The Retreat of Local Banking: Spillover Effects on SME Credit*

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Abstract

As technological transformation leads banks to retreat from local markets, in a frictionless credit market, firms can be expected to rely on other lenders to step in as substitutes. Instead, using Italian loan-level data with lenders' default forecasts, we find that when a bank leaves a municipality, an affected firm's incumbent co-lenders act as complements and cut credit as well. One year after the exit, incumbent co-lenders account for 69 percent of the decline in the firm's credit from its incumbent banks. Relative to their other borrowers in the same municipality, they cut credit to affected firms by an extra 4.2 percent. The cut reflects both an increase in borrower risk and a deterioration of lender information: affected firms default more often, and the co-lenders' default forecasts become less accurate. Co-lenders with a branch in the municipality lose little forecast accuracy and cut about half as much as those without one, implying that lost information accounts for 29 percent of the cut. Lending by a firm's other banks is thus complementary to local banks' presence, implying that branch closures generate negative externalities across the wider credit market.

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Keywords: branch closures, multiple banking, relationship lending, spillovers, credit registers.

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1 Introduction

With rapid technology development since the global financial crisis, the number of bank branches has fallen by more than 40 percent in the euro area and by about a fifth in the United States.[1] This retreat reverses decades of branch expansion and threatens the special role of banks in lending to borrowers that capital markets find hard to assess. Banks have long performed this role through local presence, observing borrowers firsthand to gather soft information beyond their financial statements and monitoring them at close range (Petersen and Rajan, 1994; Stein, 2002; Agarwal and Hauswald, 2010). When a bank leaves a local market, it gives up this proximity and credit to local firms falls (Nguyen, 2019; Amberg and Becker, 2025). However, for firms that rely on bank credit, the cost of this retreat depends not only on the bank that leaves but also on how their other lenders respond. Although one bank's withdrawal from a local market naturally creates an opportunity for other lenders to step in as substitutes, this paper provides the first evidence that a firm's existing co-lenders cut their credit as well.

This paper studies how a firm's incumbent co-lenders respond when one of its banks leaves a local market and what drives the response. When a firm borrows from several banks, its other incumbent lenders already know the borrower and are the natural candidates to cushion the loss of a local lender (Detragiache et al., 2000). Yet these lenders' willingness to lend can itself depend on the closing bank. Closing a local branch leads the bank to scale back its lending and impairs its ability to monitor and gather soft information (Hauswald and Marquez, 2006; Agarwal and Hauswald, 2010). Each of these losses can make the firm's incumbent co-lenders pull back as well. First, each bank's credit supports the firm's liquidity and lowers its chance of failing (Hertzberg et al., 2011; Morris and Shin, 2004), so the closing bank's pullback makes the firm riskier for every lender (the *borrower-risk channel*). Second, the co-lenders may rely on what the closing bank knows. Through the credit register,[2] the closing bank's information reaches co-lenders (Fama, 1985; Pagano and Jappelli, 1993). Once that bank leaves, its decisions rest on less local information and tell the co-lenders less about the firm (the *information channel*).

We answer this question with the closures of a bank's last branch in a municipality in Italy, which we call last-branch exits. Italy is a natural setting for the question. From September 2020 to November 2024, 101 banks ended their presence in 1,846 municipalities where they

[1] See European Central Bank (2026), Keil and Ongena (2024), Mariani et al. (2025), Narayanan et al. (2025), and Federal Deposit Insurance Corporation (2010, 2024) on the post-crisis contraction of branch networks in Europe and the United States.

[2] Lenders learn from the register in two ways. First, they see each month the firm's total credit from all its banks and use it to assess the firm. Second, the register notifies them immediately when any lender classifies its exposure to the firm as a bad loan.

still had borrowers, across the whole country. These exits happen under bank-wide programs that the banks present as a response to their customers' move to digital channels. At the same time, Italian firms routinely borrow from several banks (Kosekova et al., 2026), so that we can follow the closing bank's borrowers to their other incumbent lenders. We focus on the closing bank's local borrowers that are small and medium-sized enterprises (SMEs).[3] Branch closures, multiple banking, and information sharing among lenders are common well beyond Italy (Keil and Ongena, 2024; Ongena and Smith, 2000), so our results are not restricted to the specific setting in Italy. Our data also allow us to test the borrower-risk channel and the information channel directly, because we observe how lenders assess a firm. We link AnaCredit, the credit register of the euro area, to the Bank of Italy's branch register. AnaCredit records each month how much each bank lends to each firm, and banks with internal rating models also report the one-year probability of default (PD) that they assign to the firm.[4] For the borrower-risk channel, the level of the PD shows how risky the lender judges the firm. For the information channel, its accuracy as a forecast of default shows how well the lender knows the firm.

Our main finding, as shown in Figure 1, is that the incumbent co-lenders act as complements to the closing bank. When a local bank leaves, the co-lenders' credit to the affected firms falls as well. Within one year after the exit, affected firms' credit from their existing banks falls by 14.7 percent. The closing bank accounts for only 31 percent of this decline, while the remaining 69 percent comes from the co-lenders. To separate the effect of the exit from local economic conditions and from the co-lenders' own lending policies, we compare each co-lender's credit to the borrowers it shares with the closing bank (affected firms) with its credit to its other borrowers in the same municipality and month (comparison firms). Relative to the average relationship co-lenders have with comparison firms, over the first year after the exit, their credit to affected firms falls by an additional 4.2 percent compared to its pre-exit level. To further control for factors that affect firm credit beyond the local economy and bank lending policies, we compare each affected firm only with comparison firms that also borrow from several banks and are similar in industry and size. The additional decline still holds and the magnitude is as large. The estimate would be biased if the closing bank left because its borrowers were getting riskier or harder to assess than other local firms. However, the additional decline appears only after the exit, and the level and the accuracy of the PDs

[3]SMEs make up about four fifths of the closing banks' local borrowers (Table A3). SMEs also account for about three quarters of employment and two thirds of value added in the Italian business economy (European Commission, 2026).

