Bankers on the Move: Relationship Capital in Credit Markets *

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Abstract

Information is a core input in financial intermediation, yet little is known about how it is transmitted through labor mobility. In this paper - for the first time - we are able to link administrative data on loan contracts and employment histories to track the movements of bank managers and their portfolios of client firms across financial institutions. We show that when a manager switches employers, firms in their prior portfolio are three times more likely to initiate a lending relationship with the new bank. This effect reflects both a higher propensity of firms to apply for credit and a greater likelihood of loan approval. We further document that the resulting lending relationships are associated with lower interest rates and lower default rates. To isolate the causal role of manager mobility, we exploit variation in the timing of job switches and leverage exogenous shocks to mobility induced by branch closures. Our findings underscore the importance of individual-level human capital in shaping credit market outcomes and highlight a novel channel for information transmission in the financial sector.

Keywords: Banking, Credit allocation, Human capital, Manager mobility

JEL Codes: G21, G32, J24, J62

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1 Introduction

The allocation of human capital in the financial sector has long attracted attention in both public debate and academic research (Philippon and Reshef, 2012; Boustanifar et al., 2018). Economists have focused on understanding the drivers of high wages in finance, showing that they are only partially attributable to a distinctive talent pool (Böhm et al., 2023), but rather to incentive-based contracts designed to limit managers' mobility (Bénabou and Tirole, 2016). Banks seek to retain their managers since their tasks consist of screening, monitoring and collecting information (Stiglitz and Weiss, 1981; Diamond, 1984; Stein, 2002) on their clients. If such information is portable, their mobility can change the competitive dynamics in the credit market (Patault and Lenoir, 2024).

Existing research has examined how bankers' skill investment shapes their mobility (Gao et al., 2024b), and how monitoring behavior changes when bankers are rotated across branches within the same institution (Hertzberg et al., 2010). However, no study has yet been able to measure the client base of bank managers and follow it as they move across banks.

In this paper, we are able to combine for the first time data on financial workforce mobility and credit allocation for the 3rd largest economy in the EU. We examine firms' credit relationships in Italy from 2009 to 2018 and track bank managers' career movements. Using manager transitions as a source of variation in a generalized Difference-in-Differences framework, we find that a manager's new bank becomes significantly more likely to establish a credit relationship with a former client of the manager after the manager has moved there. This result is valid even when we focus on managers who were forced to relocate after a branch closure.

We find no evidence of a "dark side" of portability: firms' Z-score riskiness does not predict probability to follow the manager, and relationships formed through portability default less often than comparable new relationships. Instead, firms more likely to follow their manager are younger, smaller, which are typically more dependent on soft information (Huber, 2021). In these new relationship-originated loans, firms pay lower interest rates than before, yet they do not receive preferential treatment at the new bank, as their rates are in line with those of similar borrowers.

Using loan application data, we show that portability operates through both higher application and approval rates, with the increase in applications accounting for the bulk of the effect. This pattern indicates that managers primarily lower search frictions by facilitating firms' access to credit rather than by influencing screening decisions.

Italy provides an ideal setting for our analysis. First, Italian credit registry data are highly granular and detailed (Malgieri and Citino, 2025; De Marco et al., 2023; Bolton et al., 2016; Rodano et al., 2018; Gobbi and Sette, 2014), offering information on loan amounts, interest rates, and banks' loan inquiries about firms. Crucially, it includes the identifier of the bank-municipality pair issuing the loan, a key element in our analysis. Italian social security data cover the entire financial sector workforce, allowing us to identify bank managers and their characteristics. Second, the institutional context is particularly suitable. Italian firms maintain multiple banking relationships (Barone et al., 2024; Kosekova et al., 2024), which enables us to disentangle credit supply from demand by augmenting our regressions with high-dimensional fixed effects, following Khwaja and Mian (2008). Moreover, from the 1990s through the 2010s, Italy's banking sector underwent significant consolidation, with many local banks merging into a few national champions (Focarelli and Panetta, 2003), and thus reorganizing (and sometimes laying off) their workforce. At the same time, labor laws facilitated mobility within the sector, leading to a large-scale reallocation of workers during our analysis period.

Our analysis employs a generalized difference-in-differences empirical strategy, leveraging two dimensions of variation: the bank branch with which a firm has credit and whether the bank manager responsible for that credit has moved to a different bank. Under the parallel trends assumption, this variation enables us to estimate the effect of a manager's move on the likelihood of a firm establishing a credit relationship with the manager's new bank. Our approach allows us to rule out several confounding factors. First, we control for time-invariant characteristics of the firm-bank relationship that influence their probability of matching, such as industry specialization (Paravisini et al., 2023) or geographical proximity (Nguyen, 2019), through firm-bank fixed effects. Second, we account for credit supply shocks that affect a bank's overall lending propensity with bank-time fixed effects. Third, we address credit demand shocks that influence a firm's likelihood of applying for a loan by using firm-time fixed effects (as in Khwaja and Mian, 2008). Finally, we control for the possibility that a manager's move is endogenous to a firm's credit decision by focusing on cases where the move is triggered by a branch closure —an event exogenous to the firm's choice to shift credit relationships.

The main finding of the paper is that bank managers' information about their clients is portable. Four years after a manager moves, the probability of a firm establishing a credit relationship with the manager's new bank rises from a baseline of 1.3% to 5%. We provide two benchmarks for this result. First, we compare transitions between banks to transitions within the same bank group (i.e., loan officer rotations, as in Hertzberg et al., 2010). We find that managers who switch to a different bank group bring more than twice as many clients with them compared to those who move within the same group. Second, we contrast our estimate with client portability in the context of sales managers (Patault and Lenoir, 2024), showing that the effect of managerial information is particularly strong in banking—approximately an order of magnitude greater than in sales.

To understand the mechanisms driving this result, we analyze loan applications. We find that managers directly affect firms' search: after a move, the probability of a portfolio firm applying for a loan at the manager's new bank increases by 5 percentage points, compared to a baseline of 2%. Additionally, managers influence banks' screening: conditional on applying, the likelihood of a portfolio firm receiving a loan rises from 35% to 37%.

We then examine how our results vary across three key dimensions: firm, bank, and manager characteristics. First, we find that the impact of a manager's move is stronger for younger and smaller firms, for whom soft information is more critical due to the lack of hard information.Second, we show that managers' information is particularly valuable when they move from a large bank group to a smaller one, as larger banks tend to rely on more standardized credit allocation processes. Finally, we find that the effect is stronger for managers with greater experience and those from branches with fewer managers, as they have had more time and interactions to build relationships with their clients.

Taken together, our findings provide direct evidence that bank managers generate and utilize soft information to allocate credit. The academic debate has often centered on the effects of de-branching (Amberg and Becker, 2024; Nguyen, 2019) or banking crises (Chodorow-Reich, 2014) on credit allocation. Meanwhile, policy discussions—particularly following the 2008 financial crisis—have focused on strengthening bank stability while ensuring credit access to the real economy (Philippon, 2015). Diamond (2001) argued that banks with personal information about borrowers should be protected through government intervention during crises. Our findings suggest an additional channel through which bank stability can be influenced: the reallocation of human capital within the banking sector.

Our results are robust to several tests. We show that our results are valid even if we aggregate branches at the provincial level. This operation serves two purposes: first, it allows us to reduce the dimensionality of our dataset, which is particularly important when we consider the large number of branches in our sample. Second, and more important, it allows us to rule out the fact that the moving firm had a pre-existing relationship with the new bank, but in a different municipality. Furthermore, our results are obtained using an estimator that accounts for the staggered nature of our treatment, allowing for cohort-specific effects (Sun and Abraham, 2021). We also estimate our main results with a poisson specification, and results are consistent with our baseline linear probability model.

Our paper contributes to three strands of literature. First, we add to the extensive research on bank branching and relationship lending, which — since the seminal work of Stiglitz and Weiss (1981) — has examined how soft information in banking relationships influences credit allocation (Amberg and Becker, 2024; Babina et al., 2022; Fisman et al., 2017) and loan pricing (Beraldi, 2025). Scholars have used mainly two approaches to measure the effects of soft information on credit: geographical proximity (Bonfim et al., 2021; Degryse and Ongena, 2005; Petersen and Rajan, 2002) and cultural homophily (Frame et al., 2025; Fisman et al., 2017; Cornell and Welch, 1996). Nguyen (2019) and Duquerroy et al. (2022) exploit branch closures to assess the impact of losing a local branch on credit allocation and sectoral specialization. Fisman et al. (2017) find that in India, cultural homophily between loan officers and borrowers affects both the likelihood of loan approval and loan success. Hertzberg et al. (2010) use internal bank data to show how loan officer rotations influence screening and monitoring incentives, ultimately shaping credit allocation. We contribute to this literature in two key ways. We adopt methods from labor and trade economics (Patault and Lenoir, 2024; Kramarz and Skans, 2014) to construct a portfolio of client firms for each bank manager, allowing us to directly measure individual relationships. In addition, the richness of our dataset enables us to track managers and their clients across banks — not just within the same banking group — allowing us to quantify the portability of managerial information across the financial sector. Additionally, we show that personal relationships, rather than physical distance, are the primary determinant of a firm's bank selection, as clients follow managers up to a long distance.

A second strand of literature explores the intersection of labor market dynamics and finance. Acabbi et al. (2024) and Jasova et al. (2021) combine workforce administrative data with credit registry data to examine how labor responds to credit and monetary shocks. We contribute to this literature by considering the opposite direction of causality—how labor reallocation within the financial sector influences credit allocation. To do so, we build on prior research examining occupation and wages in finance. Philippon and Reshef (2012) initiated a line of work documenting key features of the financial labor force, including the drivers of wage premia (Bell and Van Reenen, 2014) and concerns about "brain drain" following financial sector deregulation (Boustanifar et al., 2018; Böhm et al., 2023). **?** develop a career model for bank employees, arguing that much of their human capital is not portable, leading to penalties when they switch banks. Our contribution lies in linking these stylized facts about the financial workforce to core banking functions such as credit allocation. We show that, contrary to some prior findings, bank managers' human capital is portable because it is rooted in personal relationships with clients.

Personnel economics has extensively documented the impact of managers on firm performance (Bloom et al., 2013; Bandiera et al., 2020; Lazear et al., 2015). Building on Minni (2025), who shows that manager rotations can have long-term effects on subordinates' careers, we show that bank managers similarly contribute to the long-term performance of their client firms. The study that has most closely examined the portability of managerial relationships - although in the context of French exporting firms - is Patault and Lenoir (2024), who defines "customer capital" for sales managers, showing that they can retain clients even after switching employers. We extend this insight to the banking sector, revealing that the portability of managerial relationships is more pronounced in finance than in sales. Moreover, we show that this phenomenon not only benefits the receiving bank but also enhances outcomes for the client firms.

The remainder of the paper is organized as follows. In Section 2, we describe our data sources and sample construction. Section 3 outlines our empirical strategy. Section 4 presents our main results. In Section 5, we analyze information requests to uncover the mechanisms driving our findings. Section 6 examines heterogeneity across different dimensions. Section 7 explores the impact of managerial information on loan contract terms and default rates. Finally, Section 8 concludes.

2 Data and sample construction

In the following paragraphs we first present the datasets we use, then we describe how we perform our matching procedure, and finally we describe the resulting dataset that we use in our empirical analysis.

2.1 Main datasets

We combine three different datasets, which are provided by the Bank of Italy and refer to the period 2009-2018. The first one is the credit registry data, which contains all loans granted by Italian banks to Italian firms. The second one is the social security data, which contains all the workforce of the Italian financial sector. The third one is the Cerved data, with balance sheet information on all incorporated Italian firms (around 500 thousand unique firms).

Credit information The credit registry data is a panel of all outstanding loans greater than 30 thousand euros granted by Italian banks to Italian firms in the years 2009-2018, provided by the Bank of Italy. Each loan is identified by the receiving firm, the year and the granting bank branch.[1] We observe the total amount of outstanding debt at the end of each year, as well as the breakdown by type of loan (credit line, self-liquidating or term loan). We also track the status of each loan (performing or non-performing) at the end of each year. From two separate sections of the credit registry we also retrieve data on interest rates and loan applications. Interest rates are coded at the bank group - firm level, so that we can tell the aggregate average interest rate that a firm has paid to a bank group in a given year. For loan applications, we use a dataset containing the requests for information ("Richieste di prima informazione" in Italian) that banks make to the credit registry in order to screen potential borrowers or monitor existing ones (Branzoli and Fringuellotti, 2020; D'Andrea et al., 2023). We consider these requests for information as an intermediate step between the first contact between a firm and a bank, and the actual granting of a loan. The availability of such data is unique in the context of credit registry data, and allows us to investigate the mechanisms behind our main results. As for the interest rates, requests for information are coded at the bank group - firm level, so that we can tell if a bank group has requested information about a firm in a given year.

