup the initial discounts by charging higher loan spreads later on. We find a very similar pattern if we look backward that the spread differential returns back to zero in about one year after the switch.

[Insert Table 6 here]

Taken together, the results suggest that even within the same bank, firms would eventually pay a substantially higher loan spread if they borrow from the same branch for a longer period of time. In other words, we find the existence of the informational lock-in within the same bank, and expands the across-bank findings of Ioannidou and Ongena (2010). This is further confirmed by the dynamic patterns in other loan conditions, such as loan amount and maturity. In Table 6, we investigate the changes in loan amount, loan maturity, and collateral around and after the switching. We match on the same set of variables as in Table 5 and now also include loan spread. The findings for the decisions of pledging collateral are mixed and economically close to zero, potentially reflecting the fact that collaterals are important for risk management and are seldomly being adjusted during the credit cycles. Regarding loan amount and maturity, we find similar patterns of which switching initially involves better loan conditions (larger in amount and longer in maturity), but that afterward conditions seem to tighten up again (loan amount declines and loan maturity shortens).

4.6. Window Dressing

One key finding of Ioannidou and Ongena (2010) is that switchers are "window dressing" their performance just before switching. In their setting, the credit registry would only reveal the borrowers' repayment history in the past two months to the outside bank that requests it. This gives borrowers the incentive to strategically "window dress" their repayment history in the two months prior to a switch. Specifically, they find that 75% of the switchers with nonperformance in the [-4, -3] month period become performing during the critical [-2, -1] month period, while the number is only 46% for nonswitchers. But this is unlikely to be the case in our setting where borrowers switch from one branch to another within the same bank, because the complete repayment history is fully observable for all branches and there is no way of hiding.

[Insert Figure 7 here]

We formally investigate if this is the case in Figure 7. After matching, we compare between 1,874 switchers and 3,301 nonswitchers for their repayments during the [-4, -3] and [-2, -1] month periods, to calculate the percentage of borrowers that are previously nonperformance in [-4, -3] becomes performance in [-2, -1]. Generally, before the switch date, the share of nonperforming loans is comparable between switchers and nonswitchers. For example, during [-4, -3] period, 0.27% of the switchers do not perform (i.e., have overdue payments on one of their outstanding loans), and this ratio is 0.3% for nonswitchers. In the 2 months prior to the switch, 0.69% and 0.73% of the switchers and nonswitchers have nonperforming loans, respectively. Again, these numbers are similar and there is no visible difference between the two groups of borrowers. When we look at the percentage of firms that improved just before the switch, we find the same story that no matter it is a switcher or a nonswitcher, the percentage of nonperformers that improved and become performers remains at zero. This is in contrast with Ioannidou and Ongena (2010) but supports our prior that the window dressing behavior, or in other words adverse selection, is nonexistence in the case of switching within the same bank.

However, an interesting pattern is observed if we look at the share of firms that worsened just after the switching. From the general numbers, we first document that the share of nonperformers is significantly larger among the switchers in the two months after the switching, compared to the nonswitchers. Specifically, 6.78% of the switchers are nonperformers during [0, 1], a sizable increase compared to the number of 0.69% in the [-2, -1] period. In contrast, there is no significant change among the nonswitchers. Additionally, if we calculate the share of performers that worsen right after the switch, we find that 6.39% of the switchers with performance in the [-2, -1] period become nonperforming during the following [0, 1] period after the switching. In sharp contrast, the corresponding figure for nonswitchers is 0.61%. This pattern suggests that firms use the observation window prior to the switch strategically. Since the outside branches are reluctant to extend credit to firms with observable repayment problems, firms would try to keep a clean sheet before the switching but soon stop to behave after they successfully switch to new branches. These results also suggest that some of the nonperformers adversely mix with performers by making a good appearance before the switching, suggesting that a certain level of information asymmetries still remain, even within the same bank!

4.7. Deployment of FinTech

In this section, we examine how the hold-up problem would be affected by the utilization of FinTech in our sample bank. Specifically, we re-estimate our model in column 2 of Table 3 after adding an index for the application of FinTech in our sample bank and its squared, as follows:

$$r_{switch} - r_{nonswitch} = \beta_0 + \beta_1\, FinTech + \beta_2\, FinTech^2 + \varepsilon \qquad (2)$$

where β_0, β_1, and β_2 are the coefficients to be estimated, and ε is the error term. *FinTech* is an index proxying the level of digitalization of our bank, obtained from the Institute of Digital Finance at Peking University.[15] The estimated parameters are β_0=-5.89, β_1= 13.66***, and

[15] A brief overview of the index is shown in Table A3. The index measures the level of digital transformation at the bank branch level. The Bank-level Digital Transformation (BDT) index is constructed through a textual analysis of banks' annual reports and comprises three sub-indices: the Cognitive Digital Transformation Index (CDTI), the Organizational Digital Transformation Index (ODTI), and the Product Digital Transformation Index (PDTI). The CDTI reflects commercial banks' understanding and prioritization of "technological changes in digital finance" and related key terms like "digital" and "digital finance." The ODTI focuses on the establishment of relevant digital finance departments within banks, the appointment of directors and executives with IT backgrounds, and banks' investments in digital finance initiatives. The PDTI covers four key areas: e-banking, internet wealth management, internet credit, and e-commerce. It represents the most direct and crucial

β_2 = -3.91***. Hence, our estimates suggest that the impact of fintech on hold-up cost is a reversed U-shape: the earlier stage of FinTech utilization reduces hold-up but the deployment of FinTech in larger scope and depth may intensify hold-up. This relationship is shown in Figure 8, by the solid curve on the left part of the figure.

[Insert Figure 8 here]

Information is an essential component in lending and a major advantage of banks lies in their ability to collect, process, and transmit information. Historically, banks have been a repository of information about borrowers' creditworthiness. This information was collected over time through frequent and personal contacts between the borrower and loan officers. Over time, the banks built up a more complete and precise picture of the borrower than was available from public records. This private information, so-called *soft information*, is valuable to the bank. Its value arises not only from its ability to inform the bank's lending decisions but also because of the difficulty of replicating and transmitting the information outside the bank. FinTech changes the way that soft information is processed and communicated. The deployment of FinTech in banking is initially more adept at processing and transforming the currently available soft information into quantifiable numbers that can be readily transmitted. We call this process as the *hardening of the soft information* and one typical example is the credit rating systems (Liberti and Petersen, 2019). In our survey, almost all respondents agree that FinTech provides great opportunities for banks (84%) and banks are taking it seriously (89%). For example, this kind of FinTech is able to reduce information asymmetries, enriching the banks' knowledge about their customers (79% agrees). The findings are presented in Panel A of Figure 9.