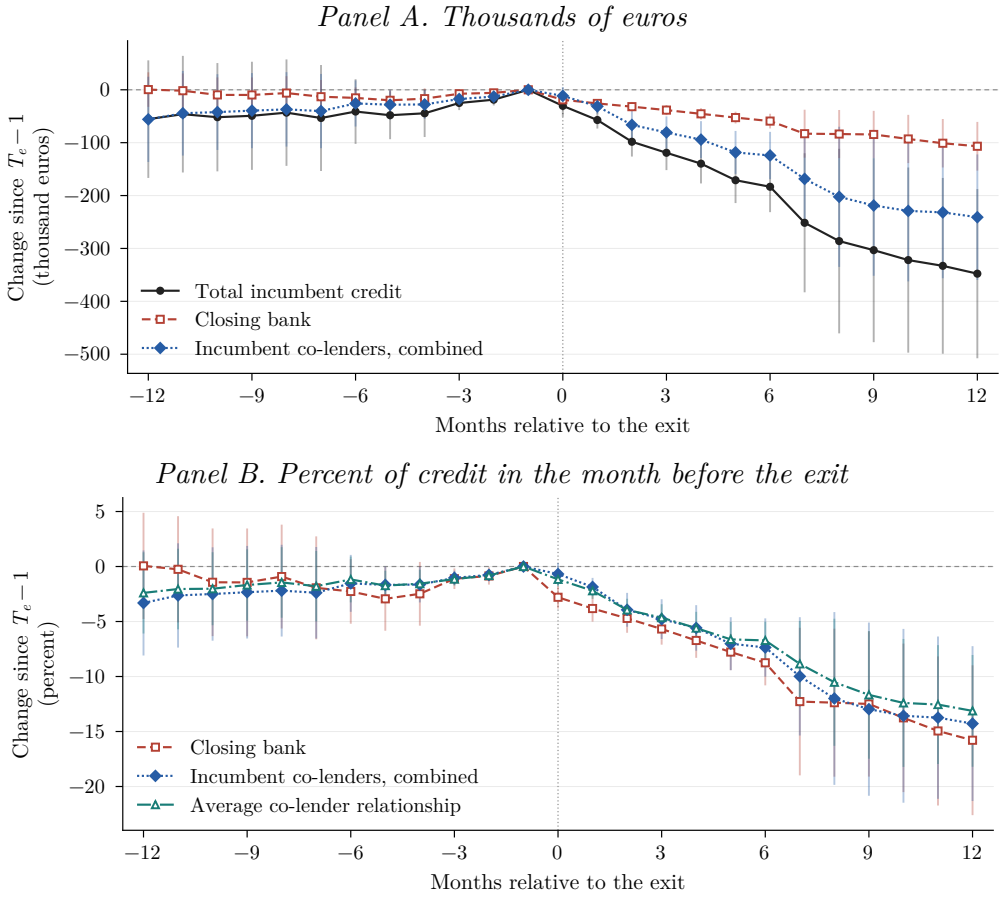
[4]Only banks that use the internal ratings-based approach to capital regulation report PDs (European Parliament and Council of the European Union, 2013). In our sample, 25 of the 192 incumbent co-lenders report PDs, and they do so for about 60 percent of the co-lender relationships (Section 3.1).

Figure 1. Credit from the Closing Bank and Incumbent Co-Lenders around the Exit

This figure reports the coefficients θ_k^r and their 95 percent confidence intervals from the event-study regression

$$Credit_{iet}^r = \alpha_{ie}^r + \sum_{k \neq -1} \theta_k^r \, Event_{t-T_e=k} + \varepsilon_{iet}^r, \qquad r \in \{CB,\ CL,\ Total\},$$

estimated on affected firms in the 1,829 exits of the analysis sample. *CB* denotes credit from the closing bank, *CL* credit summed over incumbent co-lenders, and *Total* their sum. α_{ie}^r is a firm-event fixed effect; the omitted month is $T_e - 1$. Panel A reports the coefficients in thousands of euros. Panel B expresses the closing-bank and combined co-lender coefficients in percent of their respective average credit at $T_e - 1$ and adds the corresponding estimate for the average co-lender relationship, using relationship-event fixed effects. The lending network is fixed at $T_e - 1$, and relationships that end remain with zero credit.



of a bank's local borrowers do not predict which of the bank's last branches close in a given month.

We show evidence that the co-lenders act as complements through both channels. First, for the borrower-risk channel, we find that the closing bank's pullback makes the firm riskier and reduces the co-lenders' willingness to lend. Relative to comparison firms, affected firms' default rate rises by 1.27 percentage points over the year following the exit, and the co-lenders' reported PDs for these firms rise by 1.66 percentage points, corresponding to 23 percent of their level before the exit. The co-lenders' cut is larger where the firm depended more on

the closing bank. When the closing bank accounted for an above-average share of the firm's credit before the exit, the co-lenders cut their credit by 6.9 percent of their pre-exit level relative to comparison firms, against 2.7 percent where it provided less.

Second, we show evidence for the information channel. Lenders use a firm's record in Italy's Central Credit Register when they decide how much to lend, and the closing bank's decisions move this record. After the exit, this record becomes noisier and leaves the co-lenders more uncertain about the firm. We show that the co-lenders' default forecasts for affected firms indeed become less accurate. Relative to comparison firms, the Brier loss of their forecasts rises by 53 percent of its level before the exit. The rise is concentrated where the closing bank was the firm's only local lender, and the co-lenders' credit cut is also larger there. To separate this loss of information from higher borrower risk, which affects all of a firm's creditors alike, we compare co-lenders with and without a branch in the municipality. Nonlocal co-lenders have fewer local sources with which to assess the firm independently and are therefore more exposed when this record becomes noisier. Local co-lenders lose little forecast accuracy, whereas the Brier loss of nonlocal co-lenders roughly doubles. This contrast indicates that the closing bank's loss of local information spills over to the co-lenders that rely on it most. Nonlocal co-lenders also cut almost twice as much, €35,180 per relationship relative to comparison firms, against €19,040 for local co-lenders. If the extra cut by nonlocal co-lenders reflects lost information, the information channel accounts for about 30 percent of the co-lenders' cut, and higher borrower risk for the rest.

We contribute to three strands of literature. First, we contribute to the literature on bank branch closures. A number of papers have documented that closures reduce credit to local firms (Nguyen, 2019; Amberg and Becker, 2025; Duquerroy et al., 2022; Jiménez et al., 2022). In the Italian market, Garrì (2019) finds that credit decreases as well and shows that the decrease concentrates among small firms.[5] We show that the credit decrease is not confined to the closing bank's credit. Rather, there are spillover effects among lenders when a local bank withdraws. In addition, compared to previous work that infers information loss from loan terms, we have direct observations of how lenders assess the firm. Recent work has started to use banks' PDs as proxies for their information about the firm (Howes and Weitzner, 2025; Simoens and Tamburrini, 2025). We base our information measure on PDs as well and show that one bank's exit can make the co-lenders' default forecasts less accurate.

Second, we contribute to the literature on multiple banking. A firm's several lenders can insure it against the withdrawal of one of them (Detragiache et al., 2000), and an incumbent

[5]Garrì studies last-branch closures from 2010 to 2014. Total credit falls by an insignificant 0.6 percent over all borrowers and, in the year after the closure, by 3.7 percent for small firms (fewer than 20 employees) with several banks, the group closest to our affected firms (Garrì, 2019).

lender that already knows the firm has an information advantage over an outside one (Sharpe, 1990; Rajan, 1992). But different lenders can also complement one another when one lender's monitoring benefits all of the firm's creditors (Holmström and Tirole, 1997; Carletti, 2004; Carletti et al., 2007), or when an informed lender's information reaches other lenders (Fama, 1985; Pagano and Jappelli, 1993). Empirically, lenders respond to what a credit register shows (Hertzberg et al., 2011) and to other lenders' visible decisions (Darmouni and Sutherland, 2021; Albertazzi et al., 2014, 2017), whereas Degryse et al. (2016) find substitution when an exclusive borrower takes on a second lender. We show that when one of a firm's lenders loses its local presence, multiple banking does not always insure the firm. The evidence points to two drivers: the firm becomes riskier, and its other lenders know less about it. Multiple banking protects the firm least where the closing bank mattered most and where the co-lenders have no branch of their own in the municipality.

Third, we contribute to the literature on how shocks to individual banks reach their borrowers. Studies of bank funding and liquidity shocks typically find that a firm's other lenders partially replace the shocked bank's credit (Khwaja and Mian, 2008; Chodorow-Reich, 2014; Bolton et al., 2016; Beck et al., 2021). We study a shock to a bank's local presence, which changes its monitoring and information capacity while leaving its lending capacity intact. We find that the firm's other lenders amplify the contraction rather than absorb it. The contrast suggests that whether a firm's lending network cushions or magnifies a shock to one of its banks depends on what the shock takes away from that bank. Where the network magnifies the shock, the within-firm comparison of the shocked bank with the firm's other lenders understates how much credit the firm loses. Loan-level estimates of the bank lending channel of monetary policy rely on the same comparison (Jiménez et al., 2012; Cappelletti et al., 2024), so how they translate into firm-level financing also depends on the response of the firm's other lenders.