We consolidate the bank group identifier at the end of the sample, in order to avoid considering any mechanical credit relocation due to M&As.[2] The dataset contains

[1] In this paper we identify bank branches in the credit registry by the unique combination of municipality and bank group codes.

[2] Consider indeed the case in which Bank group A acquires Bank group B in 2015, and the two banks have a branch each in the same municipality. Right after the M&A operations the two branches would be considered as the same branch in the credit registry. Therefore we would observe credit (and also people, as we will see later) moving mechanically from one branch to the other. As we are interested only in firm's decision to move credit, we use a version of the credit registry that sets the bank group at the end of the period (2018) as the identifier of the branch for the

8 million observations (one for each firm-branch-year triplet), 440 thousand unique firms, and 31 thousand unique branches.

Workforce information We access a subset of Italian Social Security data, which contains the universe of workers in the Italian financial sector for the years 2009-2018. The dataset is provided to the Bank of Italy by INPS (Istituto Nazionale della Previdenza Sociale, the Italian National Institute of Social Security). We observe for each worker, at yearly level, her bank group, the municipality where she works,her type of contract (managerial or not), her wage and a set of demographic characteristics (such as age or gender). As for the credit registry data, we identify a branch by the unique combination of municipality and bank group. The dataset comprises around 3.5 million observations, resulting in 350 thousand workers per year.

Firm characteristics The third dataset, which contains firm-level charactersistics on all incorporated Italian firms, is administered by Cerved Group and licensed to the Bank of Italy. The unique number of firms in the dataset is around 500 thousand. The dataset provides balance sheets and income statements, that we use to obtain standard firm-level variables, such as size, industry, assets, investments, credit score, and profits. Sole proprietorships, small household producers, or unincorporated partnerships are not covered. A firm is identified by a unique fiscal code, which we then match to the credit registry through a crosswalk provided by the Bank of Italy.

2.2 Sample construction

We construct our sample by adding to the credit registry information on workforce transitions. Therefore our final dataset will be built with the same structure of the credit registry (firm-branch-year triplets), and an additional column that keeps track of manager moves, matching firms that the managers have known in the past to the branches where they move. Our matching procedure relies on the fact that we can identify where a manager is employed in the social security data, and where a firm has received credit from in the credit registry data. We measure knowledge flow through transitions, of which Figure 1 provides a schematic representation. Consider two banks, that we just label as old and new bank (with respect to the manager's move). At time $t = 0$, the manager is in her old bank, where she gives credit to firms

whole period. In the previous case we then would have a unique branch of Bank group A in the municipality for the years 2009-2018.

A and B. At the same time, the new bank she will move to has credit relationships with firms C and D. At time $t = 1$, the manager moves to the new bank, and the credit relationships change. Both firm A and B are part of the manager's portfolio as she moves. Firm A actually follows the manager to the new bank, while firm B does not. In order to measure this phenomenon in the data, we need to define who the branch managers are, which firms are in their portfolio, and what a move is.

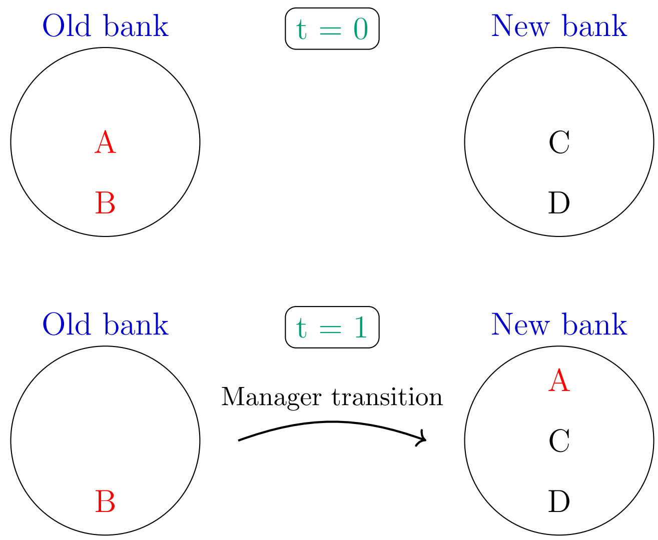


Figure 1. Representation scheme of the manager transition.

Notes: Figure represents the impact of a manager transition from the old bank to the new bank. Firms A and B were part of its portfolio at the old bank, A follows her.

Branch managers In both the credit registry and the social security data, a branch is identified by the unique combination of municipality and bank group codes. In order to define who the branch managers are, we select: the workers that are labelled as top or middle managers in the social security data, as well as those whose wage was in the top decile of the wage distribution in her branch. Without making the assumption on wages, we would not be able to identify any manager in 35% of the branches. However, our results hold regardless of this assumption. At the same time, we need to identify within managerial workers, those who actually are in charge of their branch and make decisions about lending. As a consequence, we focus only on a particular subset of branches. First, we select only branches of bank groups that have had only one physical address in the municipality where they operate. While the credit registry (nor the social security data) does not provide physical addresses, we rely on a publicly available data source on the Bank of Italy website that provides the physical addresses of all bank branches in Italy.[3] Second, within those branches, we select the ones that had given credit to at most 150 unique firms per year in the two years before a manager moves. The average number of managers per branch is 2, and we still keep more than 80% of the branches in our sample. This choice allows us to be sufficiently sure that the manager has had direct contact with the firms which had loans with the branch, as well as to avoid branches that are too large and may have multiple managers with different responsibilities. In Appendix we provide additional robustness checks to confirm that our results are robust to the threshold choice.

Portfolio Once we have established who the branch managers are, and what are the relevant branches, we need to pin down the portfolio of clients each branch manager has. We label as portfolio firms all the firms that have had active loans with the branch where the manager works in both the two years before the manager moves. We do it to accomplish two results: first, we want to make sure that the manager was in direct contact with those firms up until she moved (i.e. we want to exclude firms that left the branch before the manager moved). Second, we want to consider as portfolio firms only the ones who have had a sufficiently long relationship with the branch, so that the manager could have actually acquired soft information on them. The resulting average portfolio size is around 20 firms per manager. Notice that we are not able to tell which firm was interacting with which manager within the branch. Therefore, our choice of restricting to small branches is crucial, as it increases the likelihood that the manager was actually in contact with the firms that we consider as her portfolio. Consider also that the possible noise in our portfolio construction would bias our results towards zero, as we introduce in a manager's portfolio firms that she may not have known. Any measure of the portability of credit relationships that we find is therefore conservative. We test the robustness of our results by focusing on subset of branches that had a smaller number of managers, and our results are - as expected - stronger.

Moves The third part of our matching procedure is how to define a move. In social security data, we observe where the branch manager works in each year. We know both her municipality and the bank group she works for. Our baseline definition of a move is a change in the bank group of the manager from year t to year $t+1$. Since

[3] See https://www.bancaditalia.it/compiti/vigilanza/albi-elenchi/

we are interested in permanent moves and not temporary relocations, we constrain our set of moves such that at $t-1$ the manager was still in the same branch where she worked at time t, and at $t+2$ she is still in the branch where she moved at $t+1$. However, there is also another type of move, which is a change in the municipality of the manager within the same bank group. The two types are inherently different. In the baseline case, which accounts for 4.1% of the yearly moves in our data, the manager transfers information from one bank to another, and create a new credit access for the client firms (**?**). The second case, which accounts for 95.9% of the yearly moves, corresponds to a more traditional definition of loan officer rotation, or may be generally due to personnel management within the bank (Minni, 2025; Gao et al., 2024a). Even in this latter case there is room for information transmission, as personal information is specific to the branch manager, and the relationship lending literature has shown that even within the same bank, loan officers have incentives to hoard information about borrowers (Hertzberg et al., 2010). Our baseline specification will consider only moves between bank groups, as they constitute a unique feature of our dataset. The total number of moves in our sample is 609. We will use the second type of moves in our heterogeneity exercises, to benchmark the results with the more traditional definition of loan officer rotation.

2.3 Resulting dataset

We use the definitions of branch managers and moves in the social security data, and build for every manager that has moved her portfolio of firms. Our main interest is to measure the increase in the probability that a portfolio firm gets credit from the branch where the manager has moved, after the move has taken place. In order to do so, we need to act on the credit registry to properly measure this probability. The credit registry is a panel of firm-branch-year triplets, but contains only the pairs that have realized (i.e. the firm has a loan with the branch).

We then need to modify the credit registry to account for all potential firm-branch relationships, not just the realized ones. This means we need to create a balanced panel of firm-branch-year triplets for the years 2009-2018, where each triplet represents a potential relationship between a firm and a branch in a given year.

To do this, we first filter the credit registry considering only all firms and branches that have been active (i.e. received or given credit in each year) during the period of interest. We do it to avoid any bias that may derive from the fact that some firms or branches may have entered or exited the credit market during the period of analysis.

The resulting filtered credit registry contains 4 million realized matches (one for each firm-branch-year triplet), of 160 thousand unique firms and 14 thousand unique branches. All the 160 thousand firms in our filtered sample are present in Cerved data.

Then we expand this filtered credit registry to include all potential firm-branch-year triplets for the years 2009-2018. From the perspective of the firm, we need to consider all the branches it could have asked credit from, consider the ones that have realized, and measure if the presence of a manager that knew the firm has affected this matching realization. Similarly, from the perspective of the branch, we need to consider all the possible firms it could have given credit to. Panetta et al. (2009), Crawford et al. (2018) and Barone et al. (2024) define credit market at the provincial level,[4] so that we consider only firm-branch potential pairs that are in the same province. Then our final dataset is the aggregation of the 110 provincial markets, where a market is defined as the set of all potential firm-branch pairs in a province. Each potential firm-branch pair is represented in each year from 2009 to 2018.

The dataset has a size of 231 million observations, which makes computationally expensive the estimation of our model. In our main regressions we sample around 40% of the data, and we repeat our exercises to validate our results.

3 Empirical Strategy

Our main goal is to quantify how portable are the relationships that bank managers build with their clients. We measure it by computing the probability of a firm establishing a credit relationship with the new bank of the manager, as opposed to any other bank in the same province. As explained in Section 2, in order to measure this probability, we have to create matching pairs of firms and banks. With respect to banks, we can identify the branch through the unique combination of municipality and bank group. Then our unit of analysis is a potential match between a branch and a firm. It is treated when the branch hires a manager that has given credit to the firm in the past (i.e. the firm is in the manager's portfolio).[5] We rely on two sources of variation: the cross-section (i.e. movements from one branch to another) and the timing of the moves. We employ a difference-in-differences strategy, explained in Equation (1).

[4] See the discussion in the previous paragraph.

[5] See the discussion in subsection 2.2 for the definition of the portfolio.

$$I(\text{credit})_{bft} = \beta I(\text{Inflow})_{bft} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft} \tag{1}$$

$I(\text{credit})_{bft}$ is an indicator equal to one if the firm f has been granted a loan by branch b in year t, and zero otherwise. $I(\text{Inflow})_{bft}$ is an indicator equal to one if the branch b has hired a manager that had firm f in her portfolio. It is equal to one for all the years after the pair has been treated for the first time (i.e. for the first time a manager knowing firm f has moved to branch b). Notice that since we are using worker relocations, it can be possible that a pair is treated more than once, as two or more managers having the same firm in portfolio can move to the same branch, contemporaneously or in different years. We check in the data that it is a residual case (around 3% of the treated pairs are treated more than once). Notice also that the timing of the event is specific to the firm-branch pair, i.e. some units are treated at the beginning of the sampling period, and some in later years.