[Insert Figure 9 here]

At this earlier stage, the deployment of FinTech reduces the importance of soft information, making the context under which the information is collected less essential, and ultimately make the information more transmittable across loan officers and branches within the bank. This would, in the end, reduce the hold-up problem and the switching costs for borrowers (Sutherland, 2018). In our bank, we find that when the index of FinTech utilization increases

aspect for evaluating the digital finance strategy of commercial banks (Cao et al., 2022; Yang and Masron, 2024). Despite cost constraints, branches of the same bank share a common FinTech system. However, the level of fintech penetration in the city also influences the depth of the branch's usage and understanding of the system. Therefore, we use the fintech penetration level at the city level as a capability parameter for how different bank branches utilize the headquarters' FinTech system. This is then multiplied by the Bank-level Digital Transformation (BDT) index for that year, which represents the level of FinTech development at the branch level for that year.

from its minimum of 0.10 to 1.8, the hold-up cost is decreasing monotonically. We find that bank branches located in cities on the eastern China have consistently been at the forefront of digital transformation compared to other regions, while branches in the western regions have fallen behind. Before 2016, the FinTech of most branches was below 1.8, which led to a declining trend in hold-up costs.

In the more recent stage of FinTech application, banks try to utilize technologies such as big data to expand the information that they are able to collect from their potential borrowers. Such information could be diverse and huge in amount, from structured data like transaction logs to unstructured data like customer reviews. For example, borrower narratives that claim the borrower is trustworthy and successful increase the probability of the loan being funded and lower the loan rate (Herzenstein, Sonenshein, and Dholakia, 2011). Berg, Burg, Gombović, and Puri (2020) even find that information that users leave online simply by accessing or registering on a website is able to predict default. However, such information could be abundant and loan officers may face difficulties in selecting and processing the useful information from this vast amount of contents. In other words, attention is limited and to prevent information overload, loan officers need to boil down the information to what is most important. There would be significant heterogeneity in such ability across loan officers (Bertrand and Burietz, 2023).

If this is the case, the particular way that loan officers process information may generate hold-up that even though the vast amount of borrower information is readily accessible to all branches within the same bank, the creditworthiness of borrowers generated from the information cannot be easily communicated across branches without a loss of information. In this sense, when FinTech is developed to a stage of significantly expanding the information base, and in the absence of an efficiently shared information processing system, hold-up may intensify again. Indeed, we find that when the index of FinTech utilization increases from 1.8 to the current maximum of 4.7, the deployment of FinTech actually increases hold-up cost. This is also supported by our survey evidence. We find that 68% of bank employees believe that the use of FinTech actually increases their customers' reliance on their branch, especially for the small-and-medium-sized enterprises (SMEs). See Panel B of Figure 9 for the numbers.

We also observe that, starting from 2016, the branch-level FinTech indices in most cities gradually exceeded 1.8, coinciding with a reversal in the trend of hold-up costs, which began to rise. This rapid development of FinTech appears to be driven by strong policy initiatives. For example, in August 2016, the State Council released the *13th Five-Year Plan for National Science and Technology Innovation* (hereafter, the "Plan"), which explicitly fostered the innovation of FinTech products and services and aimed to establish a national center of FinTech innovation. Similarly, the launch of the *G20 Digital Economy Development and Cooperation Initiative* in Hangzhou in September 2016 further accelerated the technological transformation of financial institutions. While these reforms create new growth opportunities for financial institutions, they may also result in information overload, potentially reducing the efficiency of loan pricing in credit markets.

But this might not be the end of the story. If advances in machine learning, algorithms, and AI technologies enable automatic processing of vast amounts of information that big data currently obtains—transforming it into easily interpretable metrics or even automating decision-making—the hold-up costs we discuss could be significantly reduced or potentially eliminated, at least within the same bank. This possibility is illustrated by the dashed curve in Figure 8, which extends beyond the current stage of FinTech development in our bank.

Overall, the deployment of FinTech in banking is not necessarily mitigating hold-up and the impact might be non-linear at different stages of technology development. The use of FinTech to transform the current information into more easily transmittable numbers illustrate the bright side of FinTech in reducing hold-up. On the dark side, information overload without an efficient processing system may also intensify hold-up. Therefore, the hold-up problem and the resulting switching costs remain relevant in a digitalized world.

5. Conclusions

This paper is inspired by an earlier strand of literature which identifies a dynamic change in loan rates when borrowers switch banks. They are the first to empirically identify the existence of hold-up in bank lending. But an open question that is often ignored remains: does hold-up also exist when borrowers switch across branches within the same bank? In this paper, we try to answer this question by utilizing the population of 119,270 corporate loans originated by a large commercial bank in China during 2010 and 2020.

We find that when borrowers switch from their current inside branches to a new outside branch, the new loans carry a loan spread that is 5.85 bps lower than the spreads on comparable new loans originated by their outside branches to the existing customers. The reduction in loan spreads is 5.71 bps when compared with nonswitching loans issued by the inside branches. Such a preferential treatment persists for another two quarters after the switch and the loan spreads further decreases another 18.38 bps in existing branches. In the newly established branches, the preferential treatment is more pronounced and lasts for three quarters, during which the loan spread further decreases by 52.34 basis points. But after this period, the outside branch starts to charge higher loan rates on these switched borrowers, even higher than their quality warrants. This evidence together suggests the existence of hold-up within a bank. It is intuitive to note that the hold-up problem is less severe within a bank than across banks, as the numbers we estimated are smaller and the dynamic cycle is shorter, compared to the ones in Ioannidou and Ongena (2010), among others. Simultaneously, we discover that compared to existing branches, newly established branches attract switchers with larger discounts in loan pricing, which further lends credence to the existence of intra-bank competition across branches. We also observe that FinTech utilization in our bank has a non-linear impact on hold-up. Initially when FinTech mainly enables the flow of information, it reduces hold-up, but later when FinTech generates excessive information to process, it may conversely intensify hold-up. It is also expected that when FinTech can automatically and sensibly process the big data it generates, hold-up would eventually diminish in banking landscape.

Our findings enhance the understanding of information in bank lending. Frictions in the collection and communication of information within a bank would further distort the efficient allocation of credit, potentially worsening the efficient functioning of the banking market.