The remainder of the paper proceeds as follows. Section 2 describes the Italian setting: how banks close branches, how a firm's lenders learn from one another, and the external validity of our setting. Section 3 presents the data and the empirical strategy. Section 4 shows that the incumbent co-lenders cut their credit instead of stepping in, and Section 5 tests the two channels and measures how much of the cut each accounts for. Section 6 concludes.

2 Institutional Background

This section describes the institutional setting. Section 2.1 introduces the branch closures that we use as events and shows how these events are distributed across regions and over

time. Section 2.2 describes multiple banking in Italy and how a firm's lenders learn from one another. Section 2.3 discusses the external validity of our setting in other markets.

2.1 Branch Closures and Exit Waves

Italian banks are closing branches at a steady pace. Panel A of Figure 2 follows the branches of banks that lend to firms in the Bank of Italy's branch register. Between January 2018 and December 2025, their number fell by 29 percent, from 26,414 to 18,714. Banks also left municipalities. The number of bank-municipality pairs in which the bank has at least one branch fell by 24 percent, and the number of municipalities with at least one bank branch fell by 18 percent, from 5,417 to 4,422.

The event we study is a bank's exit from a municipality: the closure of its last branch there, which we call a *last-branch exit*. Panel B of Figure 2 plots the 3,819 last-branch exits in the register between September 2018 and November 2025, month by month and by closing bank. They are made by 205 banks and occur in 2,946 municipalities in all 20 regions. Most occur in small municipalities: among exits from a whole municipality, 48 percent are from municipalities with fewer than 5,000 inhabitants and 10 percent from municipalities with more than 20,000.

[Insert Figure 2 here]

Exits come in waves, because banks close branches through programs that close many branches across their network at once. We define a wave as a month in which the same bank leaves at least ten municipalities. Of the 2,124 last-branch exits that we study, between September 2020 and November 2024, 76 percent belong to one of 41 such waves. On average, a wave closes the bank's last branch in 39 municipalities, spread over 22 provinces in about half of the 20 regions. The largest waves follow the programs that the banks announced: Banco BPM left 179 municipalities in May 2021, and Intesa Sanpaolo left 172 municipalities in 69 provinces and 18 regions in October 2024. The banks present these programs as a response to their customers' move to digital channels and as a way to cut costs.[6] Four banks, Intesa Sanpaolo, UniCredit, Banco BPM, and BPER Banca, account for 56 percent of all last-branch exits in the register. Within each bank, the exits follow the geography of its

[6]Banco BPM announced in December 2020 that it would close 300 small branches in response to the decline in purely transactional activity and the development of digital banking (Bluerating, 3 December 2020). UniCredit's plan to close 450 branches in Italy over three years came with a target to raise the share of its customers who bank digitally from 45 to 60 percent (Finextra, February 2020). Intesa Sanpaolo's 2022 to 2025 business plan, presented on 4 February 2022, combined the closure of 1,050 branches with the creation of a digital bank, Isybank.

branches: across banks and regions, the correlation between a region's share of a bank's exits and its share of the bank's branches is 0.90 (Appendix B).

Table 1 asks whether exits respond to local conditions, using branch-level regressions of exits as in Amberg and Becker (2025). Panel A fits a linear probability model of a last-branch exit in each bank-municipality-month in which the bank has a branch, with one set of fixed effects at a time. Bank-by-month fixed effects, which capture each bank's restructuring program, fit 21 percent of the variation in exits, whereas province-by-month fixed effects, which capture local shocks, fit only 1.4 percent. Panel B compares a bank's last branches in different municipalities in the same month and absorbs local conditions with municipality-by-month fixed effects. The average probability of default (PD) of the bank's local borrowers does not predict which of these last branches close, and neither does the accuracy of the bank's own default forecasts for them.

[Insert Table 1 here]

2.2 Multiple Banking and Information Sharing among Lenders

Even small firms in Italy borrow from several banks. In AnaCredit, 57 percent of the small and medium-sized firms that borrow from a closing bank in the month before the exit also borrow from at least one other bank. As Table 2 in Section 3 shows, the affected firms in our sample borrow from almost four banks on average, and no single lender dominates: the closing bank provides about a quarter of an affected firm's credit, and an incumbent co-lender about as much. The closing bank is a typical lender of the firm, not a marginal one.

A firm's lenders do not directly share their assessments of the firm, but they see what the other lenders do. One of the main channels is the Bank of Italy's Central Credit Register (*Centrale dei Rischi*). Every bank operating in Italy reports to it each month its exposure to each borrower above €30,000, and every month the register returns to each lender the firm's total position toward the banking system: credit granted and drawn by type of instrument, overdrawn and past due amounts, the number of lenders that report the firm, and inquiries by other lenders.[7] Because a firm borrows from a few banks, a decision by any one of them to grant, renew, or cut credit, or to tolerate an overdraft, moves the record of the firm, which

[7]Banca d'Italia (2025). The register reports the firm's position toward the lender's own banking group separately, so a lender can see how much the firm borrows from all its other lenders together and how that amount changes. Positions classified as bad loans are reported from €250. The return flow does not report another lender's classification of the firm as unlikely to pay, the identity of the firm's other lenders, or the municipality of the branch that serves the firm (Banca d'Italia, 2025), and the register contains no ratings or probabilities of default. Banks do not exchange their assessments of a firm bilaterally, since they are bound by bank secrecy.

all of the firm's lenders receive. Besides the changes in the firm's position toward other banks, the register also reports bad loans directly. When one lender classifies its exposure to the firm as a bad loan, it must report the classification within three working days of making it, and the register passes it on to the firm's other lenders at once.[8] Another channel is the firm itself. When a firm applies for credit or renews a line, banks ask it to list its credit lines at other banks, with their type and guarantees, so that a lender knows which other banks finance the firm and on what terms.[9]

Lenders are required to use what they see from the Central Credit Register. A bank that rates borrowers with internal models, as the banks whose PDs we observe do, must take into account all relevant and current information, and the less information it has, the more conservative its ratings must be.[10] Italian banks rank a firm's credit relations with the banking system first among the inputs of their scoring models, ahead of its financial statements (Albareto et al., 2008), and in the Bank of Italy's own rating model for nonfinancial firms, a decline in the number of a firm's lenders predicts default (Narizzano et al., 2024). The credit officers of the largest banks describe the same practice. Intesa Sanpaolo computes a monthly behavioral score, which it uses both to assign ratings and to monitor borrowers and which includes the firm's use of credit outside the group; UniCredit's credit officers check the register for past due amounts at other banks, persistent overdrafts, guarantees granted to other lenders, changes in the number of lenders, and bad-loan classifications (ODCEC Torino, 2014).

Lenders also weigh another lender's decisions by how much that lender is likely to know. Italian banks are less likely to lend to applicants that other banks have recently turned down (Albertazzi et al., 2017), and they give these rejections more weight when they expect them to come from banks closer to the applicant than they are themselves (Albertazzi et al., 2014). A local bank's decisions about a firm draw on what it learns from following the firm at close range. Through the register they reach the firm's other lenders, which give them extra weight because they come from a lender close to the firm. After the bank leaves the municipality, its decisions rest on less local knowledge and tell the other lenders less about the firm. Section 5.2 tests whether the other lenders' forecasts suffer as a result.