We include a vast array of fixed effects, that control for the time-invariant characteristics of the firm-branch relationship, and for the time-varying policies of the branch and the firm. More extensive discussion on the identification strategy and the use of fixed effects is provided in subsection 3.1. We cluster standard errors at the bank-firm level. Our control group is composed of all the firm-branch potential pairs within the same province, that have not been involved in any manager transition. [6]

The coefficient β measures the increase in the probability of a firm establishing a credit relationship with the new branch of the manager, as opposed to any other branch in the same province. In our main specification we will only rely on variation coming from moves between bank groups, that have a more profound impact on information transmission throughout the financial system. However, we will use the same empirical strategy to detect the effect of moves within the same bank group, both to benchmark our results and to inform the literature on loan officer rotation.

We estimate Equation (1) also through an event study specification. It allows us to provide a visual representation of our main results, and to rule out any anticipation of the move by the firms. If indeed the branch where the manager was working had poor performance, firms may have reacted to such poor performance by moving their credit relationship elsewhere. And if the manager was aware of the poor performance, she may have decided to relocate exactly to the branch where the firm had already moved.

Our setup allows us to test for this anticipation effect, in two ways. First, if

[6] For more details on the sample construction, see subsection 2.3.

the firm had relocated by shutting down the credit relationship with the manager's old branch before her move, it would not be part of the portfolio, and hence not treated. Second, if the firm had relocated but kept the credit relationship with the manager's old branch at least until the time of the move, we would observe a higher probability of the firm establishing a credit relationship with the new branch before the event. This would be a sign of anticipation of the move, and would suggest that the manager's move was not the cause of the firm's relocation. Equation (2) provides a formal representation of the event study specification.

$$I(\text{credit})_{bft} = \sum_{\tau=-4}^{4} \beta_\tau \times I\{t = t_{bf} + \tau\} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft} \tag{2}$$

The term t_{bf} is the year in which the manager that knows firm f moves to branch b. $I\{t = t_{bf} + \tau\}$ is an indicator equal to one if the year is τ years before or after the manager's move. The coefficient β_τ measures the year-specific variations in the matching probability between the firm and the branch. We standardize β_{-1} to zero, so that the other coefficients represent variation with respect to the baseline year. All fixed effects, sample and control group are the same as in Equation (1). We take into account the staggered nature of the treatment, using estimators that are robust to negative weights or cohort-specific effects (Sun and Abraham, 2021).

3.1 Identification discussion

We exploit the dyadic structure of our data, and include three types of fixed effects.

First, we include pair fixed effects α_{bf}, that control for the time-invariant characteristics of the relationship between the firm and the branch. In the context of our analysis, they represent the assortative matching probability between firms and branches. They control for geographical characteristics - i.e. firms that are close to the branch are more likely to have a loan with the branch, as in the relationship lending literature (Bonfim et al., 2021; Keil and Ongena, 2024; Nguyen, 2019) - or industry components - in the case of lending specialization, as in Paravisini et al. (2023); Duquerroy et al. (2022); Goedde-Menke and Ingermann (2023).

Second, we include branch-time fixed effects δ_{bt}, that take into account for branch-level time-varying policies, such as credit supply, branch size (hirings or layoffs), deposit inflows or outflows.

Third, as Khwaja and Mian (2008), we include firm-time fixed effects γ_{ft}, which account for firm-level time-varying characteristics, such as credit demand, investments, or financial health of the firm. A unique feature of the Italian banking sector is the presence of multi-bank relationships, even for small firms (the average number of bank relationships per firm in the credit registry is 2.76), as documented also by Gobbi and Sette (2014) and Kosekova et al. (2024). Therefore, the inclusion of firm-time fixed effects appears to be even more crucial in this context, as firms may direct their credit demand to different banks and branches over time.

Then the parameter β is identified by any variation that, at the event time, changes the matching probability between the firm and the branch.

Absent any confounders, we attribute the change in the matching probability to the manager's move, as Patault and Lenoir (2024). However, there is still a threat to our identification strategy, coming from the potential endogeneity of the manager's move. Indeed, the decision of the manager to move may be driven by shocks that also change the matching probability between the firm and the branch. An example of that is some poaching activity, where the new bank actively tries to attract the firms of the manager (and maybe wants to expand in the same industry), and as a consequence the manager decides to move. An event study regression can help us control if the managers' new branch was already attracting the firms in the portfolio before the move, but cannot rule out simultaneity. β would not correctly identify the portability of the relationship if, at the same time, but separately, both the manager and the firm decided to move.

We address this concern by estimating equation (2) by restricting our sample of moves to those that are caused by branch closures, as in Eliason et al. (2023). Italian labor law tries to protect workers from the consequences of branch closures, and facilitates their relocation within the financial sector. Most of the relocations happen within the same bank group, but we discard them for two reasons. First, in our main specification we are interested in bank-to-bank moves. Second, when a bank group decides to close a branch, all borrowers of the branch are moved to another branch of the same bank group.

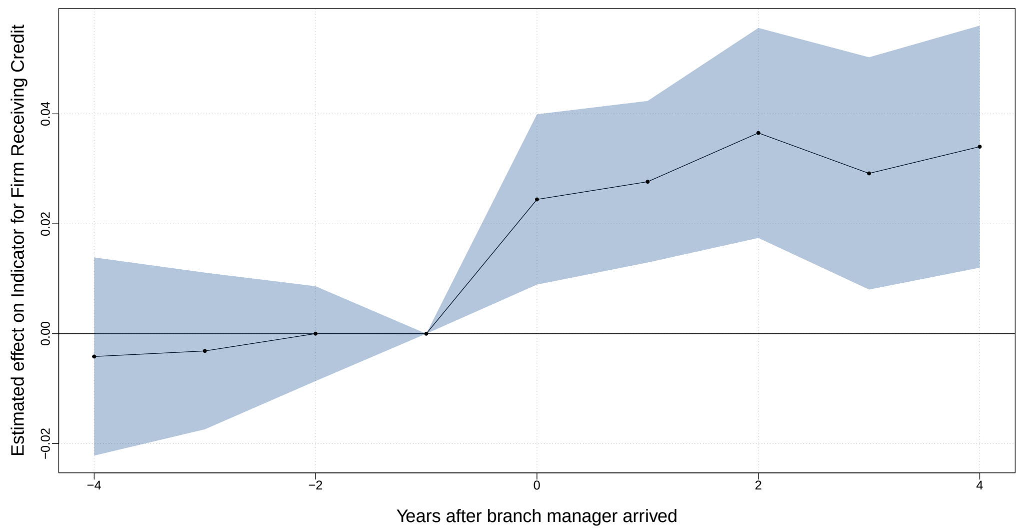
We want to avoid any mechanical credit relocation, so we consider only moves in which the manager has moved to a bank group that was not involved in the decision to close the branch. By including fixed effects, and using an instrument for the manager's move, we are thus able to identify the effect of the manager's knowledge on the matching probability between the firm and the branch.

4 Main Results

Figure 2 shows the event study representation for Equation (2). It represents the time variation of the probability that the branch b that hires the manager establishes a credit relationship with the firm f that was in the manager's portfolio. As one can notice, there is no significant variation in the probability of creating such relationship before the manager moves. To provide a benchmark for our estimates, consider that the average probability of a firm establishing a credit relationship with any branch in the same province is around 1.3%. In the year right after the manager moves, the probability increases by 2 percentage points, further increasing by another percentage point in the following years. One can notice two main facts. First, the increase is sizable, as it represents a 300% increase with respect to the baseline probability. Second, the dynamics show that managers are able to bring their clients with them right after they move, as most of the increase happens in the first two years.[7]

[7] Notice that obtaining credit in Italy is rather a fast process, with the average time between the application and the disbursement of the loan being around 30 days.

Figure 2. Increase in probability of giving credit to portfolio firms after the move



Notes: Event study estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved. Plot shows OLS estimates and 95% confidence intervals for the coefficients β_τ in equation (2). Branch - firm, branch - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

Table 1 shows the DiD estimates for β across different specifications. The first column shows the baseline specification, with just the inclusion of branch-firm fixed effects, to capture the assortative matching time invariant characteristics. In columns (2) and (3) we include branch-time and firm-time fixed effects, while column (4) shows the results with the whole set of fixed effects. Estimates are stable across all specifications, indicating that our results are not driven by credit demand or supply shocks. The coefficient hovers around 0.025.

Table 1. DiD estimates for β

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

Notes: Estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved. Column (1) includes only branch fixed effects, column (2) includes branch and time fixed effects, column (3) includes branch and firm fixed effects, and column (4) includes all fixed effects. Standard errors are clustered at the bank group - firm level. The sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1 Branch closures identification

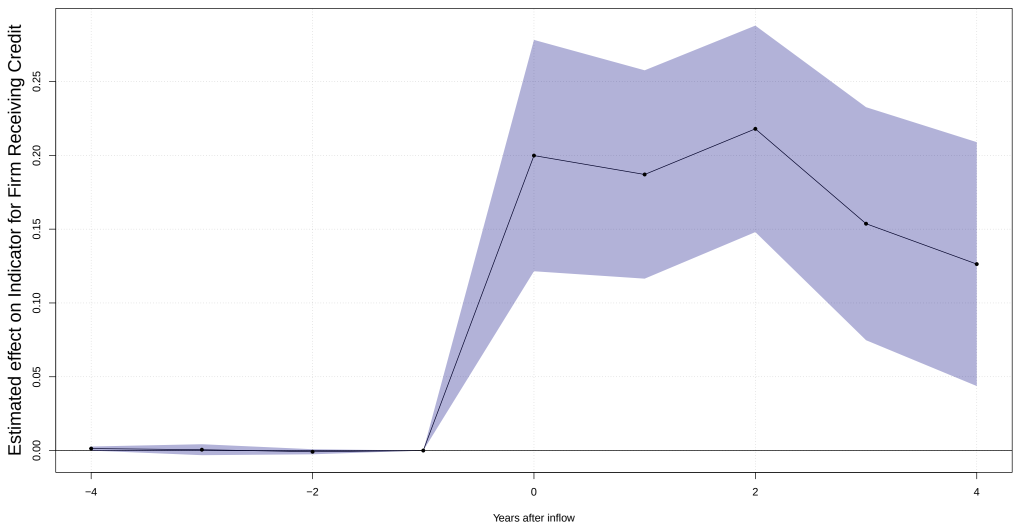
In order to address the potential endogeneity of the manager's move, we estimate Equations (1) and (2) considering only moves that are caused by branch closures. As in the previous case, we consider only bank-to-bank moves. It is noteworthy that considering only bank-to-bank moves allows us to rule out any form of mechanical credit relocation. Indeed, if a bank group decides to close a branch, it will move both the managers and the credit relationships to a different branch. By considering only managers that have moved to a different bank group, we can be sure that the increase in the matching probability is due to the manager's knowledge, and not to the bank's decision to move the credit relationships.

Using branch-closure induced moves as a source of identification helps us to address the potential endogeneity of the manager's move. However, we expect a different dynamic pattern. We can decompose the probability of a firm following the manager into two components: the probability that the firm decides to leave its current branch, and the probability that the firm decides to apply to the manager's new branch.

In the case of branch closures, the first component is likely to be higher, as the firm is more likely to search for credit elsewhere. Firms are automatically relocated to a different branch of the same bank group (Papoutsi, 2025), so they can decide whether to accept this relocation or to search for credit elsewhere. In the latter case, they may decide to follow the manager to her new bank or to simply shop around. Therefore, we expect that the overall effect of the manager's move on the matching probability is higher, and more sudden, than in the case of all bank moves.

Figure 3 shows the event study representation. As for the previous case, there is no anticipation of the move by the firms, that do not move to the new branch before the manager has moved. The right-hand side of the graph confirms our hypotesis: the matching probability increases more rapidly than the case of all bank moves, then stays stable for two years, and slightly decreases in years 3 and 4. The overall effect is much larger than the previous case, hovering around an increase by 20 percentage points in the matching probability. We attribute this larger magnitude exactly to the augmented separation probability from the previous branch, that forces firms to search for credit elsewhere. The decrease in years 3 and 4, although present, still leaves the matching probability 10 percentage points higher than the baseline probability. Appendix Table A2 reports the DiD estimates with the progressive inclusion of fixed effects, that - as in the previous case - are stable across specifications.