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Table 1. Selected characteristics of switching loans and nonswitching loans
The table reports the mean and median for selected firm and 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	Median	Mean	Median
Loan spread	90.20**	87	88.11	87
Loan amount（in logs of CNY）	15.02***	15.42	15.36	15.42
Loan maturity (in months)	13.66***	12	12.29	12
Collateral	0.91***	1	0.89	1
Credit rating	1.09***	1	1.07	1
Credit line	0.59***	1	0.79	1
Corporations	0.97***	1	0.98	1
Private	0.94***	1	0.93	1
SMEs	0.83***	1	0.78	1
Relationship length	25.96***	22***	32.41	25
Relationship num	2.88***	2***	6.11	3
Multiple branch relationships	0.23***	0	0.4	0

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 l 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 insider branch	Yes			
Set of outside branch		Yes	Yes	Yes
Credit rating	Yes	Yes		
Prior credit rating from inside branch			Yes	
Prior relationship length				Yes
Prior relationship density				Yes
Prior multiple branch relationships				Yes
Firm city	Yes	Yes	Yes	Yes
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 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 columns 2 to 4 focus 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.

Matched Branches	Switching to Existing Branches	Switching to Newly Established Branches		
Matching Variables	(1)	(2)	(3)	(4)
Year: month	Yes	Yes	Yes	Yes
Set of insider branch	Yes	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	961	42	44	12
Number of nonswitching loans	2,295	108	109	17
Number of observations (matched pairs)	2,735	123	127	17
Spread (bps) with weighting	-5.50**	-26.79**	-30.69**	-60.55**
	(2.54)	(10.90)	(12.89)	(23.11)

Table 5. Loan spread differences before and after switching
In Panel A, we calculate the difference in loan spreads between new loans obtained by the switcher from the newly established outside branch and the switching loan. In Panel A, we calculate the difference in loan spreads between new loans obtained by the switcher from the existing outside branch and the switching loan. In Panel C, 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 newly established 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 vars	Yes	Yes	Yes	Yes	Yes
Number of observations (matched pairs)	19	14	10	82	687
Spread (bps) with weighting	-15.29*** (0.00)	-36.86*** (0.00)	-52.34*** (0.00)	14.00*** (0.00)	26.22*** (0.00)
Panel B: Difference in loan spreads between new loans from existing 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 vars	Yes	Yes	Yes	Yes	Yes
Number of observations (matched pairs)	632	159	247	1283	5969
Spread (bps) with weighting	-7.66*** (0.00)	-18.38*** (0.00)	0.56*** (0.00)	5.07*** (0.00)	17.00*** (0.00)
Panel C: 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 vars	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*** (0.00)	-4.02*** (0.00)	4.54*** (0.00)	9.33*** (0.00)	10.60*** (0.00)

Table 6. Other loan condition differences 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 12" 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 loan			
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***

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

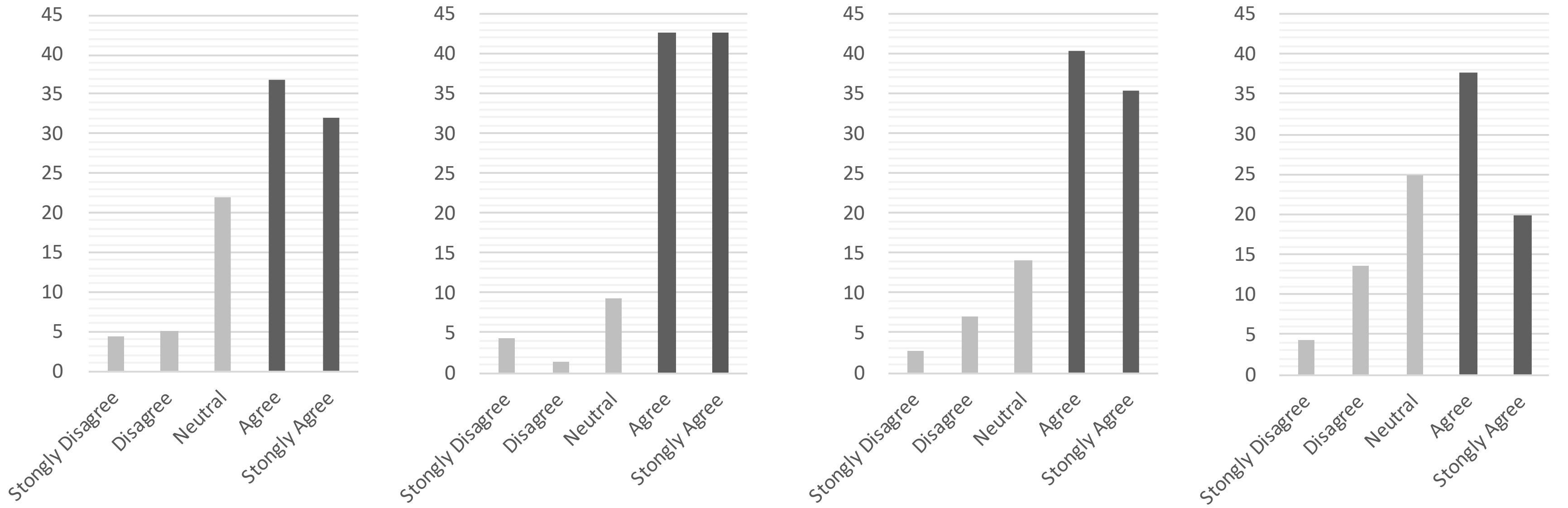

Figure 1. Intra-bank competition

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.