[8] Banca d'Italia (2025).

[9] For example, Intesa Sanpaolo's list of documents for a credit application requires a "list of any other banking relationships, with the technical form of each credit line and any guarantees" (Intesa Sanpaolo, n.d.a).

[10] Capital Requirements Regulation, Article 171(2) (European Parliament and Council of the European Union, 2013). The Bank of Italy also requires banks' early warning systems for credit risk to draw on the register (Banca d'Italia, 2018).

2.3 External Validity

Our setting is not special to Italy. Banks are leaving local markets in many countries, and multiple banking and information sharing among lenders are common in other markets as well.

First, the retreat of branch banking is a feature of advanced economies in general. Since the global financial crisis, the number of bank branches has fallen by more than 40 percent in the euro area and by about a fifth in the United States (European Central Bank, 2026; Keil and Ongena, 2024; Mariani et al., 2025; Narayanan et al., 2025; Federal Deposit Insurance Corporation, 2010, 2024). As in Italy, banks close branches as their customers move to digital channels (Keil and Ongena, 2024; Narayanan et al., 2025). The last-branch exits that we study, which follow bank-wide programs motivated by the same move to digital banking (Section 2.1), are therefore an instance of a much broader trend. Second, multiple banking is also common across countries. Among 11 euro area countries covered by AnaCredit, firms in Italy, Spain, and Portugal borrow from the most banks, and large firms there borrow from four to five banks on average (Kosekova et al., 2026). When firms borrow from several banks, the loss of one lender would lead to other lenders' responses. Finally, information sharing among lenders is widespread. Public credit registers like the Italian Central Credit Register operate in most of continental Europe (Jappelli and Pagano, 2002), and in 2003 public registers operated in 71 of 129 countries and private credit bureaus in 55 (Djankov et al., 2007). Information shared through these registers and bureaus also makes lenders interdependent.

3 Data and Empirical Strategy

This section describes our data, defines the firms and lenders that we study, and sets out the empirical strategy. We link two sources: the Bank of Italy's branch register, which identifies last-branch exits and tells us where each lender has branches, and AnaCredit, the credit register of the euro area, which gives each firm's credit from each of its lenders and the default probability that banks with internal rating models assign to the firm. Appendix A describes both sources, how we identify exits, and how the sample is built.

Section 3.1 describes the exit events and the credit data. In addition, this section introduces the two measures that we use to proxy for lenders' information about the firm. The first one is the probability of default that a lender assigns to the firm, which measures how risky the lender judges it to be. The second one is the accuracy of that probability as a forecast of default, which measures how well the lender knows the firm. These two

measures allow us to test the borrower-risk channel and the information channel in Section 5. Section 3.2 defines the affected firms, their incumbent co-lenders, and the comparison firms, and it summarizes the samples. Section 3.3 introduces the empirical tests for how we estimate the co-lenders' responses. For each local bank closure event, we show that the decrease in affected firms' credit comes from the closing bank and from their incumbent co-lenders. We then compare each co-lender's credit to affected firms with its credit to comparison firms in the same municipality and month, to isolate the effect of the local bank exit from other factors that impact the co-lender's lending. Section 3.4 discusses the assumption under which this comparison identifies the effect of the exit and the main threats to it.

3.1 Exits, Credit, and Lenders' Risk Assessments

Last-branch exits. The branch register records every bank branch in Italy with its address, the bank that operates it, and the dates on which it opened and closed. We use its monthly snapshots from January 2018 to December 2025 and identify a last-branch exit when a bank closes its last branch in a municipality.[11] We call this bank the *closing bank* and the month of the exit T_e. Using the register data, we can identify, for every lender of a firm, whether it has a branch in the firm's municipality.

AnaCredit starts in September 2018. We study exits between September 2020 and November 2024, so that AnaCredit covers the two years before each exit, which we use to identify the relationships that already existed a year before it, and the year after it. In this period, 2,124 last-branch exits, by 101 banks in 1,846 municipalities in all 20 regions, involve a closing bank with at least one borrower in the municipality in AnaCredit.

Credit, default probabilities, and defaults. AnaCredit records every loan that a euro area bank extends to a firm whose total commitment with that bank reaches €25,000, month by month, together with the firm's revenue, total assets, number of employees, and industry. A firm's credit from a bank consists of instruments such as term loans, credit lines, and overdrafts. For each instrument, AnaCredit records the outstanding amount (i.e., the amount of credit that the firm has drawn), and the off-balance-sheet amount (i.e., the amount of credit that the bank has committed but the firm has not yet drawn). We measure lender k's credit to firm i in month t as the sum of the two over all instruments j between them,

$$Credit_{ikt} = \sum_{j \in J_{ikt}} \Big(Outstanding_{jt} + OffBalance_{jt} \Big), \tag{1}$$

[11] In the 42 cities that span several postcodes, such as Rome and Milan, we treat each postcode zone as a separate municipality.

so that both drawn credit and undrawn credit lines count.

We use this credit in two forms. The first is credit in thousands of euros, winsorized at the 1st and 99th percentiles of its pre-exit distribution, which measures how much credit firms lose. The second expresses each co-lender relationship's credit in percent of that relationship's own credit in the month before the exit, so that every relationship counts equally and the larger size of the relationships with affected firms does not drive the comparison with comparison firms (Section 3.2 defines both groups):

$$Credit^{\%}_{ibet} = 100 \times \frac{Credit_{ibet}}{Credit_{ibe,T_e-1}}, \tag{2}$$

where $Credit_{ibe,T_e-1}$ is the same relationship's credit in the month before the exit, winsorized as in the euro measure. A relationship that ends stays in the sample at zero, with a loss of 100 percent of its pre-exit credit. Averaged over a group, the change in this measure since $T_e - 1$ is the average percentage change of the group's relationships, with each relationship weighted equally.

For each lender and firm, AnaCredit also records the probability of default (PD) that the lender assigns to the firm over the following year and whether the lender classifies the firm in default, that is, unlikely to pay or more than 90 days past due. PDs are reported by banks that rate the borrower with internal models, and they equal 100 percent for firms in default. In the month before the exit, the co-lender reports a PD for about 60 percent of the affected and of the comparison relationships in our sample. Of the 192 incumbent co-lenders in the basic sample, 25 report PDs.[12]

A bank's PD for a firm is the output of its own internal rating system, which the supervisor must approve before the bank can use it to compute its capital requirements.[13] The rating is produced by a statistical model that the bank develops internally and that a credit risk control unit, independent of the staff who grant the credit, designs and oversees. The model combines the firm's financial statements, its credit relations with the banking system as reported by the Central Credit Register, its relationship with the bank itself, such as its use of accounts and credit lines, and qualitative information about the firm (Albareto et al., 2008). The qualitative information, for example on the firm's management, ownership, and market

[12]Banks may use internal ratings to compute their capital requirements only after the supervisor has approved their models (European Parliament and Council of the European Union, 2013). Because developing and validating these models requires long data histories and substantial resources, the banks that use them are mainly large banking groups. In Italy, they include Intesa Sanpaolo, UniCredit, Banco BPM, and BPER Banca, the four banks that account for 56 percent of the last-branch exits in the branch register (Section 2.1). We count banks as legal entities.