Figure 3. Increase in credit probability to portfolio firms after branch closures



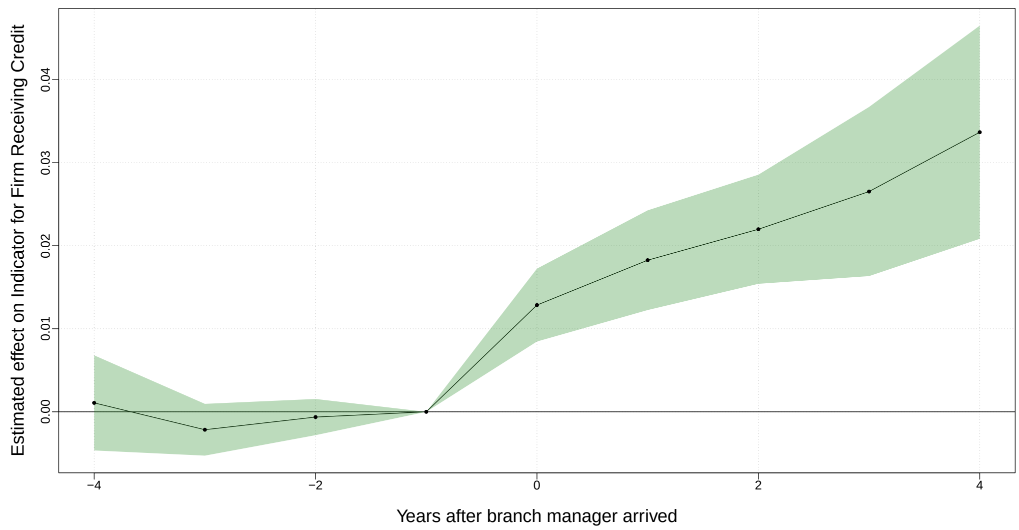
Notes: Event study estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved due to a branch closure. Plot shows OLS estimates and 95% confidence intervals for the coefficients β_τ in equation (2). Branch - firm, branch - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another, and the originating branch has closed. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

4.2 Within bank moves

We now turn to the case of moves within the same bank group. Moves between bank groups are most likely caused by career choices of the manager, who actively sought a new position, or by external circumstances such as branch closures. Here we consider a different type of transition: within group moves are often decided by the bank. Managers can be rotated across branches, or promoted to a different position, maybe in a larger or more strategic branch. The case of loan officer rotation has been vastly studied by theoretical (Stein, 2002) and empirical literature (Hertzberg et al., 2010), and is a policy designed by the bank to ensure a more trasparent monitoring, reducing the incentives for loan officers to grant credit to undeserving borrowers. However, notice that the presence of personal ties between the loan officer and the borrower can also have a positive impact on the bank's profits. Indeed, more profound knowledge between the two parts may increase the probability that the borrower stays with the bank, and can even increase the loan performance outcomes (Fisman et al., 2017). So, while an effective design of such policies would rely on the fact that the loan officer is not able to bring her clients with her, it is not straightforward that the bank would reduce this possibility to zero.

In Figure 4 we show, indeed, that even in the case of within group moves, the manager is able to bring some of her clients with her. Table A3 in the Appendix shows the DiD estimates for the within group moves. The probability of moving is lower than in the case of between group moves, but still significant, and it exhibits a different dynamic pattern with the case of between group moves, where the welcoming bank has no incentive to delay the transfer of new clients (if valuable). Also in this case firms do not anticipate the move. But the matching probability, instead of increasing sharply right after the move, increases constantly, and peaks 5 years after, at a level that is 3 times the baseline probability. We can interpret it as the interplay of two forces: while the manager may like to bring her clients on, the bank may have policies that prevent internal relocations. So, for the manager it may take a longer time to progressively bring her clients with her.

Figure 4. Credit probability increases, within bank moves



Notes: Event study estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved. Only moves within the same bank group are considered. Plot shows OLS estimates and 95% confidence intervals for the coefficients β_τ in equation (2). Branch - firm, branch - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers within the same bank group. To keep consistency with the sample definition, only moves that occur within the same province are considered.

This result provides a benchmark for the previous estimates: bank moves cause a increase in the matching probability that is 2.5 times as large as the one caused by within bank moves. We can at least partially attribute this difference in size to the bank's incentives. It also complements the existing literature on loan officer rotation. In the period covered by our sample, the number of bank groups has decreased. In our data we set the bank group at the end of the period, so that our results are net of any merger and acquisition activity. As a consequence, some of the within bank moves that we observe have happened in the context of consolidation processes. In such events, banks may have an incentive to exploit their managerial human capital to retain clients (which is what we observe in our results), but at the same time this fact reduces the monitoring effectiveness (Hertzberg et al., 2010).

In the following section we focus on the process by which the bank that hires the manager decides to grant credit to the firms that were in the manager's portfolio. We use data from loan applications to see if the manager is able to affect the screening process of the bank, and if the bank is able to capture the value of the manager's portfolio.

5 Mechanism: credit applications

In the previous section we provided evidence on the fact that when a manager moves, the firms that were in her portfolio are more likely to establish a credit relationship with her new branch. In this section we uncover the mechanism behind this phenomenon. We still focus on bank-to-bank moves, and we rely on a different data source from the credit registry, which is a request for information that the bank sends to the Bank of Italy. The object of the request is a firm, and the Bank of Italy provides the requesting bank with the firm's credit history, or its non-performing loans. It is a tool that can be used both in screening a potential borrower, so to acquire more information on the firm, or in monitoring the firm's behavior in the following years (D'Andrea et al., 2023; Branzoli and Fringuellotti, 2020). We focus on requests for information that were filed from banks to firms that did not have previous credit relationships with the bank, so to isolate the screening component of the request. Noting that filing request for information is a rather standard procedure in the screening process, we can also interpret those requests as a proxy for loan applications. Indeed, since requests for information come from the bank, we can reasonably assume that they come after the screened firm has previously applied for a loan.

The Bank of Italy stores requests for information data at the firm - bank group - year level. We are not able to identify the branch from which the request comes, but we can still reliably assume that the request is sent by bank where the manager has moved, and where the firm will eventually have credit, if the request is accepted. Notice also that we are interested in differences in the probability of the request being sent (or accepted), so measurement error is constant throughout the sample, and does not affect our estimates. We make two conjectures on the manager's role in the screening process. First, we expect branch managers to influence search, i.e. to induce the firms that were in her portfolio to apply for a loan. Second, we expect managers to influence the screening process, i.e. to increase the probability of the request being accepted.

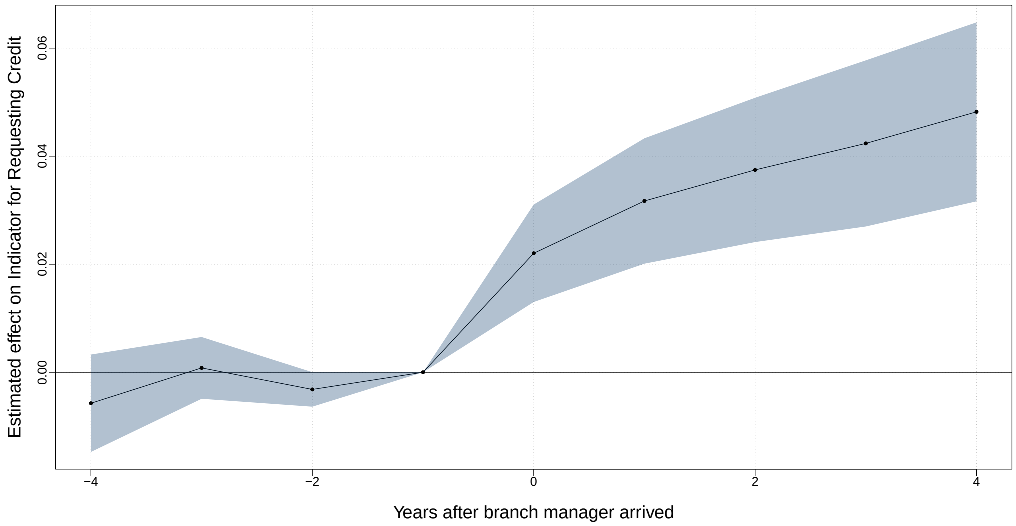
5.1 Search

Proxing loans applications with requests for information, we can test if the manager is able to affect the probability of the firm applying for a loan. If this is the case, we should see an increase in the requests of portfolio firms after the manager moves. Equation (3) shows the empirical strategy we use to test this conjecture.

$$I(\text{applied})_{bft} = \sum_{\tau=-4}^{4} \beta_\tau \times I\{t = t_{bf} + \tau\} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft} \tag{3}$$

The dependent variable $I(\text{applied})_{bft}$ is an indicator equal to one if the bank b has requested information on firm f in year t or earlier, and zero otherwise. The right-hand side of the equation is the same as in Equation (2), with the only difference that observations are collapsed at the firm-bank group level. The unit of observation becomes then the bank-firm pair, as opposed to the branch-firm pair in the previous analysis. Therefore fixed effects capture the underlying matching probability between a bank group and a firm, and the time-varying characteristics of the bank group (as well as the firm). Figure 5 shows the event study representation of the results. The baseline probability of a bank requesting information on a firm is 2.5%. Four years after the manager moves, the probability increases by 4.5 percentage points, reaching a level that is almost three times higher than the baseline probability.

Figure 5. Increase in probability of applying for credit to the new bank



Notes: Event study estimates for the probability of a firm applying for credit in the bank where its bank manager has moved. Plot shows OLS estimates and 95% confidence intervals for the coefficients β_τ in equation (3). Bank - firm, bank - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - bank pairs, for the period 2009-2018. A pair is considered potential if in the province where the firm was present, there was at least one branch of the bank. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

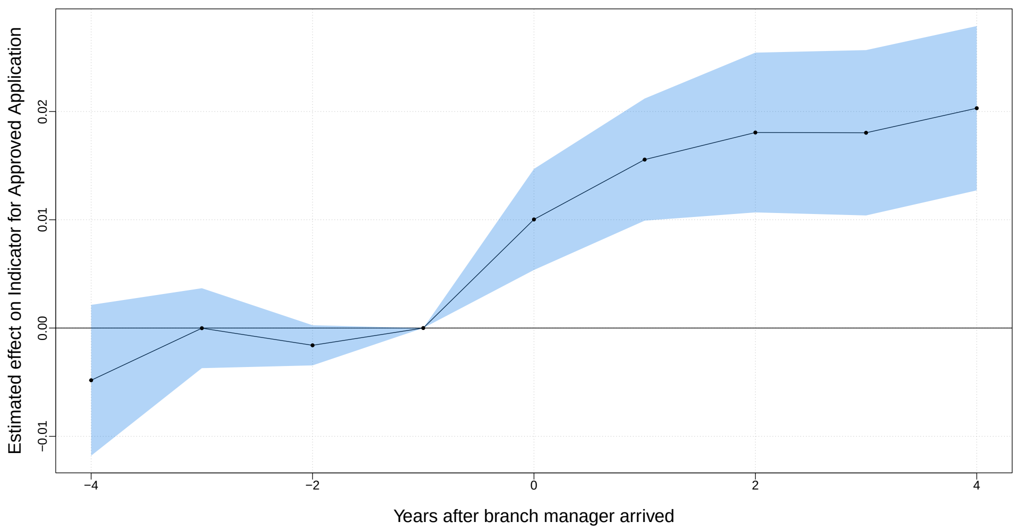
5.2 Screening

Our second conjecture is that the manager not only affects the probability of the firm applying for a loan, but also the probability of the request being accepted. In order to test this conjecture, we estimate Equation (4), by regressing the conditional probability of the request being accepted on the manager's move. We build the conditional acceptance probability $I(\text{accepted}|\text{applied})_{bft}$ in our dataset by checking the rows in our dataset where the firm has requested for information, and the bank has granted the loan. The equation reads as follows:

$$I(\text{accepted}|\text{applied})_{bft} = \sum_{\tau=-4}^{4} \beta_\tau \times I\{t = t_{bf} + \tau\} + \alpha_{bf} + \delta_{bt} + \gamma_{ft} + \epsilon_{bft} \quad (4)$$

The conditional acceptance probability mean in our sample is 0.35, which means that the bank accepts a loan request in 35% of the cases. Figure 6 shows the event study plot. Four years after the manager has moved, the probability of the request being accepted increases by 2 percentage points, reaching a level that is almost 6% higher than the baseline probability. Therefore, not only the manager's firms are more likely to apply for a loan, but also the bank is more likely to accept the request.