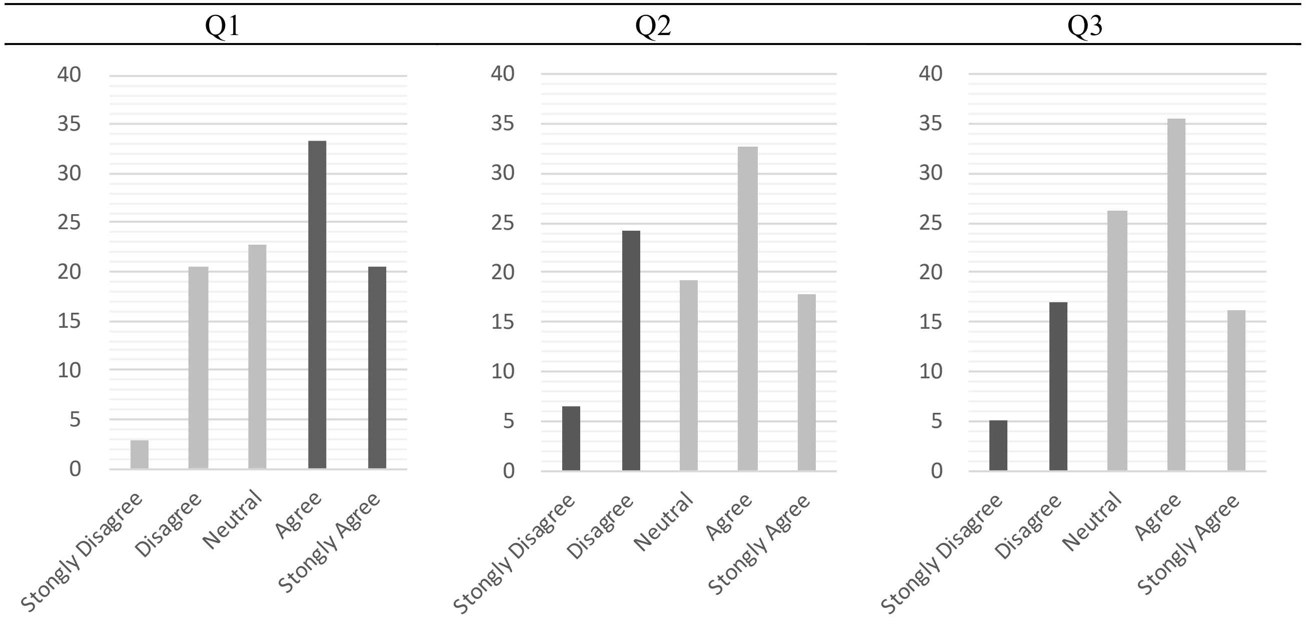

Figure 2. Information communication

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.

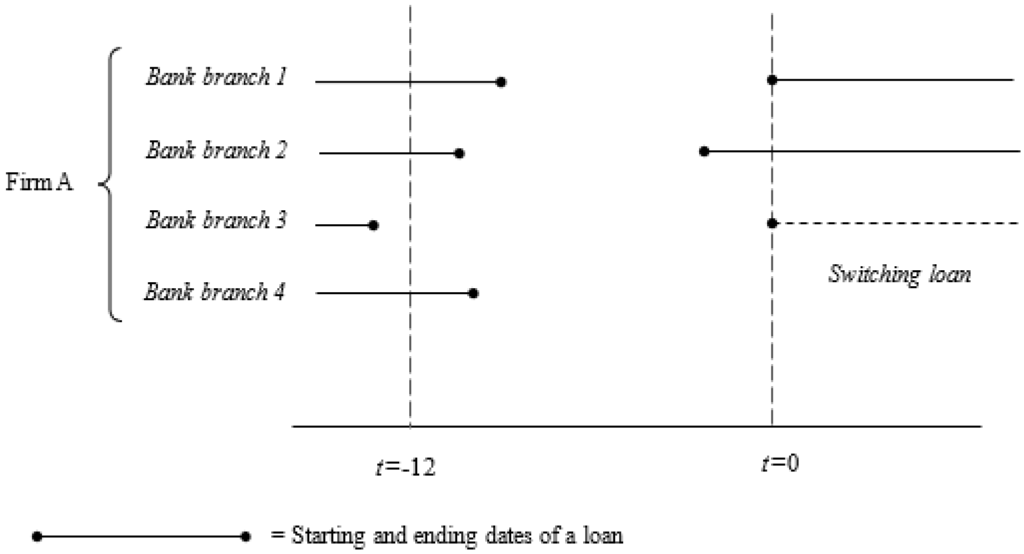

Figure 3. Switchers, inside branches, and outside branches
The figure depicts the definition of switchers, inside branches, and outside branches. We call firm A the switcher and branch 3 the outside branch for firm A, as branch 3 did not lend to firm A during the last 12 months. Branches 1 and 2 are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

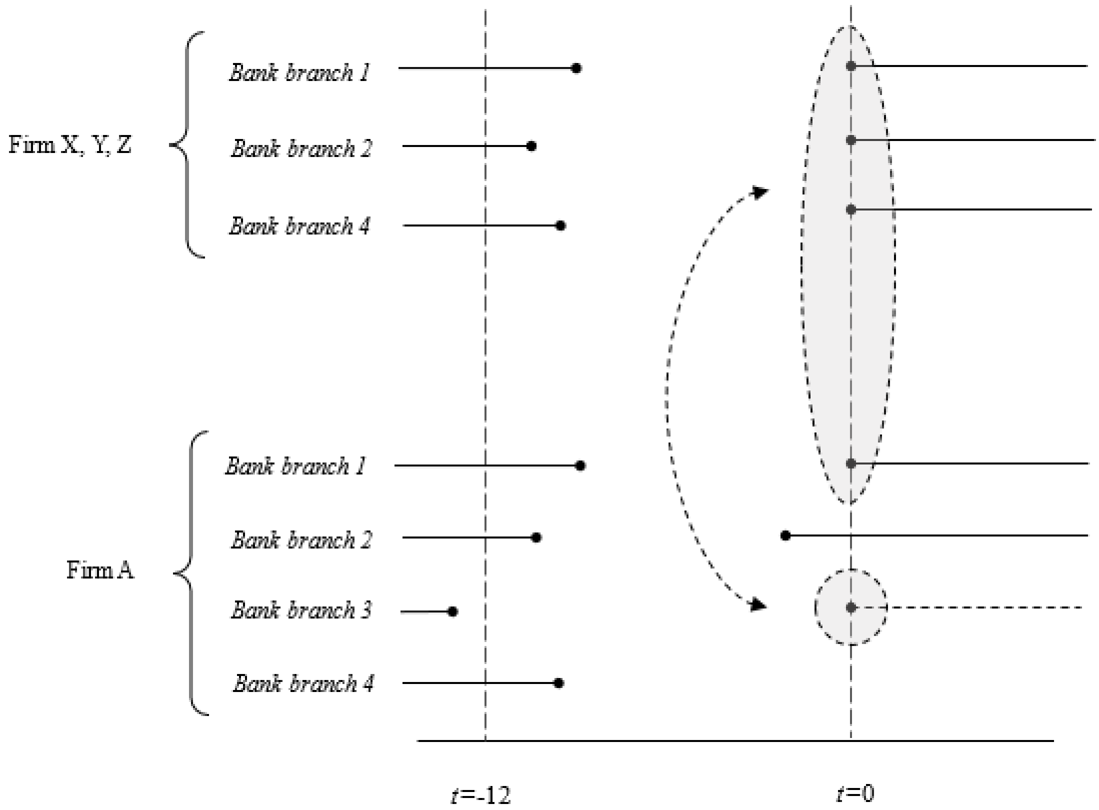

Figure 4. Switching versus nonswitching loans at the switcher's inside branch
The figure displays the analysis in column 1 of Table 3, where we compare the rate of the switching loan with the rate of comparable nonswitching loans from the switcher's inside branches at the time of the switch.