[13]Banks do not see one another's PDs: the Central Credit Register reports no ratings or probabilities of default, and the PDs that banks report to AnaCredit are not returned to them (Banca d'Italia, 2025, Chapter I, Section 2, paragraph 5.1; European Central Bank, 2021). Section 2.2 describes what the register reports.

position (Intesa Sanpaolo, n.d.b), is collected by the relationship manager who deals with the firm. The rating is therefore not purely the output of an algorithm. Banks must complement the statistical model with human judgment that takes into account relevant information the model does not consider, and loan officers can propose to depart from the model's score (Albareto et al., 2008). Such overrides must be documented, and ratings must be assigned or approved by a party that does not benefit from the decision to extend the credit.[14] The rating must also be reviewed at least once a year and whenever material information about the borrower becomes available, and it must draw on all relevant information the bank has, including what the register shows about the firm's borrowing elsewhere.[15] A bank's PD for a firm thus combines hard information, processed by a central model, with soft information collected by the staff who deal with the firm, and it is the lender's own summary of what it knows about the firm.

Lenders' information. The two channels of Section 1 leave their marks on these assessments: the borrower-risk channel on how risky the co-lenders judge the firm, and the information channel on how well the co-lenders know the firm. We measure borrower risk by the lender's PD and by whether the firm defaults. We measure how well a lender knows a firm by how well its PD forecasts the firm's default, using the Brier loss (Brier, 1950). The Brier loss is the squared error of a probability forecast, so its average over firms is the mean squared error familiar from other forecasting problems. The Brier loss of lender b's forecast for firm i in month t is

$$Brier_{ibt} = \left(PD_{ibt} - Default^{b}_{i,t+1:t+12}\right)^2, \tag{3}$$

where PD_{ibt} is the PD as a probability and $Default^{b}_{i,t+1:t+12}$ equals one if lender b classifies firm i in default in any of the following twelve months. The loss penalizes a lender for assigning low PDs to firms that subsequently default and high PDs to firms that continue to perform. Having better information about the borrower helps to avoid these mistakes, so a lower loss indicates better information.

One caveat of the Brier loss is that it rises with the default rate of the firms being forecast, even if the lender knows each firm equally well. Consider a lender that assigns a PD of 50 percent to every firm that will default and of 1 percent to every firm that will not. In a group of firms in which 2 percent default, its Brier loss is 0.005. In a group in which 10 percent

[14]Capital Requirements Regulation, Articles 143, 172(3), 173(1)(a), 174(e), and 190 (European Parliament and Council of the European Union, 2013).

[15]Capital Requirements Regulation, Articles 171(2) and 173(1)(b) (European Parliament and Council of the European Union, 2013).

default, its Brier loss is 0.025, five times as large, although the lender knows the firms in both groups equally well (in both groups, it assigns the same high PD to every firm that will default and the same low PD to every firm that will not). To adjust for this, we also measure forecast skill, which compares the lender's Brier loss with $p(1-p)$, where p is the observed default rate of the same group of firms. Because default is a binary outcome that occurs with probability p, $p(1-p)$ is its variance, and it is also the expected Brier loss of a forecaster who knows only the default rate and assigns it to every firm.

Forecast skill is

$$S = 1 - \frac{\overline{Brier}}{p(1-p)}, \tag{4}$$

the share of this uninformed loss that the lender's information about individual firms removes. Because the uninformed loss rises with the default rate in the same way as the lender's loss, skill adjusts the Brier loss for the default rate. In the example, $p(1-p)$ is 0.020 in the first group and 0.090 in the second, so the lender's forecast skill is 0.74 and 0.72, almost the same in both groups. Skill is a common way to compare default forecasts across groups with different default rates (Murphy, 1988; Krämer and Neumärker, 2016), and it equals the R^2 of the PDs as forecasts of default (Fuster et al., 2022). We use it alongside the Brier loss to compare the co-lenders' forecasts for affected and comparison firms before and after the exit (Section 5.2).

3.2 Affected Firms, Co-Lenders, and Comparison Firms

Figure 3 shows the lending network around an exit. Let a be the closing bank of exit e in municipality m. A relationship between bank k and firm i is *established* at exit e if the bank lends to the firm in the month before the exit and already lent to it a year earlier, at some point between 24 and 13 months before the exit:[16]

$$Est_{ike} = \mathbf{1}\Big[Credit_{ik,T_e-1} > 0\Big] \times \mathbf{1}\Big[\textstyle\sum_{t=T_e-24}^{T_e-13} \mathbf{1}\Big[Credit_{ikt} > 0\Big] \geq 1\Big]. \tag{5}$$

Affected firms are small and medium-sized firms located in m with an established relationship with the closing bank, $Est_{iae} = 1$. An affected firm's *incumbent co-lenders* are the other banks $b \neq a$ with which it has an established relationship, $Est_{ibe} = 1$, and that do not themselves have change of its locality status with respect to m. An incumbent co-lender's *comparison firms* are its other borrowers in m that do not borrow from the closing bank, $Est_{jbe} = 1$ and $Credit_{ja,T_e-1} = 0$. We call a co-lender's relationships with affected firms *affected relationships*

[16]This is the twelve-month look-back that Bonfim et al. (2021) use to identify a firm's existing lenders, applied one year before the exit; Cole (1998) finds that much of a bank's private information about a borrower is collected in the first year of the relationship.

and its relationships with comparison firms *comparison relationships*. A co-lender is *local* if it has a branch in m in the month before the exit, and a firm's *dependence* on the closing bank is the closing bank's share of its credit before the exit,

$$Dep_{ie} = \frac{Credit_{ia,T_e-1}}{\sum_k Credit_{ik,T_e-1}}. \tag{6}$$

The heterogeneity tests of Section 5 use the share of equation (6) at the level of the co-lender and the exit: the closing bank's share of the combined credit of the co-lender's affected firms, so that each group is compared with that co-lender's comparison firms.

[Insert Figure 3 here]

Not all of the closing bank's local borrowers can tell us how incumbent co-lenders respond. A local borrower enters as an affected firm only if it is a small or medium-sized firm with an established relationship both with the closing bank and with at least one incumbent co-lender. Multiple banking is the binding condition: a firm that borrows only from the closing bank has no co-lender whose response we could study. The analysis sample contains 11,902 affected firm-exits in 1,829 exits. Appendix A describes the samples of the comparison with the co-lenders' other borrowers.

Table 2 reports summary statistics for these samples. The basic sample of the comparison contains 17,322 affected and 121,453 comparison relationships (Appendix A). The closing bank typically has a dozen borrowers in the municipality, and the exits are mostly from small municipalities. The affected firms are established small and medium-sized businesses, with a median of 9 employees and 24 years of age, and they borrow from almost four banks. Their relationships with the incumbent co-lenders are sizable and mostly secured.

[Insert Table 2 here]

3.3 Event Study and Within-Lender Comparison

For each exit and affected firm, we follow the credit from the closing bank, the credit summed over the firm's incumbent co-lenders, and their total, and estimate

$$Credit^r_{iet} = \alpha^r_{ie} + \sum_{k\neq -1} \theta^r_k \, Event_{t-T_e=k} + \varepsilon^r_{iet}, \qquad r \in \{CB,\ CL,\ Total\}, \tag{7}$$

where i indexes firms, e exits, and t months. $Credit^{CB}_{iet}$ is the credit from the closing bank, $Credit^{CL}_{iet}$ the credit summed over the firm's incumbent co-lenders, and $Credit^{Total}_{iet}$ their sum. $Event_{t-T_e=k}$ equals one in month k relative to the exit, with $k=-1$ as the reference month,

and the firm-event fixed effect α^r_{ie} makes θ^r_k the average change in credit between $T_e - 1$ and $T_e + k$. Each exit forms its own stack, with a window from 12 months before to 12 months after the exit, as in the stacked difference-in-differences design of Cengiz et al. (2019) (see also Baker et al., 2022; Wing et al., 2024). We fix the lending network at $T_e - 1$, and a lender whose credit falls to zero stays in the sample. The coefficients capture how the firm's existing lenders change their credit, including relationships that become inactive.