Figure 6. Increase in probability of being approved for credit in the new bank



Notes: Event study estimates for the probability of a firm being approved for credit in the bank where its bank manager has moved. Plot shows OLS estimates and 95% confidence intervals for the coefficients β_τ in equation (4). Bank - firm, bank - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - bank pairs, for the period 2009-2018. A pair is considered potential if in the province where the firm was present, there was at least one branch of the bank. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

Appendix figures A3 and A4 show the results of the same exercise, but using a Poisson model instead of a linear probability model. In the following sections we will explore the features of the match between the manager and the firm, and will investigate what kind of value the manager brings to the bank that hires her.

6 Heterogeneity

We provide evidence on the three actors that are involved in the relationship lending process: the bank manager, the bank, and the firm. We uncover their role in the portability of the manager's clients by interacting the treatment effect in equation (1) with characteristics of the three actors.

First, we look at the characteristics of the bank, and we show that the structure of information within both the welcoming and the departing bank matters for the portability of the manager's clients. Second, we look at the characteristics of the firms, and we show that younger and smaller firms are more likely to follow their manager when she moves, being the actors for which the manager's soft information is more valuable (Huber, 2021). Third, we look at managers, showing that older managers coming from smaller branches bring a larger fraction of their clients with them. We also show that former loan size matters, with managers bringing a larger fraction of their clients that had mid-size loans (between 100 and 500 thousand euros). With respect to competition, we show that the portability of the manager's clients is larger in more concentrated local banking markets, where competition is less fierce.

6.1 Bank organization

The first dimension of heterogeneity we investigate on relates to the characteristics of the banks. As Stein (2002) explains, the structure of information within a firm has a crucial role on the internal organization. He argues that his model is mostly suited for the banking sector, where there is the contemporaneous presence of hard and soft information. Some banks - the large ones in the model - may rely more on hard information, and so have a centralized credit awarding process, where the role of the branch is limited to the collection and the "hardening" of credit information, so that it can be used by the central office. On the other hand, another type of banks - typically smaller - may rely more on soft information, and so have a decentralized credit awarding process, where the branch manager has a more prominent role in the credit allocation.

We test this conjecture by interacting the manager's move with a dummy that captures the size of the bank. We define large banks as banks that have more than 5 percent of the total number of employees in the banking sector, and small banks as the remaining ones. There are then 4 categories, interacting the previous bank size (large or small) with the size of the manager's new bank.

In this context, Stein (2002) would predict that small banks are more likely to let the manager bring her clients with her, as they rely more on soft information. At the same time, they are the ones that are more willing to keep the clients within the bank, as they may implement more devices to keep the information within the bank, such as having the client firm interact with more than one manager, so to build a relationship that is personal (i.e. with the manager) but ties the client to the bank as well. Therefore, we expect that transitions that attract the most clients are the ones from large to small banks, as the information is "softened" by the moving manager and the new bank is willing to use it. On the other hand, transitions from small to large banks are expected to be the least effective, as the manager would be less able to use her soft information in the new bank, and the new bank would be less willing to let the manager bring her clients with her. Table 2 shows the results. For each regression we estimate the baseline effect (first row of the table), and then the interaction term between the manager's move and the bank size.

Table 2. Heterogeneity by type of bank move

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow	0.013***	0.023***	0.026***	0.039**
	(0.004)	(0.008)	(0.008)	(0.016)
Big to small × Inflow	0.042*			
	(0.022)			
Big to big × Inflow		0.021		
		(0.017)		
Small to big × Inflow			-0.029	
			(0.022)	
Small to small × Inflow				-0.026*
				(0.015)
R^2	0.793	0.793	0.793	0.793
Observations	97,198,970	97,198,970	97,198,970	97,198,970
Firm-Time fixed effects	✓	✓	✓	✓
Branch-Time fixed effects	✓	✓	✓	✓
Branch-Firm fixed effects	✓	✓	✓	✓

Notes: DiD estimates for β in equation 1 for different types of bank moves. Column (1) includes an interaction term with moves from a large bank to a small bank, column (2) includes an interaction term with moves from a large bank to a large bank, column (3) includes an interaction term with moves from a small bank to a large bank, and column (4) includes an interaction term with moves from a small bank to a small bank. Small banks are defined as the ones which have less than 5 percent of the total number of employees in the banking sector. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Consistently with the theory, we find the strongest effect for movements from a large bank to a small bank. If moving from a large to a small bank, manager's clients are 4.2 percentage points more likely to follow her, which is around double the baseline effect of 2.3 percentage points in Table 1. The effect is statistically significant at the 10% level. The other estimates are noisier, but smaller (or even negative) in magnitude, reflecting the fact that the process of "softening" creditor information (as for movements from large to small banks) is more effective than the opposite "hardening" process (as for movements from small to large banks). Interestingly, the estimates for transitions between large banks exhibit a positive (although not significant) interaction term, hinting that the relevant dimension of heterogeneity may be the size of the leaving bank, rather than the size of the welcoming bank.

We also analyse the role of the internal organization of the bank. Independently of the size of the bank, local headquarters may employ managers that perform a wider range of tasks, and so they may be less likely to bring their clients with them. If soft credit information was easily "hardenable", then managers moving to local headquarters would be as effective as managers moving to smaller branches. On the other hand, if soft credit information still resides in individuals, that have to perform credit allocation tasks even in local headquarters, then managers moving to local headquarters would be less effective. We define local headquarters as branches that are located in the city that is the capital of the province (capoluogo di provincia). There are 110 provinces in Italy, and so 110 local headquarters, and provinces correspond to a standard definition of local credit market in Italy (Crawford et al., 2018). We then interact the manager's move with a dummy that captures if the manager moved to a local headquarters. Table 3 shows the results.

Table 3. Heterogeneity by moves to provincial capitals

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

Notes: DiD estimates for β in equation 1 for different types of bank moves. Column (1) includes an interaction term with moves to provincial capitals, and column (2) contains only the interaction term. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimate for the interaction term is negative and significant, suggesting that managers moving to local headquarters are less likely to bring their clients with them. Notice that also the magnitude is relevant: as shown in column (2), that contains only the interaction term, managers moving to local headquarters bring less than 1 percent of their clients with them, which is around one third of the baseline effect of 2.3 percentage points in Table 1.

6.2 Firm characteristics

We then turn to the second actor in the relationship lending process: the firm. We examine three aspects of the firms: size, age, and credit risk. Smaller firms should be more likely to rely on relationship lending (Huber, 2021), as they do not have the same access to credit as larger firms. Similarly, younger firms do not have a long credit history, and thus soft information may be more valuable for them. With respect to credit risk, two contrasting theories can be formulated. On the one hand, bank managers can engage in cream-skimming (Di Maggio and Yao, 2021), and so they may be more likely to bring with them less risky clients. On the other hand, if soft information is more valuable for riskier clients, then managers may be more likely to bring with them riskier clients.

We start with firm size. We follow Eurostat cathegorization and define four bins of firm size: micro firms, with less than 10 employees, small firms, that have less than 50 employees (thus including the micro firms), medium firms, that have less than 250 employees (thus including small and micro firms), and large firms, that have more than 250 employees. We then interact the treatment with dummies that capture the size of the firms. Table 4 shows the results.

Table 4. Heterogeneity by firm size

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow	0.019***	0.021***	0.024***	0.028***
	(0.006)	(0.008)	(0.008)	(0.008)
Micro × Inflow	0.012			
	(0.008)			
Small × Inflow		0.007*		
		(0.004)		
Medium × Inflow			-0.005	
			(0.008)	
Big × Inflow				-0.030***
				(0.010)
R^2	0.793	0.793	0.793	0.793
Observations	97,198,970	97,198,970	97,198,970	97,198,970
Firm-Time fixed effects	✓	✓	✓	✓
Branch-Time fixed effects	✓	✓	✓	✓
Branch-Firm fixed effects	✓	✓	✓	✓

Notes: DiD estimates for β in equation 1 for different types of firms. The dependent variable is the credit indicator. Standard errors are clustered at the branch-firm level. Column (1) includes an interaction between β and a dummy for the firm being micro (less than 10 employees), column (2) includes an interaction with a dummy for the firm being small (less than 50 employees), column (3) includes an interaction with a dummy for the firm being medium (less than 250 employees), and column (4) includes an interaction with a dummy for the firm being big (more than 250 employees). Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Although with a noisy estimate, the interaction term for micro firms is positive, suggesting that when firms are so little, they need a more direct relationship with the bank manager, and so they are more likely to follow her. As firms grow, the effect decreases, and it becomes negative for medium and large firms.

Table 5. Heterogeneity by firm age and credit risk

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

Notes: DiD estimates for β in equation 1 for different types of firms. The dependent variable is the credit indicator. Standard errors are clustered at the branch-firm level. Column (1) includes an interaction with a dummy for the firm being young (less than 5 years old), column (2) includes an interaction with a dummy for the firm being old (more than 10 years old), column (3) includes an interaction with a dummy for the firm being safe (credit score below 4 in a 1-10 scale), and column (4) includes an interaction with a dummy for the firm being risky (credit score above 6 in a 1-10 scale). Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 shows the results for the age and credit risk of the firms. We define two bins of firm age: young firms, that had been founded in the 5 years before the manager moved, and old firms, that had been founded more than 10 years before the manager moved. As for risk, the Italian credit registry provides a credit risk score for each firm, which is computed every year by Cebi-Cerved (Rodano et al., 2018). The score ranges from 1 to 10, where 1 is the lowest risk and 10 is the highest risk. We take the Cebi-Cerved definitions and label as low risk firms that have a score lower or equal than 4, and as high risk firms that have a score higher or equal to 7.

The estimate for the interaction term with young firms is positive and significant, suggesting that younger firms are far more likely to follow their manager when she moves, as the increase is of the same order of magnitude of the baseline effect. On the other hand, the estimate for older firms is almost zero and non significant. With respect to credit risk, both estimates are non significant, and they are very close to zero. We then do not find evidence of cream-skimming, nor that riskier firms are more likely to follow their manager. Notice however that these results do not imply that - within the same risk category - the manager is not able to tell apart riskier and less risky firms, and so to bring with her the less risky ones. Results on the performance of the loans that are brought by the manager are provided in Section 7 and show that these loans perform better than the average loan of the welcoming bank. What is more, results in this subsection hint that bank manager moves can be effective in increasing the amount of information in the economy, as they help smaller and younger firms to access credit.

6.3 Manager characteristics

The third element in our analysis - for which we have unique data - is the bank manager. Relationship lending literature has speculated on the cultural (Fisman et al., 2017) and geographical (Amberg and Becker, 2024) proximity between the branch and the borrower, but has not been able to investigate individual characteristics of the bank manager, due to lack of individual level data. Frame et al. (2025) use loan level data with the identity of the loan officer to measure the impact of loan officer ethnicity on home mortgages in the US, but they do not follow loan officers when they move to a new bank, and so they cannot investigate the portability of the loan officer's clients. Theoretical literature (Gennaioli et al., 2015) suggests that trust may be a key element in banking activity. Guided by this intuition, we expect older managers to be more effective in bringing their clients with them, as they may have built a larger relationship capital with their clients. At the same time, in smaller branches, managers may have a more direct relationship with their clients, and so being more effective in bringing them with them. Indeed, if a manager was working in a larger branch, with more managers, although possibly interacting with all the firms that were receiving credit from the branch, she may have had less chances to build a relationship with all of them, and maybe she focused on interacting with a subset of them. We then interact the treatment effect in equation (1) with the age of the manager, and with the number of managers in the branch. Table 6 shows the results for the age of the manager.

Table 6. Heterogeneity by managers' age

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

Notes: DiD estimates for β in equation 1 with heterogeneity by managers' age. Column (1) includes an interaction between β and a dummy for the manager being younger than 45 years old at the time of the move. In column (2), the interaction is with a dummy for the manager being older than 45 years old. Columns (3) and (4) repeat the exercise with a cutoff at 55 years old. Notice that in all specifications there is no baseline effect, so the estimates can be interpreted as the total effect for each group. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (1) and (3) show results for young managers, being respectively younger than 45 and 55 years old. Comparing these estimates with the results in columns (2) and (4), that show the results for older managers, we find that older managers are more effective in bringing their clients with them. Specifically, the estimate for managers older than 55 years old is 0.043, which is almost double the effect of 0.022 for managers younger than 55 years old.