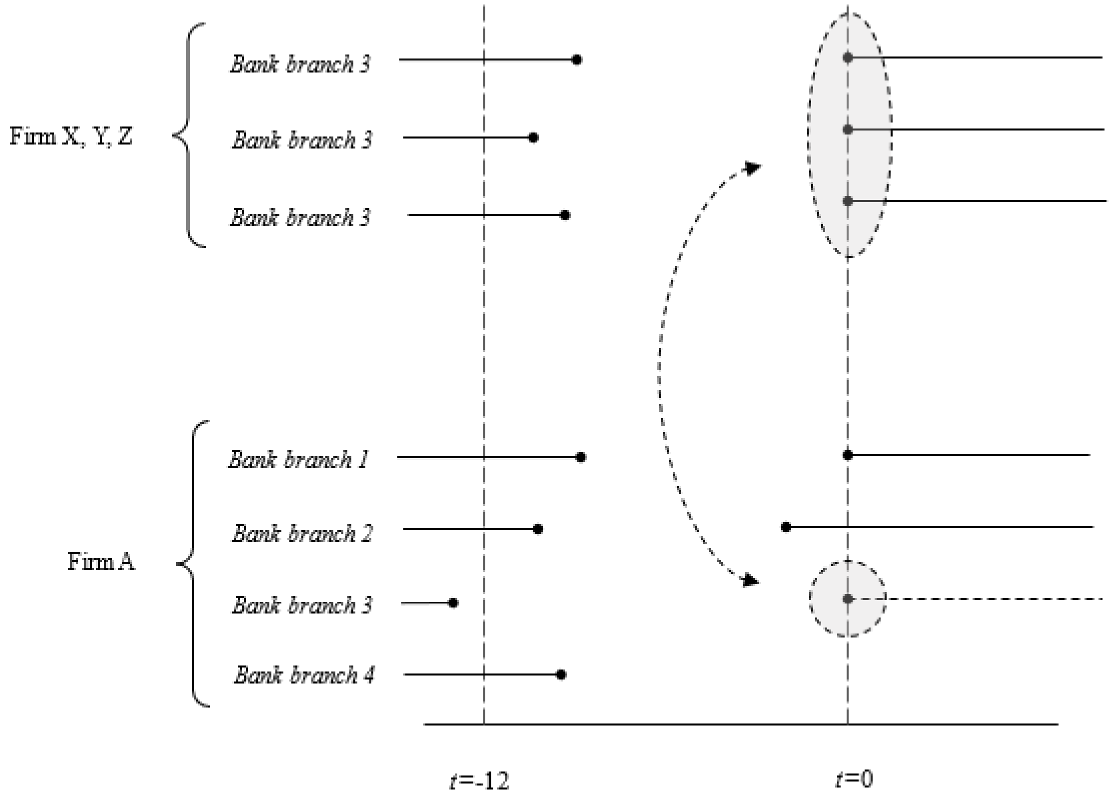

Figure 5. Switching versus nonswitching loans at the switcher's outside branch
The figure displays the analysis in column 2 of Table 3, where we compare the rate of the switching loan with the rate of comparable nonswitching loans that the switcher's outside branch at the time of the switch.