The event study shows how much of the credit that affected firms lose from their existing banks is lost at the closing bank and how much at the incumbent co-lenders. It cannot show that the exit caused the co-lenders' part. For example, a local economic downturn could lead banks to leave the local market and reduce their willingness to lend in the municipality. The co-lender's own lending policy may change around the same time as well. We therefore compare each incumbent co-lender's credit to affected firms with its credit to its comparison firms, its other borrowers in the same municipality that do not borrow from the closing bank. Both groups borrow from the same co-lender in the same local economy and month, and only the affected firms lose the closing bank's local presence. We estimate

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, \mathit{Treated}_i \times \mathit{Event}_{t-T_e=k} + \varepsilon_{ibet}, \tag{8}$$

where Y_{ibet} is co-lender b's credit to firm i in month t of event e, $\mathit{Treated}_i$ equals one for affected firms and zero for comparison firms, α_{ibe} is a relationship-event fixed effect, and λ_{bet} is a bank-event-time fixed effect for the co-lender. With the relationship-event fixed effect, the estimate uses only changes within each relationship, and the bank-event-time fixed effect limits the comparison to a co-lender's affected and comparison relationships in the same exit and month. β_k is then the change in the co-lender's credit to affected firms since $T_e - 1$ minus the change in its credit to comparison firms. It is positive if the co-lenders substitute for the closing bank and take over part of the business it gives up, and negative if they act as complements and cut as well.

We estimate equation (8) with both measures of credit of Section 3.1 as the outcome, in euros and in percent of the relationship's level before the exit, equation (2). With the second measure, β_k is the average change in the co-lender's credit to affected firms minus the average change in its credit to comparison firms, each in percent of the relationship's own level before the exit. We summarize the response by the first-year average of $\beta_1, \ldots, \beta_{12}$. In the matched sample, comparison relationships are weighted by their matching weights. We

cluster standard errors by exit, since the treatment is assigned at the exit level.[17] Section 5 estimates the same equation with the co-lender's PD, the firm's default status, and the Brier loss of the co-lender's forecast as outcomes.

To test the channels, we let the response differ across groups of co-lender-exit pairs in which, as Section 5 explains, the channels should matter to different degrees:

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \Big(\beta_k + \delta_k \, G_{be}\Big) \, \mathit{Treated}_i \times \mathit{Event}_{t-T_e=k} + \varepsilon_{ibet}, \tag{9}$$

where G_{be} is an indicator fixed before the exit: high dependence of the affected firms on the closing bank, the closing bank being their only local lender, or the co-lender having no branch in the municipality. The coefficient β_k is the response where $G_{be} = 0$, and δ_k the additional response where $G_{be} = 1$. Because G_{be} is defined at the level of the co-lender and the exit, each group is compared with the co-lender's own comparison firms.

3.4 Identification

The comparison identifies the effect of the exit on the co-lenders' credit if, without the exit, a co-lender's credit to affected and to comparison firms in the same municipality would have evolved in parallel. We discuss five threats to this assumption in turn.

First, banks could close their last branch where their borrowers are deteriorating, so that affected firms would differ from comparison firms in ways that predict lower credit. The evidence of Section 2.1 speaks against this. Exits come in waves set by bank-wide programs, bank-by-month fixed effects fit far more of the variation in exits than local fixed effects do, and within a bank and month neither the PDs of the bank's local borrowers nor its own forecast errors predict which of its last branches close. Appendix B shows that each bank's exits are spread across the country roughly in proportion to its branches.

Second, even if exits are not chosen because of the affected firms, those firms could be on a different path from comparison firms. Three features of the design address this concern. Before the exit, the co-lenders see no deterioration of the affected firms: their PDs for affected firms move with their PDs for comparison firms, and their credit to affected firms does not decline relative to their credit to comparison firms (Section 4.2). The matched sample, in addition, compares affected firms with comparison firms of the same co-lender that also borrow from a third bank and are similar in industry and size. And in exits in which the closing bank had more than 50 borrowers in the municipality, the decision to leave

[17] Clustering at the level at which treatment is assigned follows Abadie et al. (2023). Clustering by exit also allows for any correlation among the relationships of the same exit, across co-lenders and over the months of the window (Bertrand et al., 2004).

cannot hinge on the prospects of the few affected firms that also borrow from a co-lender (Section 4.3).

Third, affected relationships are larger than comparison relationships, and affected firms borrow from more banks. The relationship-event fixed effect removes these differences in levels, but a common percentage decline would still remove more euros from larger relationships. The percentage outcome of equation (2), which measures each relationship against its own pre-exit credit, and the matched sample, in which affected and comparison relationships are of similar size, address this concern.

Fourth, the comparison would overstate the cut at affected firms if the co-lenders redirected credit from affected firms toward comparison firms after the exit. The co-lenders' credit to comparison firms does not rise after the exit; over the first year it is 4.7 percent below its level before the exit on average in the basic sample.

Fifth, exits happen at different dates, and two-way fixed effects estimates are biased when they compare firms treated at different times (Cengiz et al., 2019; Sun and Abraham, 2021; Baker et al., 2022). Our estimate makes no such comparisons: each exit forms its own stack, in which affected and comparison firms are observed over the same months around the same exit. Because the lending network is fixed before the exit, the estimates also do not depend on which relationships the firms start after it.

4 Incumbent Co-Lenders Cut Rather Than Step In

This section shows that a firm's incumbent co-lenders cut their credit when one of its banks leaves the municipality. Section 4.1 uses the event study to measure how much of the credit that affected firms lose from their existing banks is lost at the closing bank and how much at the co-lenders. Section 4.2 compares each co-lender's credit to affected firms with its credit to comparison firms in the same municipality, to establish that the co-lenders cut in response to the exit and not because of local or bank-wide conditions that affect all their borrowers. Section 4.3 shows that the cut remains when affected firms are compared with similar comparison firms and when the sample is restricted to exits that are unlikely to have been driven by the affected firms.

4.1 Where Affected Firms Lose Credit

The incumbent co-lenders do not take over the closing bank's business; they cut their credit as well. Figure 1 plots the affected firms' credit from the closing bank and from their incumbent co-lenders around the exit, in euros in Panel A and in percent of its level before the exit in

Panel B. By the twelfth month after the exit, the firms' total credit from their existing banks has fallen by €347,700, which corresponds to 14.7 percent of its level in the month before the exit. Less than a third of this decline comes from the closing bank. Its credit to the firms has fallen by €106,800, or 15.8 percent of its level before the exit, and accounts for only 31 percent of the fall in the firms' credit from their existing banks. The remaining 69 percent comes from the co-lenders, although they did not leave the municipality. Their combined credit to the firms has fallen by €240,900, or 14.3 percent, and the average co-lender relationship is 13.1 percent lower. The co-lenders thus cut their credit in about the same proportion as the closing bank. Since they held 71 percent of the firms' incumbent credit before the exit, their cut accounts for most of the drop in credit of the affected firms. If the co-lenders replaced part of the closing bank's credit, the firms' credit from their existing banks would have fallen by less than the closing bank's credit. Instead, their credit falls by more than two times as much.