Table 7 shows the results for the number of managers in the branch. Notice that this regression can be also interpreted as a robustness check of our results, as we are able to test the sensitivity of our estimates to the choice of the threshold for the number of firms in a branch. Indeed, when defining our dataset, we confined ourselves at small branches (with less than 150 firms) in order to be able to have a reliable matching between the manager and the firms. There is a clear trade-off between increasing the precision of our estimates (confining ourselves to smaller branches) and considering a sizable number of moves. However, Appendix sections D.2 and D.1 show that our results are robust to changing the threshold to 50 and 100 firms.

Columns (1) and (3) show results for small branches, respectively with 3 or less, and 5 or less managers. As it can be seen comparing these estimates with the results in columns (2) and (4), managers coming from smaller branches are more effective in bringing their clients with them by an order of magnitude - i.e. 0.12 vs 0.013 comparing columns (1) and (2). Estimates in column (3), when small branches are defined by having 5 or less managers, are smaller in magnitude (0.085 as compared to 0.12 in column (1)). We can rationalize this fact both with the measurement argument (i.e. the more managers, the less likely it is that we matched a manager with only her clients), and with the span of control argument (i.e. in larger branches, managers interact less often with their clients, and so they are less effective in bringing them with them).

Table 7. Heterogeneity by number of managers

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

Notes: DiD estimates for β in equation 1 for different number of managers in the branch the loan officer moved from. Column (1) includes moves from branches with one manager, column (2) includes moves from branches with one or two managers, and column (3) includes moves from branches with one, two, or three managers. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

However, consider that even in the presence of measurement error, it would bias our estimates towards zero. Therefore, the fact that our baseline results in Table 1 are positive and significant, and that results in this section - as well as in Appendix sections D.2 and D.1 - yield even larger estimates for smaller branches, is a strong indication that our results are economically sizable.

6.4 Loan size

Table 8. Heterogeneity by loan size

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

Notes: DiD estimates for β in equation 1 for different loan sizes of the borrower's former loan with the relocating banker. Column (1) includes an interaction term with loans smaller than 50 thousand euros, column (2) includes an interaction term with loans smaller than 100 thousand euros, column (3) includes an interaction term with loans smaller than 500 thousand euros, and column (4) includes an interaction term with loans greater than 500 thousand euros. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We then look at the role of the size of the loan that the firm had before the manager moved. We define four bins of loan size: below 50 thousand euros, below 100 thousand euros (including the previous bin), below 500 thousand euros (including the previous bins), and above 500 thousand euros. A priori, it is not clear how loan size should affect the portability of the manager's clients. Smaller loans may be more likely to be relationship loans, where the presence of hard information is limited, and so managers can transfer them more easily. At the same time, managers may have a stronger incentive to bring with them larger loans, as they may be more remunerated for them. Table 8 shows that it is mid-size loans (between 100 and 500 thousand euros) that are more likely to follow their manager, with an estimate of 0.032 that is around one and half times the baseline effect of 0.023 in Table 1. Smaller loans are as portable as the baseline effect, while larger loans are less portable, with a point estimate of 0.011 that is statistically significant only at the 10% level.

6.5 Competition

The last dimension of heterogeneity we investigate on relates to the level of competition in the local banking market. Indeed, bank managers are active in a local labor market, and their skills encompass the knowledge of the local credit market, and in particular the firms they had relationships with. Therefore worker relocations to local competitors may alter the competitive landscape of that market, especially if managers are able to bring their clients with them. We then ask if the portability of the manager's clients is affected by the level of competition in the local banking market. We measure competition by means of the Herfindahl-Hirschman Index (HHI), computed at the province level, using as weights the total amount of loans that each bank group has in that province. We exclude provinces where concentration index is above 0.25, as they are considered to be highly concentrated markets, and we also exclude provinces where the index is below 0.1, as competition is too fragmented. Appendix figure A6 shows the HHI distribution in our sample.

On this subset of provinces, we define four quartiles of HHI, and we interact the treatment effect in equation (1) with dummies that capture the quartile of the province where the manager moved to. A priori, it is not clear how competition should affect the portability of the manager's clients. On the one hand, in more competitive markets, hiring managers with a strong local network may be more appealing for banks, that use the knowledge of the manager to poach clients from competitors. On the other hand, in more concentrated markets, firms have fewer alternatives, and so they may be more likely to follow their manager when she moves.

Table 9. Heterogeneity by local market concentration

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

Notes: DiD estimates for β in equation 1 for different types of bank moves. Column (1) includes an interaction term with moves in provinces that are in the bottom quartile of the HHI distribution - i.e. the ones with in more competitive environments. Column (2) includes an interaction term with moves in provinces that are below the median of the HHI distribution, and column (3) includes an interaction term with moves in provinces that are below the 75th percentile of the HHI distribution - i.e. increasing the level of concentration in the market. The HHI is computed at the province level using the total amount of loans granted by each bank group in the province in 2018. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 shows the results. The estimate for the interaction term with the first quartile of HHI (i.e. the most competitive markets) is half the baseline effect of 0.023 in Table 1. As we move to less competitive markets, the estimate for the interaction term increases, and the estimates for the third quartile - i.e. column (3) - coincide with the baseline effect. Notice that this regression features only the interaction term, therefore the estimates in columns (1) to (3) have to be interpreted as the total effect of the manager's move. Furthermore, as for firm or loan size, bins (in this case quartiles) have been defined in a progressive way, such that each bin includes the previous one. The estimate in column (3) is the effect of the manager's move in provinces where HHI is lower or equal than the 75^{th} percentile of the HHI distribution. Since estimates in column (2) are lower than the baseline effect, it implies that the portability of the manager's clients in more concentrated markets (i.e. from the 50^{th} to the 75^{th} percentile of the HHI distribution) is higher than the baseline effect.

7 Loan terms and performance

We analyse the terms and performance of loans granted to switcher firms. We want to understand the incentives for switching firms to move their loan activity to a new bank. The key driver of the decision to switch banks is likely to be the interest rate that firms pay on their loans. We observe that switchers pay lower interest rates on their loans after the switch, compared to what they were paying before the switch. This result holds controlling for firm characteristics, such as riskiness. It is consistent with Beraldi (2025), who finds that banks do not price risk when they renew loans to existing clients, but they do when they grant loans to new clients. In this case we are able to show that when the manager changes bank, she is able to offer better terms to her clients, even when controlling for riskiness.

At the same time, banks are happy to lend to switchers, as long as their repayment performance is better than that of other firms. We find that switchers have lower default rates than other firms, even when controlling for riskiness. This suggests that bankers have superior information about their clients, and they use it to award loans to the ones that - within each riskiness category - have a higher repayment probability.

7.1 Interest rates

We estimate the following regression:

$$i_{bft} = \beta \text{Switcher}_{bft} + \gamma \log(1 + \text{credit}_{bft}) + \mathbf{X}_{bft} + \epsilon_{bft} \tag{5}$$

where i_{bft} is the average interest rate on loans granted to firm f by bank b over a two-year period t. Switcher_{bft} is an indicator equal to one if the loan was granted after the firm followed its loan officer to bank b in year t (or later). credit_{bft} is the average amount of credit granted to the firm by the bank over the two-year period t. $\mathbf{X}_{bft}$ is a vector of controls, including firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level.

We estimate equation (5) using five different comparison groups, each corresponding to a different question. First, we ask if switchers pay less when they open a new relationship with their banker, compared to what they were paying in all their other loans (before and after the switch). Second, we ask if switchers would have been better off simply shopping around, rather than following their banker to a new bank. We do this by comparing switchers to their fellow portfolio firms (i.e., firms that could have switched, but did not) and measuring if - when those firms get new loans - switchers are able to get better terms. The third comparison is similar to the second one, but we compare switchers to the old relationships of portfolio firms (i.e., relationships that existed before the banker moved to a new bank). It serves to understand if switchers would have been better off staying with one of their old relationships, rather than following their banker to a new bank. After having considered the possible choices that switchers had, we then ask if they receive some form of preferential treatment within the new branch of the loan officer. We do this by comparing switchers to the new relationships of the new branch where the loan officer moved. Finally, we zoom in on the switchers trade-off, comparing the interest rates they pay after the switch to the interest rates they were paying with their old bank (from which the loan officer moved away).

Table 10 reports the results of the five comparisons.

Table 10. Interest rates performance

	Interest rate				
	(1)	(2)	(3)	(4)	(5)
Switcher	-0.505*	-0.657	-0.289*	0.050	-0.926***
	(0.264)	(0.699)	(0.172)	(0.144)	(0.195)
Log. average credit (2y)	-0.555***	-0.669***	-0.716***	-0.268***	-0.773***
	(0.019)	(0.004)	(0.003)	(0.004)	(0.097)
R^2	0.198	0.197	0.188	0.123	0.311
Observations	6,643	23,609	35,585	68,555	1,387
Dependent variable mean	2.55	2.53	2.92	2.60	2.93

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. In all columns, the treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. What varies across columns is the definition of the control group. In column (1) the control group is made of all other loans of switchers (before and after the switch). In column (2) the control group is made of all the new relationships of portfolio firms, that did not switch with the banker. In column (3) the control group is made of all the old relationships of portfolio firms, that did not switch with the banker (i.e., relationships that existed before the banker moved to a new bank). In column (4) the control group is made of all the new relationships of the new branch of the loan officer, that were not switchers. In column (5) the control group is made of the old relationships of switchers, i.e., the loans that switchers had with their old branch before they switched with the banker. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) shows that switchers pay on average 0.5 percentage points less than what they were paying in all their other loans (before and after the switch). The result is statistically significant at the 10% level, and economically sizable, as the average interest rate in the sample is 2.55%. It suggests that - within firms that switch with their banker - following the banker to a new bank allows them to get better terms. Column (2) shows that switchers have been slightly better off following their banker to a new bank, rather than simply shopping around. However, the effect is not statistically significant. Column (3) shows that switchers pay on average 0.3 percentage points less than what portfolio firms were paying in their old relationships (i.e., relationships that existed before the banker moved to a new bank). The effect is statistically significant at the 10% level, and goes in the same direction as column (1). In column (4) we find no difference in the interest rates paid by switchers and by the new relationships of the new branch. We interpret this result as evidence that bankers do not give preferential treatment to switchers, as opposed to new relationships of the new branch. Finally, column (5) shows that switchers pay on average 0.9 percentage points less than what they were paying with their old bank (with the same loan officer), suggesting that the switch opens up new opportunities for them.

We interpret these results as evidence that banker movements create value for their clients, opening up new opportunities that would not have been available otherwise. At the same time, there is no evidence of rent-sharing between bankers and their clients, as switchers do not pay lower interest rates than new relationships of the new branch. In Appendix C we breakdown the effects by type of loan (self-liquidating loans, credit lines and term loans), showing that most of the variation is driven by credit lines.

7.2 Non-performing loans

Once we established that firms have an incentive to follow their banker to a new bank, we want to understand if banks can somehow benefit from the knowledge that bankers have about their clients. We look at ex post performance of loans granted to switchers, estimating if they have lower default rates than other firms. If managers have superior information about their clients, they should be able to identify and award loans to the more deserving ones, although hard information (e.g., credit scores) reports them as equally risky. We estimate the following regression:

$$\text{NPL}_{bft} = \beta \text{Switcher}_{bft} + \sum_{j=1}^{3} \gamma_j \log(1 + \text{credit}_{fbjt}) + \mathbf{X}_{bft} + \epsilon_{bft} \tag{6}$$

where NPL_{bft} is an indicator equal to one if firm f has at least one non-performing loan (NPL) in year t with bank b. Switcher_{bft} is - as before - an indicator equal to one if the loan was granted after the firm followed its loan officer to bank b in year t (or later). $\text{Log}(1{+}\text{credit}_{fbjt})$ is the log of one plus the amount of credit granted to firm f by bank b in year t, broken down by type of loan j (self-liquidating loans, credit lines and term loans). $\mathbf{X}_{bft}$ is a vector of controls, including firm characteristics (age, size, riskiness), bank-year, banker and municipality fixed effects. Notice that we are able to include even a finer set of fixed effects with respect to Equation (5). These fixed effects, that control for branch activity at the municipality level, are now possible because the dataset on non-performing loans is available at the branch level. Standard errors are clustered at the firm level.

Similarly to what we did for interest rates, we estimate Equation (6) using four different comparison groups, each corresponding to a different question. First, we ask if relationships originated by switchers with their own banker have lower default rates than all their other loans (before and after the switch). We then compare switchers to their fellow portfolio firms that have shopped around (i.e., firms that could have switched, but did not) and measure if - when those firms get new loans - switchers have lower default rates. The third option for switchers would have been to stay with one of their old relationships, rather than following their banker to a new bank. We do this by comparing switchers to the old relationships of portfolio firms (i.e., relationships that existed before the banker moved to a new bank). Finally, we ask if switchers have lower default rates than the new relationships of the new branch where the loan officer moved.