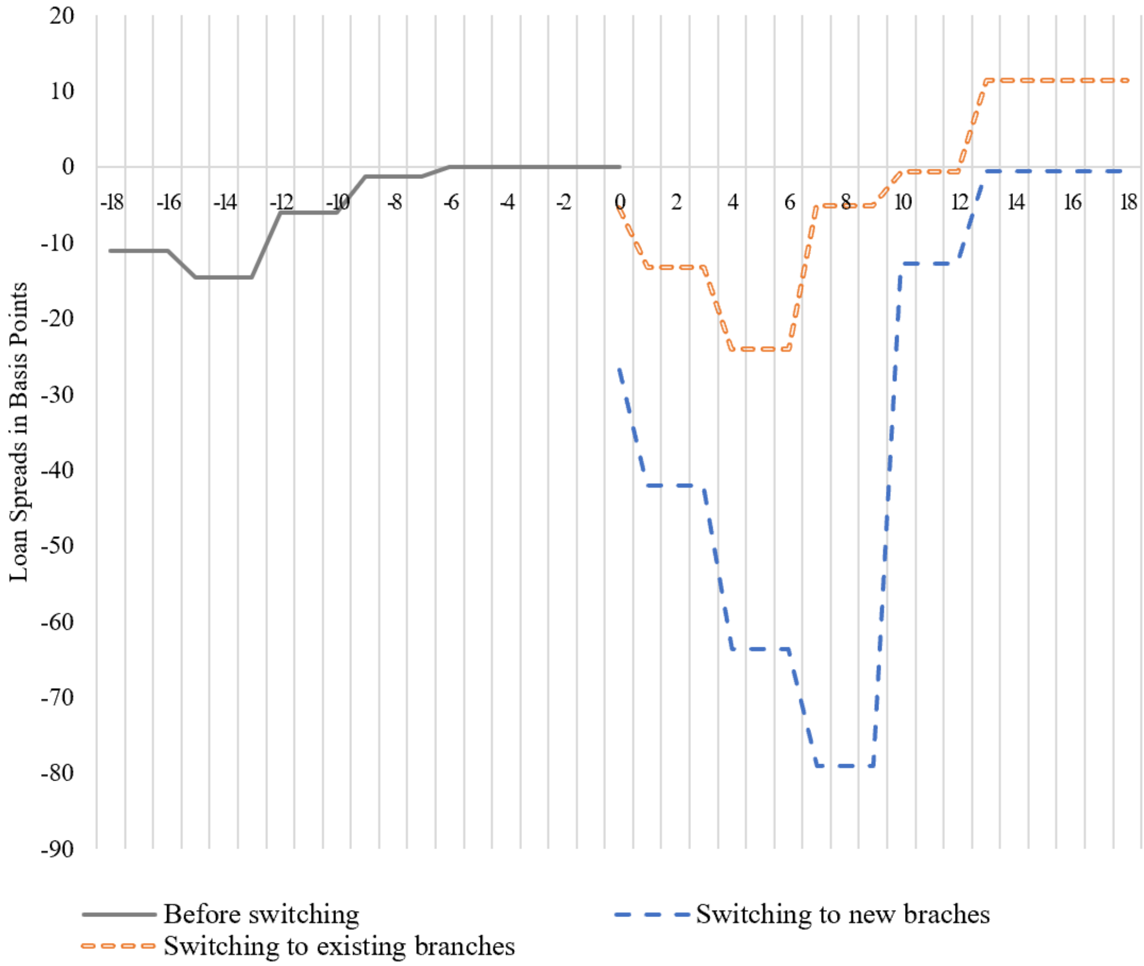

Figure 6. Loan spread differences before and after switching
The figure displays the differences in loan spread in basis points between the new loans obtained by the switcher and the loans obtained by matched firms from their inside or outside branches before, around, and after the switch. The lines are the coefficient estimates from Tables 4 (columns 1 and 2) and Table 5. The estimates of Table 5 (Panel A) are anchored at the −26.79 basis points spread from Table 4 (column 2). The estimates of Table 5 (Panel B) are anchored at the −5.50 basis points spread from Table 4 (column 1). The estimates of Table 5 (Panel C) are anchored at zero.

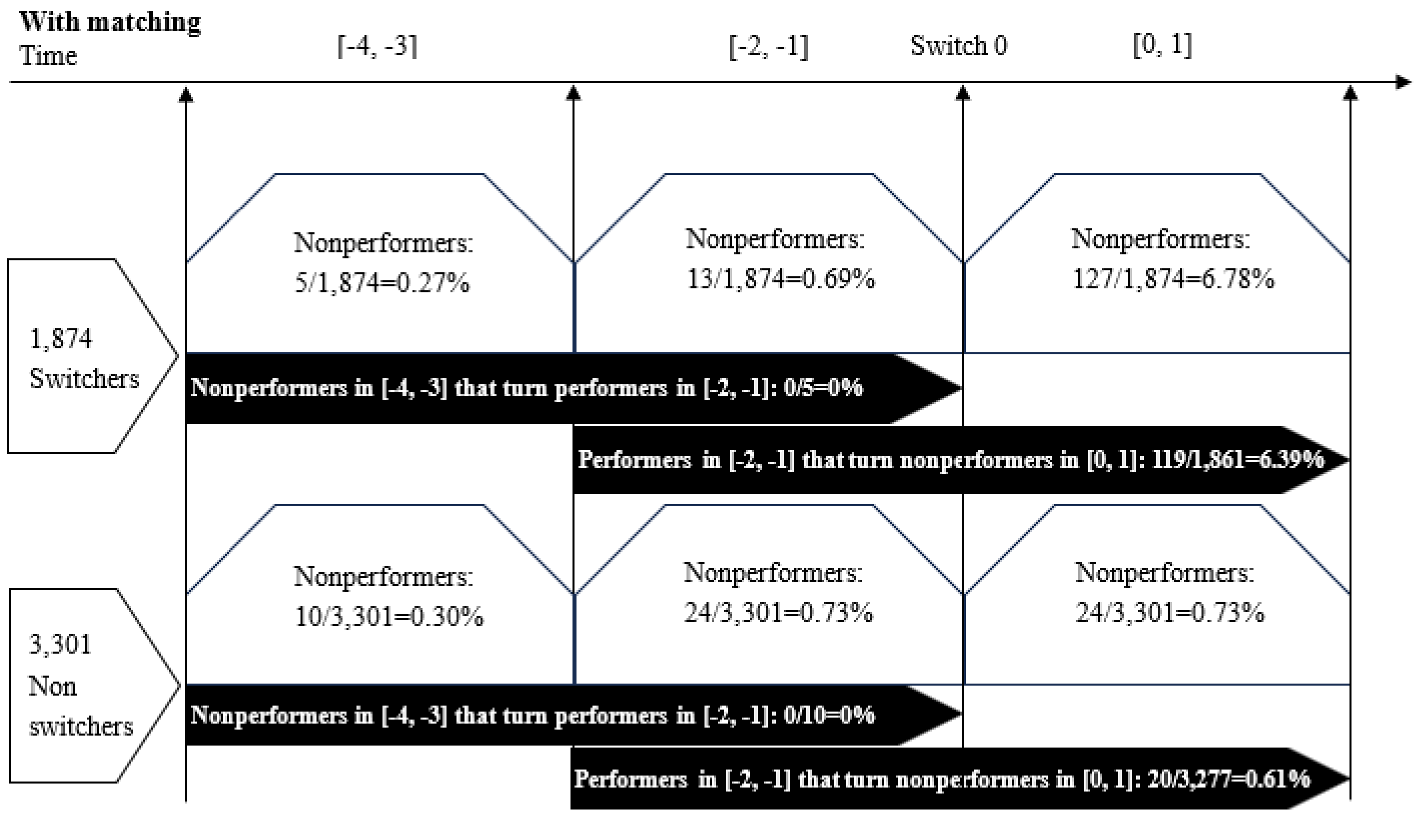

Figure 7. Number of switchers with nonperforming loans

The figure displays the number of switchers (top row) and nonswitchers (bottom row) with nonperforming and performing loans for the various time periods indicated with vertical arrows and labeled at the bottom. The black boxes provide ratios of conditional performance.