There are two features of these paths worth mentioning. First, credit declines month by month over the year, consistent with credit lines being renewed at lower amounts, or not renewed, as they come due. By month twelve, about one in eight of the co-lenders' relationships with affected firms have ended, and almost half have been cut (Figure 4). Second, the co-lenders' path tracks the closing bank's closely. One year after the exit, the closing bank's credit is 15.8 percent below its level before the exit and the co-lenders' combined credit 14.3 percent below, a difference of only 1.5 percentage points.

[Insert Figure 4 here]

The fact that co-lenders' credit also decreases after the events matters for how the effect of a bank's exit is measured. The usual way to measure the effect of a shock to one bank is to compare the credit from the shocked bank with the credit from the firm's other lenders, within the same firm (Khwaja and Mian, 2008). This within-firm comparison treats the other lenders as unaffected by the shock, which is opposite to our finding that the other lenders cut almost as much as the closing bank. Thus, the within-firm gap of 1.5 percentage points captures only about a tenth of the closing bank's own cut of 15.8 percent. Weighted by the closing bank's share of the firms' incumbent credit before the exit, the gap implies that the firms lose about 0.4 percent of their credit, whereas their credit from their existing banks actually falls by 14.7 percent. After a funding shock, a firm's other lenders partly replace the shocked bank's credit, so the within-firm comparison overstates the firm's loss. After the loss of a bank's local presence, the other lenders cut as well, so the same comparison understates it.

4.2 Co-Lender Credit Relative to Comparison Firms

[Insert Figure 5 here]

[Insert Figure 6 here]

[Insert Table 3 here]

Incumbent co-lenders cut their credit to the firms that lost a local bank, relative to their credit to other firms in the same municipality. Column 1 of Table 3 reports the first-year average of the coefficients of equation (8). Over the first year after the exit, a co-lender's credit to an affected firm falls by €26,900 more than its credit to a comparison firm. Before the exit, the average co-lender lends €638,000 to an affected firm, so this additional cut amounts to 4.2 percent of its credit to the firm. Panel A of Figure 5 shows that after the event, co-lenders' credit to the affected firms decreases faster than their credit to comparison firms. The gap opens in the months after the exit and widens until about month nine, when it reaches about €35,000. In the year before the exit, these two groups of firms have similar credit paths from the co-lender banks. Therefore, the credit decrease does not reflect a trend that started before the exit.

The credit cut is also clear when each relationship's credit is measured against its own level before the exit, as in equation (2). Over the first year, the co-lenders' credit to the average affected relationship is 6.7 percent below its level before the exit, and their credit to the average comparison relationship is 4.7 percent below. Credit to affected firms thus falls by 2.0 percentage points more, as column 3 of Table 3 shows, with a 95 percent confidence interval from 0.9 to 3.1 points. Panel A of Figure 6 shows that the gap opens after the exit, reaches about 3 percentage points by month nine, and is 1.7 points at month twelve. As in euros, credit to affected firms grows slightly faster than credit to comparison firms in the year before the exit. The gap in percent is smaller than the 4.2 percent implied by the euro measure because the percentage measure weights every relationship equally, whereas the euro gap also reflects the larger size of affected relationships. Measured either way, the co-lenders cut their credit to the firms that lost a local bank by more than their credit to comparable firms.

4.3 Robustness

Comparing affected firms with other borrowers of the same co-lender in the same municipality removes local economic conditions and changes in the co-lender's own lending policy, which affect both groups alike. However, local economic trends may not be the only important

factor that affects how the two groups of firms evolve without the exit. Many comparison firms are smaller borrowers that borrow from the co-lender alone, whereas affected firms borrow from at least two banks. To address this concern, we match each affected firm with comparison firms that resemble it. For each affected firm, the matched sample keeps up to three comparison firms of the same co-lender in the same exit that also borrow from a third bank, operate in the same broad industry, and are closest to the affected firm in total assets (Appendix A). In this sample, affected and comparison firms are also similar in revenue, employees, age, the co-lender's credit and PD, and the secured share of the relationship (Appendix Table A5). The co-lenders still cut their credit to affected firms. Over the first year, their credit to affected firms falls by €20,400 more than their credit to comparison firms, as column 2 of Table 3 shows. Before the exit, the average co-lender in this sample lends €544,000 to an affected firm, so the additional cut amounts to 3.8 percent of its credit to the firm. Measured against each relationship's own level before the exit, credit to affected relationships falls by 6.95 percent and credit to comparison relationships by 3.20 percent, a gap of 3.75 percentage points (column 4). Panels B of Figures 5 and 6 show coefficients close to zero before the exit and a gap that opens in the month of the exit and persists.

A second concern is that, even among comparable firms, the exit itself could reflect the affected firms' prospects: the closing bank might leave a municipality because its local borrowers are deteriorating. Section 2.1 shows that exits follow bank-wide programs and that the PDs of a bank's local borrowers do not predict which of its last branches close. As a further test, we restrict the sample to exits in which the closing bank had more than 50 borrowers in the municipality. In these exits, the affected firms that also borrow from a co-lender are a small part of the closing bank's local business, so their prospects are unlikely to drive its decision to close the branch. The co-lenders' cut is larger in these exits, in which the closing bank was an important local lender. Over the first year, their credit to affected firms falls by €32,900 more than their credit to comparison firms, which amounts to 5.0 percent of their credit to the firm before the exit (Appendix Figure A5).

5 Why Co-Lenders Cut: Riskier Firms and Lost Information

This section asks why the incumbent co-lenders cut their credit to affected firms. These lenders already know the firms and could take over the business that the closing bank gives up, so their cut suggests that the closing bank's local presence mattered to them. We examine the two channels introduced in Section 1, which leave different marks on the co-lenders'

own assessments of the firm that AnaCredit records. Section 5.1 tests the borrower-risk channel. If the firm loses the closing bank's monitoring and credit and becomes riskier, the co-lenders should raise their PDs, the firm should in fact default more often, and both responses should be strongest where the firm depended most on the closing bank. Section 5.2 tests the information channel. If the co-lenders lose the signals that the closing bank's decisions carried, their default forecasts should become less accurate whether or not the firm becomes riskier, and most of all where the closing bank was the firm's only local lender, so that no other local lender's decisions carry local information to them. Section 5.3 measures how much of the cut each channel accounts for. It compares co-lenders with and without a branch of their own in the municipality: both are exposed to the borrower-risk channel, but only those without a branch lose their source of local information. Section 5.4 discusses alternative explanations of the cut.[18]

5.1 The Borrower-Risk Channel

If losing the closing bank's monitoring and credit weakens the firm, its other lenders should judge it riskier and it should default more often. We estimate equation (8) with two outcomes: co-lender b's reported default probability for firm i in month t, PD_{ibet}, in percentage points, and an indicator that the co-lender classifies firm i in default in month t. After the exit, incumbent co-lenders raise their PDs for affected firms relative to comparison firms. Column 1 of Table 4 shows that over the first year, the co-lenders' PD for affected firms rises by 1.66 percentage points more than their PD for comparison firms. This increase equals 23 percent of the co-lenders' average PD for affected firms before the exit. Panel A of Figure 7 shows that the difference builds steadily over the year, whereas in the year before the exit the co-lenders' PDs for affected firms move with their PDs for comparison firms. In the matched sample, where affected and comparison firms start from similar PDs, the increase is smaller, 0.73 percentage points or 11 percent of the level before the exit (column 2 and Appendix Figure A6).