Table 11. NPL probability performance

	NPL probability			
	(1)	(2)	(3)	(4)
Switcher	-0.014**	-0.011	-0.020*	-0.043**
	(0.006)	(0.007)	(0.011)	(0.019)
R^2	0.115	0.101	0.055	0.048
Observations	13,320	45,700	65,195	187,389
Dependent variable mean	0.017	0.027	0.015	0.016

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of credit granted (broken down by type of loan), firm characteristics (age, size, riskiness), municipality, bank-year and banker fixed effects. Standard errors are clustered at the firm level. In all columns, the treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. What varies across columns is the definition of the control group. In column (1) the control group is made of all other loans of switchers (before and after the switch). In column (2) the control group is made of all the new relationships of portfolio firms, that did not switch with the banker. In column (3) the control group is made of all the old relationships of portfolio firms, that did not switch with the banker (i.e., relationships that existed before the banker moved to a new bank). In column (4) the control group is made of all the new relationships of the new branch of the loan officer, that were not switchers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11 reports the results of the four comparisons. Column (1) shows that switchers have on average a 1.4 percentage points lower probability of having at least one non-performing loan in a year, compared to all their other loans (before and after the switch). The result - which is statistically significant at the 5% level - shows us that when firms follow their banker to a new bank, they tend to perform better with respect to the other credit relationships they have. From column (2) we see that switchers also have a lower default rate than their fellow portfolio firms that have shopped around, although the effect is smaller and not statistically significant. Column (3) compares newly originated relationships of switchers to the old relationships of portfolio firms, showing that switchers have a 2 percent lower default rate than those old relationships. The effect is statistically significant at the 10% level. Column (4) is the most interesting one from the point of view of banks. It shows that switchers have a 4.3 percentage points lower default rate than the new relationships of the new branch. This result holds controlling for riskiness and other firm characteristics, and it is statistically significant at the 5% level. We interpret it as evidence that bankers can benefit their new bank, as they have superior information about their clients. In principle, there should be no difference in the quality of monitoring between switchers and new relationships of the new branch. However, switchers default significantly less (almost 3 times the sample mean). Table A13 in Appendix D shows that the effect is persistent, as it holds even two years after the loan has been granted.

In Appendix D we also reproduce the results of Table 11 interacting the switcher indicator with an indicator for riskiness. The scope of the exercise is to understand if bankers are able - within the bucket of riskier firms - to identify and award loans to the ones that have a higher repayment probability. As it can be seen in Table A13, there is no significant effect in columns (1), (3) and (4). However, in column (2) we find that risky switchers have a 3.7 percentage points lower default rate than their fellow risky portfolio firms that have shopped around. Put it differently, from the perspective of a risky firm, choosing to follow its banker to her new bank yields a significant improvement in the probability of default, compared to simply shopping around. This result can be driven both by selection (bankers are able to tell which risky firms are less likely to default) and pricing (as it was shown in the previous section, switchers pay lower interest rates). However, we regard that in both cases the key driver is the superior information that bankers have about their clients, which allows them to identify and award loans to the more deserving ones, even when hard information (e.g., credit scores) reports them as equally risky.

8 Conclusion

In this paper, we show that when bank managers move, they bring their clients with them. By building personal relationships and acquiring soft information, managers use this knowledge to benefit the bank that hires them.

A manager's move increases a firm's likelihood of establishing a credit relationship with the new bank by 4 percentage points — more than three times the baseline matching probability. Using loan application data, we identify two key channels: first, managers increase the likelihood that firms they know apply for loans at their new bank; second, they improve firms' chances of loan approval. These effects are stronger when the manager is more experienced, when she is moving from a larger bank to a smaller one, or when firms in her portfolio are smaller and younger. Furthermore, we find that managers improve credit conditions for their clients, as evidenced by lower interest rates with respect to their previous bank. Interestingly, firms that follow their manager do not pay lower interest rates with respect to other firms at the new bank, suggesting that there is no rent-sharing between the manager and her clients. Banks also appear to benefit from opening new relationships to the manager's clients, as they default 4 percentage points less than other firms at the bank.

We believe our findings show how still relevant soft information is in credit allocation, even in an era of increasing reliance on algorithms and big data. They also highlight a new channel of bank competition, through the hiring of bank managers. This opens up a new avenue for policy intervention in the banking sector, as regulators may consider bank managers as a separate actor in the credit market, with their own incentives and objectives. However, we believe our findings are only a first step in understanding the broader implications of bank manager mobility for banks, managers, and firms.

Specifically, we identify three main areas for future research. First, what are the implications for the bank? Besides the lower default rates we document, does the bank benefit from the manager's clients in terms of profitability, growth, or market share? Second, what are the implications for the manager? Does she benefit from bringing her clients along in terms of career advancement or compensation? Third, what are the implications for the firms? Do firms that follow their manager experience better survival, growth, or profitability outcomes? We believe that - especially for policy purposes - these are important questions that deserve further attention both from academic research and from regulators.

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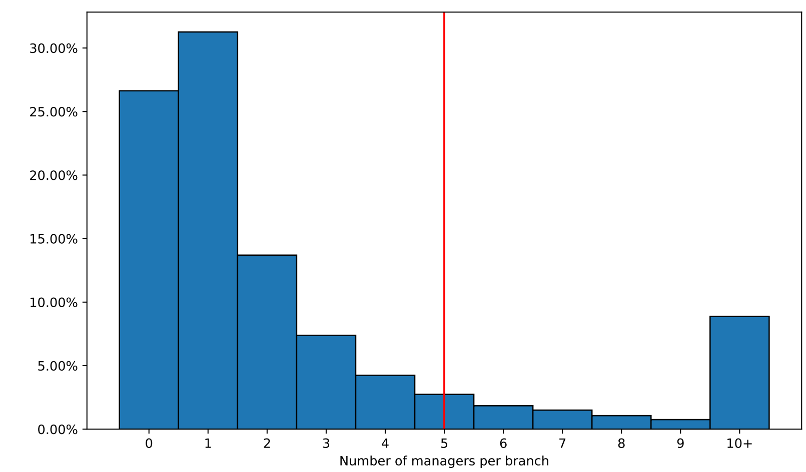
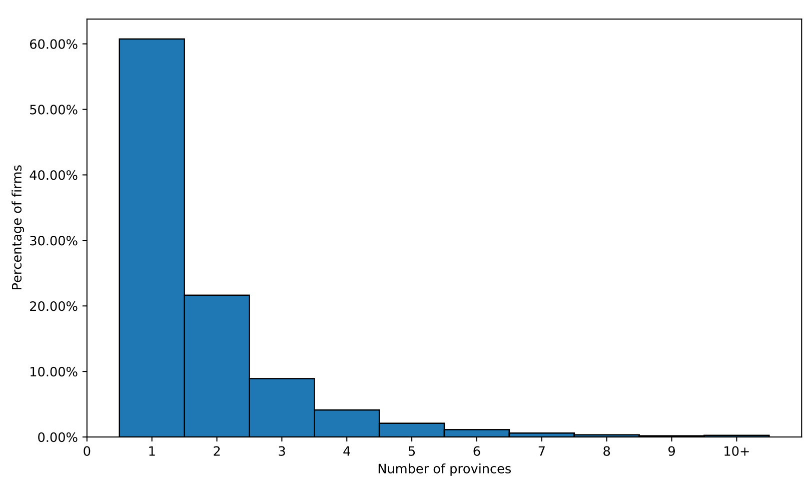
A Descriptive figures and tables



Appendix Figure A1. Distribution of the number of managers per branch.



Appendix Figure A2. Distribution of the number of provinces where firms have credit.

B Additional results

Appendix Table A2. DiD estimates for β, identified via branch closures

Average number of workers per year		345,938
Move type	Average nr. movers	Percentage
All moves	40,638	11.7 %
only municipality	38,960	95.9 %
only bank group	967	2.4 %
both	712	1.8 %

Appendix Table A1. Summary of worker movements by type.

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

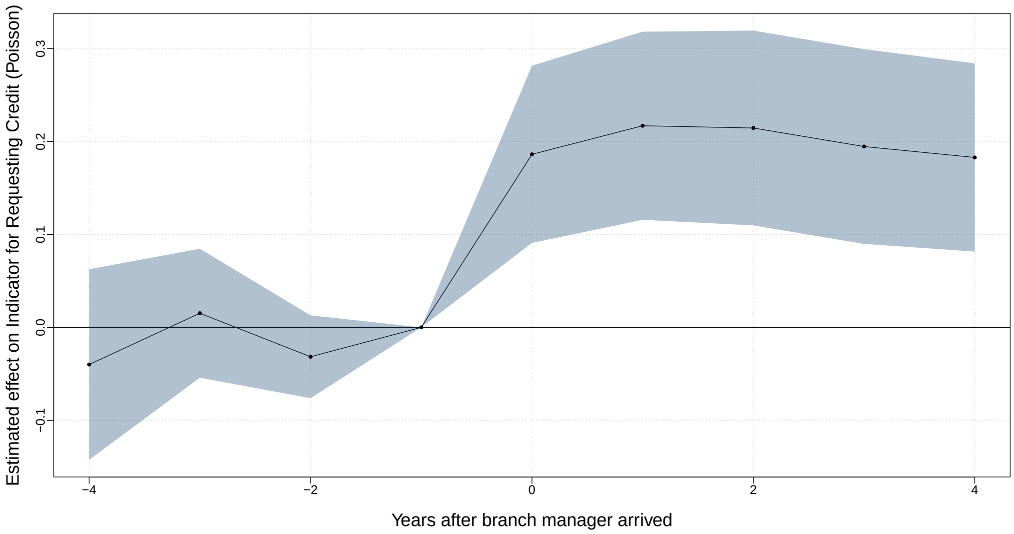
Notes: Estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved, after her branch has closed. Column (1) includes only branch fixed effects, column (2) includes branch and time fixed effects, column (3) includes branch and firm fixed effects, and column (4) includes all fixed effects. Standard errors are clustered at the bank group - firm level. The sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another, and the originating branch has closed. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A3. DiD estimates for β, within the same bank

	Credit indicator			
	(1)	(2)	(3)	(4)
Inflow × Post	0.021***	0.022***	0.021***	0.023***
	(0.006)	(0.005)	(0.006)	(0.005)
R^2	0.802	0.806	0.803	0.807
Observations	23,988,940	23,988,940	23,988,940	23,988,940
Branch-Firm fixed effects	✓	✓	✓	✓
Branch-Time fixed effects		✓		✓
Firm-Time fixed effects			✓	✓

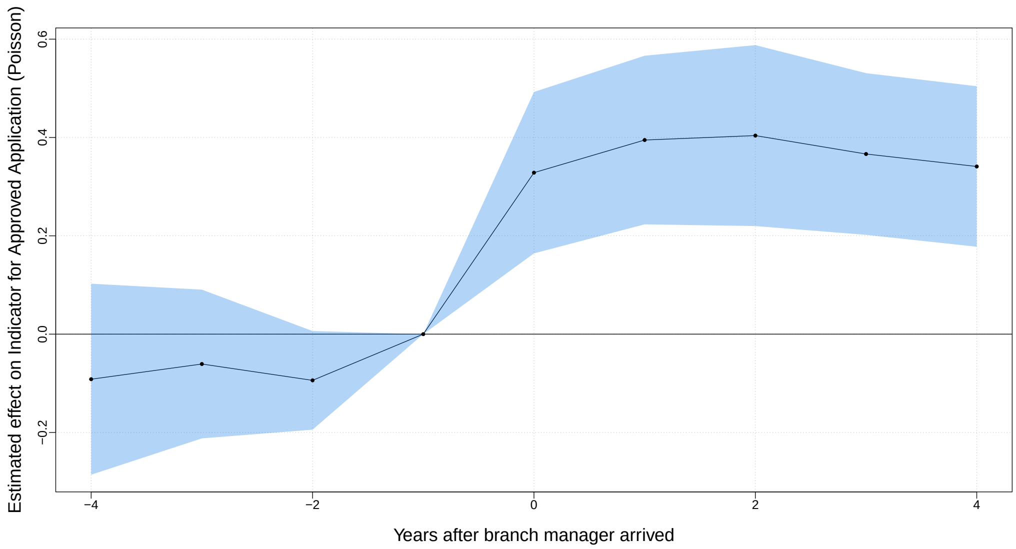
Notes: Estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved, within the same bank group. Column (1) includes only branch fixed effects, column (2) includes branch and time fixed effects, column (3) includes branch and firm fixed effects, and column (4) includes all fixed effects. Standard errors are clustered at the bank group - firm level. The sample includes all potential firm - branch pairs within a province, for the period 2009-2018. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers within the same bank group. To keep consistency with the sample definition, only moves that occur within the same province are considered. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Figure A3. Increase in probability of applying for credit to the new bank: Poisson regression