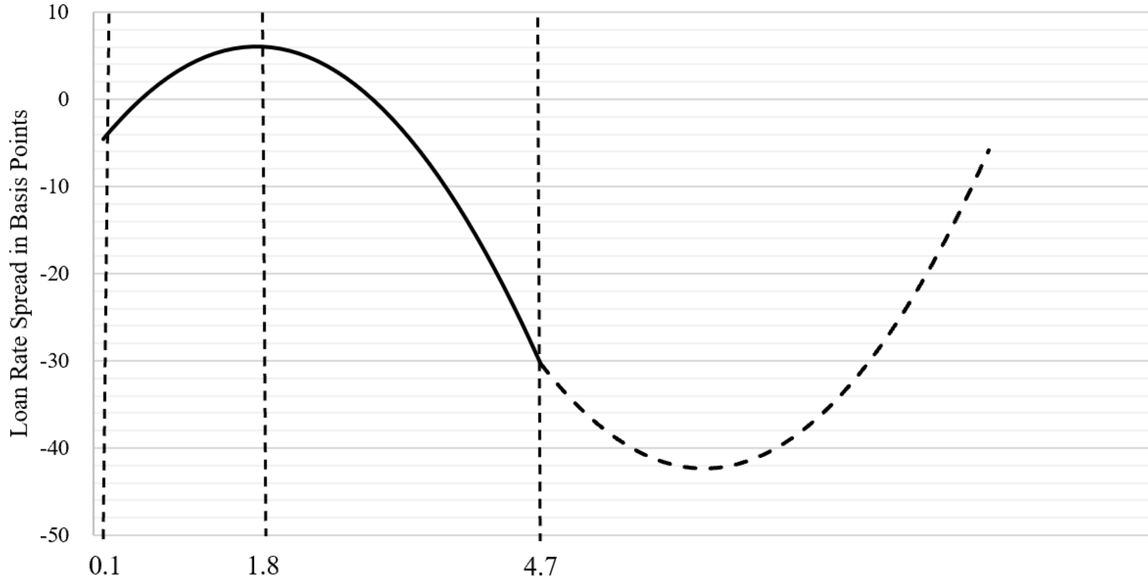

Figure 8. FinTech and hold-up cost
The figure displays the relationship between the FinTech index of our bank branches and the estimated hold-up cost in basis points. The solid curve represents the actual estimations with the three vertical lines representing the minimum, the number that maximizes the loan spread, and maximum of the index. The dashed curve indicates a hypothetical prediction of the relationship if FinTech is further developed.

Panel A: Importance of FinTech		Panel B: Reliance on Bank	
Q1	Q4	Q5	Q6

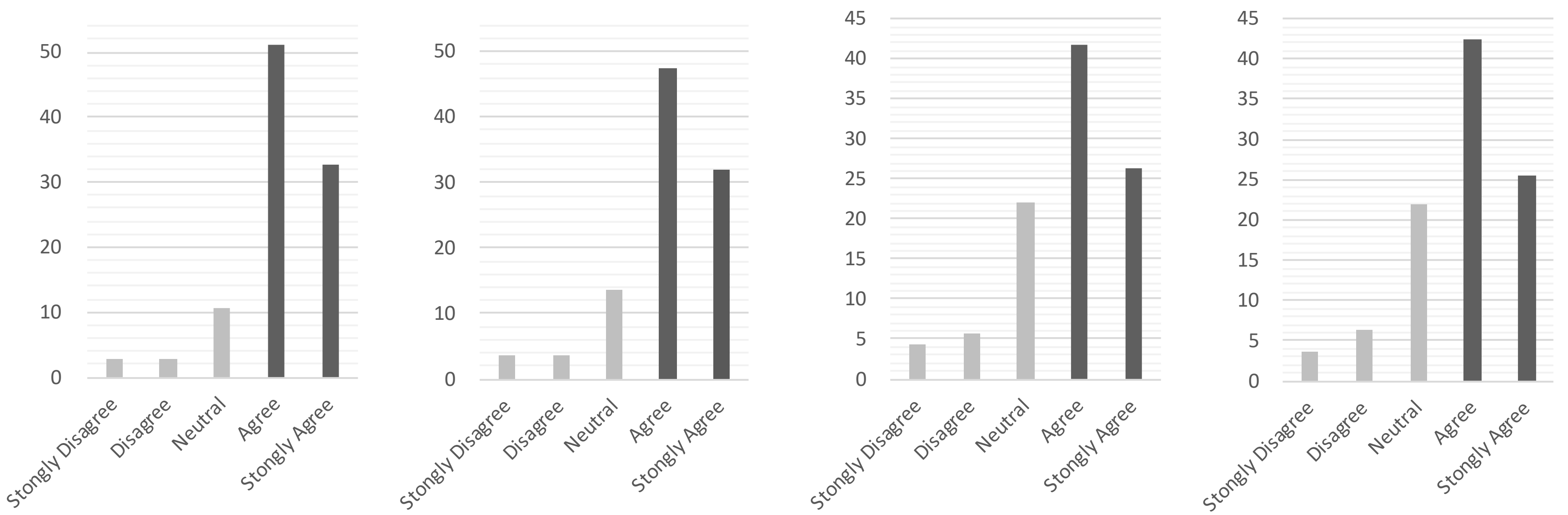

Figure 9. Application of FinTech
This figure presents the responses in percentages for each of the questions in the survey. Black indicates the responses that we are interested in and grey indicates other responses to the question.

APPENDIX

Table A1. Robustness checks

In columns 1-8, we show that our main results are robust to using 24 and 36-month cut-offs. Our results are also robust when we use the differences in loan rates in columns 9-12. 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.

	24 months				36 months				Loan rate			
Matched Branches	outside	inside	existing	new	outside	inside	existing	new	outside	inside	existing	new
Matching Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year: month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Set of insider branch		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Set of outside branch	Yes				Yes				Yes			
Credit rating	Yes	Yes	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	Yes	Yes
Firm city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
branch city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan amount	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit line	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of switching loans	2,301	1,177	1,074	43	2,444	1,251	1,147	43	2,095	1,063	961	42
Number of nonswitching loans	5,291	2,890	2,655	111	5,673	3,110	2,874	111	4,949	2,526	2,295	108
Number of observations (matched pairs)	7,115	3,469	3,135	126	7,649	3848	3513	126	6,443	3,064	2,735	123
Spread (bps) with weighting	-5.50***	-5.92***	-5.77**	-24.62**	-6.54***	-6.32***	-6.22***	-24.62**	-5.27***	-5.52**	-5.28**	-25.68**
	(1.66)	(2.29)	(2.44)	(10.21)	(1.67)	(2.19)	(2.33)	(10.21)	(1.10)	(2.36)	(2.54)	(10.41)

Table A2. Switching costs and the firm-branch distance

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 each column, we match on the indicated variables. All variables are defined in Table 2. We regress the differences on a constant and the distance proxies, and report the estimated coefficients. 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	Switching to Newly Established Branches		Switching to Existing Branches	
Matching Variables	(1)	(2)	(3)	(4)
Year: month	Yes	Yes	Yes	Yes
Set of insider branch	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	34	34	703	703
Number of nonswitching loans	75	75	1,443	1,443
Number of observations (matched pairs)	120	120	1935	1935
Difference in Firm-Branch Distance	-10.05		2.80	
	(12.82)		(1.78)	
Switch to Further Away Branch		-53.77		8.80
		(49.50)		(6.20)
Spread (bps) with weighting	-41.33*	-19.63**	-1.99	-6.51*
	(23.70)	(9.22)	(2.99)	(3.50)

Table A3. An overview of FinTech indices and their construction
The table reports the indicators of FinTech.

Variables	Definition	Measurement	Details
FinTech	Digital Transformation Index at the bank branch level	$=CFP\times BDT$	City-level FinTech Penetration (CFP) index multiplied by the bank-level Digital Transformation (BDT) index, reflecting the level of FinTech development across various branches in a given year.
City-level FinTech Penetration (CFP)	The city-level FinTech Penetration (CFP) of the city where a loan application occurs.	We employ the city-level "Peking University Digital Financial Inclusion Index of China" as the measurement of Fintech penetration, which is compiled by a joint research team from the Institute of Digital Finance at Peking University and Ant Financial Services Group. Based on the traditional financial inclusion indexes proposed by existing literature and international organizations, considering the features of traditional and Internet financial services, in combination with the availability and reliability of data, the team build an indicator system of digital financial inclusion considering three dimensions of FinTech services: Breadth of Coverage (BC), Depth of Usage (DC) and Level of Digitization (LD) (Feng et al., 2019; Ding et al., 2022).	BC is measured by the number of FinTech platform accounts per 10,000 people; DC is measured comprehensively by the number of users, transaction amounts, and transaction frequency in businesses such as credit, funds, settlement, insurance, and investment on fintech platforms; LD is measured by electronic payment amounts, market share, fintech credit interest rates, and transaction frequency (Feng et al., 2019; Ding et al., 2022).

Variables	Definition	Measurement	Details
Bank-level Digital Transformation (BDT)	BDT measures bank-level digital transformation, which describes a process in which a bank applies digital technologies to their products, processes, organizations, business models, and strategies (Liu et al., 2020; Cao et al., 2022; Yang and Masron, 2024).	BDT can be decomposed into three sub-indexes: the Cognitive Digital Transformation Index (CDTI), the Organizational Digital Transformation Index (ODTI), and the Product Digital Transformation Index (PDTI) (Cao et al., 2022; Yang and Masron, 2024).	The principal component analysis method is used to determine the weight of each indicator, the linear efficacy function method is used to perform dimensionless processing of the data, and the weighted average is graded from bottom to top. The total transformation index is obtained through the weighted average of the transformation sub-indexes (Cao et al., 2022; Yang and Masron, 2024).
Cognitive Digital Transformation Index (CDTI)	CDTI refers to a bank's strategic attention to digital technology, measured by the frequency of keywords related to digital technology in annual reports of the bank (Cao et al., 2022; Yang and Masron, 2024).	Number of occurrences of keywords about digital technology in every 10,000 words in annual reports. Based on a text learning method, a total of 124 keywords are identified in 6 categories: artificial intelligence, blockchain, cloud computing, big data, online, and mobile (Cao et al., 2022; Yang and Masron, 2024).	Following the text learning method of Hassan et al. (2019), the team first defines a “digital technology related text library” and a “digital technology unrelated text library”. According to the method of Hassan et al. (2019), subtraction set of "digital technology related text library" and "digital technology unrelated text library" represents the digital technology innovation beyond the bank's basic business. Through steps including text collection, word segmentation, text learning and manual screening, the team identified 124 keywords related to digital technology and thus realized an objective construction of keywords. After determining keywords, the team uses "jieba" in Python to perform word segmentation of annual reports (excluding financial and audit reports), and obtained the number of mentions of the above keywords and the total number of words in annual reports, so as to calculate the frequency of keywords related to digital technology. The higher frequency is, the higher attention the bank pays to digital technology, and thus the higher level of cognitive digital transformation (Cao et al., 2022; Yang and Masron, 2024).

Variables	Definition	Measurement	Details
Organizational Digital Transformation Index (ODTI)	ODTI refers to the degree of integrating digital technology into the bank’s financial services (Cao et al., 2022; Yang and Masron, 2024).	Measured through three dimensions: digital channels, digital products, and digital R&D. Among them, digital channels are measured by whether the bank has launched mobile banking and WeChat banking that year; digital products are characterized by the launch of Internet financial management, Internet credit, and e-commerce; digital research and development is constructed by the application information of the bank’s digital technology patents (Cao et al., 2022; Yang and Masron, 2024).	Firstly, in terms of digital channels, the team measures business transformation by whether the bank has launched mobile banking App and WeChat banking in a year. The information was obtained by searching the mobile application market, WeChat official accounts and WeChat mini programs. Secondly, in terms of digital products, the team uses on-line wealth management, on-line credit, and e-commerce to measure digital transformation of bank products. the team searches keywords such as "Internet," "online," "new products," "new services" and "e-commerce" in the bank’s annual reports to identify related description of new business, and then research assistants read each description to determine whether the bank had launched the above digital products. Thirdly, in terms of digital R&D, the team identifies digital technology-related patents of the bank by whether the abstract of bank’s patent applications contained the above digital technology keywords. Considering the process of obtaining patents can be long, the team uses the total number of digital related patents in three years to construct the indicator (Cao et al., 2022; Yang and Masron, 2024).
Product Digital Transformation Index (PDTI)	PDTI refers to the degree of integrating digital technology into governance structure and organizational management of the bank (Cao et al., 2022; Yang and Masron, 2024).	Measured through three dimensions: digital architecture, digital talents, and digital cooperation. The digital architecture is measured by whether the bank has adjusted its organizational structure; digital talent is measured by the proportion of executives and directors with information technology backgrounds in the bank’s executive team and board of directors; digital cooperation is measured by the bank’s cooperation with external financial technology companies (Cao et al., 2022; Yang and Masron, 2024).	In terms of digital structure, the team focuses on two main changes in organizational structure of the bank: (1) the adjustment of internal organizational structure of the bank, including the establishment of Internet finance department, digital finance department or FinTech department. (2) the set-up of FinTech subsidiaries to carry out digital innovation outside the organizational structure of the bank. In terms of digital talents, the team choses the indictor of the proportion of executives and directors with IT background in the management team and the board of directors. The IT background refers to educational background and work experience. In terms of educational background, it is determined by whether the manager was educated in majors such as computer science, software engineering, and information science. In terms of work experience, it is determined by whether the manager has worked in an IT company or served as the chief information officer of a bank. Finally, in terms of digital cooperation, the team searches keywords such as "cooperation" and "alliance" in annual reports to determine whether the bank has cooperated with external technology companies (Cao et al., 2022; Yang and Masron, 2024).

Appendix: 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 is 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.