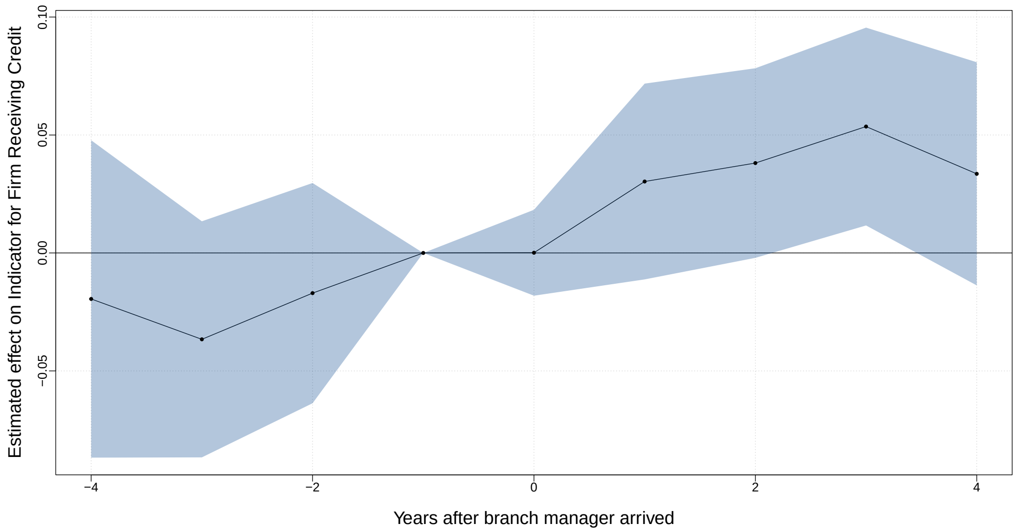
Notes: Event study estimates for the probability of a firm applying for credit in the bank where its bank manager has moved. Plot shows Poisson regression estimates and 95% confidence intervals for the coefficients β_τ in equation (3). Bank - firm, bank - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - bank pairs, for the period 2009-2018. A pair is considered potential if in the province where the firm was present, there was at least one branch of the bank. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

Appendix Figure A4. Increase in probability of being approved for credit in the new bank: Poisson regression



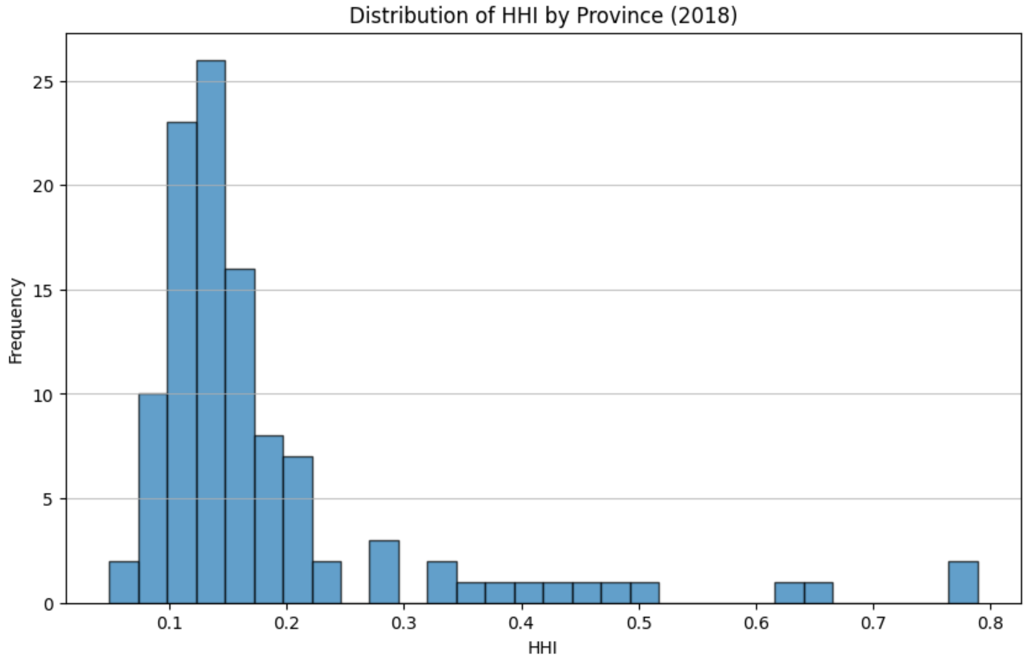
Notes: Event study estimates for the probability of a firm being approved for credit in the bank where its bank manager has moved. Plot shows Poisson regression estimates and 95% confidence intervals for the coefficients β_τ in equation (4). Bank - firm, bank - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - bank pairs, for the period 2009-2018. A pair is considered potential if in the province where the firm was present, there was at least one branch of the bank. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered. Estimates are obtained using the Sun and Abraham (2021) estimator.

Appendix Figure A5. Robustness: Sun and Abraham (2021) estimator, full sample



Notes: Event study estimates for the probability of a firm receiving credit from the branch where its previous loan officer has moved. Plot shows estimates and 95% confidence intervals for the coefficients β_τ in equation (2), estimated using the TWFE estimator proposed by Sun and Abraham (2021). Branch - firm, branch - time, and firm - time fixed effects are included. Standard errors are clustered at the bank group - firm level. Sample includes all potential firm - branch pairs, for the period 2009-2018. Branches are defined as municipality - bank group pairs. Only firms and branches that are present in the data in all years are included. Moves are defined as relocations of managers from one bank group to another. To keep consistency with the sample definition, only moves that occur within the same province are considered.

Appendix Figure A6. Distribution of HHI by province in 2018



Notes: The figure plots the distribution of the Herfindahl-Hirschman Index (HHI) by province in 2018. The HHI is computed at the province level, using as weights the total amount of loans that each bank group has in that province. Provinces where the HHI is above 0.25 are considered to be highly concentrated markets, while provinces where the HHI is below 0.1 are considered to be too fragmented.

C Interest rates breakdown

Appendix Table A4. Interest rates, within switchers comparison

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

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all other loans of switchers (before and after the switch). Column (1) estimates the effect of switching on the average interest rate. Columns (2) to (4) break down the effect by loan types, respectively self-liquidating loans (2), credit lines (3) or term loans (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A5. Interest rates, switchers vs. portfolio firms (new rel.)

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

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. What varies across columns is the definition of the control group. The control group is made of all the new relationships of portfolio firms, that did not switch with the banker. Column (1) estimates the effect of switching on the average interest rate. Columns (2) to (4) break down the effect by loan types, respectively self-liquidating loans (2), credit lines (3) or term loans (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A6. Interest rates, switchers vs. portfolio firms (old rel.)

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

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all the old relationships of portfolio firms, that did not switch with the banker (i.e., relationships that existed before the banker moved to a new bank). Column (1) estimates the effect of switching on the average interest rate. Columns (2) to (4) break down the effect by loan types, respectively self-liquidating loans (2), credit lines (3) or term loans (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A7. Interest rates, switchers vs. new branch

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

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all the new relationships of the new branch of the loan officer, that were not switchers. Column (1) estimates the effect of switching on the average interest rate. Columns (2) to (4) break down the effect by loan types, respectively self-liquidating loans (2), credit lines (3) or term loans (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A8. Interest rates, switchers v. old relationships

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

Notes: Estimates for the effect on interest rates of switching with the loan officer. The dependent variable is the average interest rate on loans over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of the loans the switchers had with the previous bank of the manager. Column (1) estimates the effect of switching on the average interest rate. Columns (2) to (4) break down the effect by loan types, respectively self-liquidating loans (2), credit lines (3) or term loans (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Npl additional tables

Appendix Table A9. NPL probability, within switchers comparison

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

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of credit granted (broken down by type of loan), firm characteristics (age, size, riskiness), municipality, bank-year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all other loans of switchers (before and after the switch). Columns (1) to (3) show NPL probabilities in different time horizons. Respectively, the same year the loan has been given, one year after and two years after. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A10. NPL probability, switchers vs. portfolio firms (new rel.)

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

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of credit granted (broken down by type of loan), firm characteristics (age, size, riskiness), municipality, bank-year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all the new relationships of portfolio firms, that did not switch with the banker. Columns (1) to (3) show NPL probabilities in different time horizons. Respectively, the same year the loan has been given, one year after and two years after. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A11. NPL probability, switchers vs. portfolio firms (old rel.)

	Npl probability		
	(0 years)	(1 year)	(2 years)
	(1)	(2)	(3)
Switcher	-0.020*	-0.017	-0.015
	(0.011)	(0.011)	(0.015)
Log. avg			
self-liquidating credit (2y)	-0.0003**	-0.0003	-0.0002
	(0.0002)	(0.0002)	(0.0003)
Log. avg			
credit line credit (2y)	-0.0002	6.14×10^{-5}	0.0003
	(0.0003)	(0.0003)	(0.0004)
Log. avg			
credit, term loans (2y)	0.0005***	0.0008***	0.001***
	(0.0001)	(0.0002)	(0.0002)
R^2	0.055	0.061	0.066
Observations	65,195	65,140	64,991
Dependent variable mean	0.015	0.023	0.032

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of credit granted (broken down by type of loan), firm characteristics (age, size, riskiness), municipality, bank-year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all the old relationships of portfolio firms, that did not switch with the banker (i.e., relationships that existed before the banker moved to a new bank). Columns (1) to (3) show NPL probabilities in different time horizons. Respectively, the same year the loan has been given, one year after and two years after. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A12. NPL probability, switchers vs. new branch

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

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is an indicator equal to one if the firm switched with the loan officer. All regressions include as controls the log of credit granted (broken down by type of loan), firm characteristics (age, size, riskiness), municipality, bank-year and banker fixed effects. Standard errors are clustered at the firm level. The treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. The control group is made of all the new relationships of the new branch of the loan officer, that were not switchers. Columns (1) to (3) show NPL probabilities in different time horizons. Respectively, the same year the loan has been given, one year after and two years after. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A13. NPL probability performance for risky firms

	NPL probability			
	(1)	(2)	(3)	(4)
Switcher	-0.015**	-0.008	-0.021**	-0.043**
	(0.006)	(0.007)	(0.011)	(0.019)
Switcher × Risky	0.011	-0.037**	0.012	-0.0007
	(0.015)	(0.017)	(0.014)	(0.011)
R^2	0.115	0.101	0.055	0.048
Observations	13,320	45,700	65,195	187,389
Dependent variable mean	0.017	0.027	0.015	0.016

Notes: Estimates for the effect on NPL probability of switching with the loan officer. The dependent variable is the probability of non-performing loans (NPL) over a two-year period. The key independent variable is the interaction between the indicator equal to one if the firm switched with the loan officer and a dummy equal to one if the firm is categorized as risky by Cebi-Cerved (i.e., it has a risk score of 7 or higher on a scale from 1 to 10). All regressions include as controls the log of average credit granted over a two-year period, firm characteristics (age, size, riskiness), bank, year and banker fixed effects. Standard errors are clustered at the firm level. In all columns, the treated group is defined by the loans that switchers receive having followed their loan officer to a new bank. What varies across columns is the definition of the control group. In column (1) the control group is made of all other loans of switchers (before and after the switch). In column (2) the control group is made of all the new relationships of portfolio firms, that did not switch with the banker. In column (3) the control group is made of all the old relationships of portfolio firms, that did not switch with the banker (i.e., relationships that existed before the banker moved to a new bank). In column (4) the control group is made of all the new relationships of the new branch of the loan officer, that were not switchers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.1 Robustness: branches with at most 100 firms

D.2 Robustness: branches with at most 50 firms