[Insert Figure 7 here]

The firms do default more often. As Panel B of Figure 7 shows, the co-lenders' default classifications of affected and comparison firms move together before the exit, and after it the gap widens steadily: over the first year, the default rate of affected firms rises by 1.27

[18]The PD, default, and Brier outcomes are observed in the months in which a co-lender reports a PD for both its affected and its comparison firms. Restricting the sample to relationships that the co-lender reports in every month of the window leaves the estimates almost unchanged, except that the rise in the Brier loss in the matched sample is smaller, 0.0054 rather than 0.0085, as Appendix Table A8 shows.

percentage points more than that of comparison firms, and by 2.28 points more by twelve months after the exit. In the matched sample the difference is smaller, 0.34 points, and not statistically significant. The co-lenders' higher PDs thus anticipate a real deterioration of the affected firms. This is what the borrower-risk channel predicts: when the closing bank cuts its credit, the firm has less liquidity with which to meet its obligations, and its probability of default rises for every one of its lenders.

If the closing bank's monitoring and credit kept the firm sound, losing them should hurt most where the firm depended most on that bank. We measure dependence by the closing bank's share of the credit of the co-lender's affected firms before the exit and estimate equation (9) with $G_{be} = HighDep_{be}$, which equals one if the closing bank held more than 25 percent of that credit at $T_e - 1$, about its average share. High dependence can mean two things, with different predictions. If it only reflects how the firm splits its borrowing among its banks, the co-lenders' cut in euros need not be larger, but because they lend less to a firm that borrows more from the closing bank, the same cut is larger in percent of their credit. If high dependence also reflects closer monitoring by the closing bank, the firm loses more support when that bank leaves, and the co-lenders' cut should be larger in euros as well.

[Insert Figure 8 here]

[Insert Table 4 here]

The co-lenders cut more, and raise their PDs more, where the affected firms depended more on the closing bank. Column 3 of Table 4 shows that where dependence is low, the co-lenders cut their credit to affected firms by €20,600 more than their credit to comparison firms over the first year, which is 2.7 percent of their credit to the firm before the exit. Where dependence is high, the cut is €14,000 larger. The total cut of €34,600 amounts to 6.9 percent of the co-lenders' credit to the firm, more than twice the percentage cut where dependence is low. The difference is significant at the 1 percent level, and it does not come from larger relationships: the co-lenders lend less to affected firms where dependence is high. Because the cut is larger in euros as well as in percent, the dependence reflects more than how the firm splits its borrowing. Column 4 shows the same pattern for the co-lenders' PDs. Where dependence is low, their PD for affected firms rises by 1.13 percentage points relative to comparison firms, or 15 percent of its level before the exit. Where dependence is high, it rises by a further 1.16 points, so that the total increase of 2.29 points amounts to 32 percent of the level before the exit. Figure 8 shows both responses month by month. The more the firm

relied on the closing bank, the riskier its other lenders judge it after the exit and the more they cut.[19]

5.2 The Information Channel: Forecast Accuracy

If the closing bank's local presence kept the co-lenders informed about the firm, their assessments of the firm should become less informative after it leaves. We measure the informativeness of a co-lender's assessment by the Brier loss of its default forecast as shown in equation (3), winsorized at the 1st and 99th percentiles of its pre-exit distribution, and estimate equation (8) at the relationship-month level, with relationship-event and co-lender-event-month fixed effects and the Brier loss as the outcome. Column 1 of Table 5 shows that over the first year, the Brier loss of the co-lenders' forecasts for affected firms rises by 0.0078 more than for comparison firms, an increase of 53 percent relative to its level before the exit. Panel A of Figure 9 shows that the increase builds over the year, and column 2 shows a similar increase in the matched sample, 0.0085. The co-lenders' assessments track what happens to the affected firms markedly less well after the closing bank leaves.

[Insert Figure 9 here]

[Insert Table 5 here]

A co-lender's default forecasts can become less accurate for two reasons. On one hand, the firm may become riskier, and a group of firms with more defaults has a higher Brier loss even if it is forecast equally well. On the other hand, the co-lender may become less informed about the firm, because the closing bank's decisions no longer carry local information. To address the first reason, we redo the information DiD test using forecast skill, shown in equation (4), a standard normalization of the Brier loss relative to a constant forecast at the group's default rate (Murphy, 1988; Krämer and Neumärker, 2016). If a firm defaults with true probability π, the expected Brier loss of a PD is the squared error in the estimated probability, $(PD - \pi)^2$, plus the uncertainty in default itself, $\pi(1 - \pi)$. This uncertainty rises with risk when $\pi < 1/2$, even for a lender that knows π exactly (Howes and Weitzner, 2025). The constant forecast has a loss of $p(1-p)$ (Basel Committee on Banking Supervision, 2005). Skill is the proportional reduction in loss relative to this benchmark, and on unwinsorized losses it equals the predictive R^2 obtained using the reported PDs as forecasts of default (Fuster et al., 2022). Skill reflects both how well PDs distinguish firms' risks and how accurately their levels

[19] A firm that depends more on the closing bank may also be one about which the closing bank's information mattered more to the co-lenders. Closer monitoring by the closing bank would then raise both the borrower-risk and the information part of the co-lenders' cut. Section 5.3 separates the two channels.

match default probabilities.[20] When the distribution of true risk is fixed, population skill moves only with the mean squared error in estimated probabilities. If the exit also raises risk, skill can move even if the lender knows as much as before, so we read it together with the comparisons across firms and co-lenders below.

Panel B of Figure 9 shows that forecast skill falls as well. Relative to comparison firms, the co-lenders' skill on affected firms declines by 0.077 over the first year (standard error 0.026). Appendix Table A9 shows that this relative decline reflects a drop in skill on affected firms. For these firms, the default rate rises from 5.38 percent in the month before the exit to 6.74 percent twelve months after it. Holding skill at its pre-exit level of 0.750 gives a Brier loss of about 0.016 at the higher default rate, compared with 0.0127 before the exit. The observed loss at twelve months is 0.0237, corresponding to a skill of 0.623. The co-lenders' PDs thus deliver a smaller proportional improvement over the constant-rate forecast after the exit. This pattern is consistent with co-lenders having less borrower-specific information, although changes in borrower risk can also reduce forecast skill.

In addition, since the Brier loss can be mechanically affected by the default rate, we examine forecasts for firms that do not default in our analysis period. We re-estimate equation (8) on the non-defaulting subsample. Figure 10 reports the estimates for the basic and matched samples.

[Insert Figure 10 here]

The information channel should matter most where the co-lenders have no other local source. Where another of the firm's lenders keeps a branch in the municipality, its decisions continue to carry local information to the co-lenders; where the closing bank was the firm's only local lender, none remains. We estimate equation (9) with $G_{be} = OnlyLocal_{be}$, which equals one if the closing bank was the only lender with a branch in the municipality among the lenders of the co-lender's affected firms at $T_e - 1$, with the Brier loss and credit as outcomes. The loss of accuracy is concentrated where the closing bank was the affected firms' only local lender. Column 4 of Table 5 shows that where the firms kept another local lender, the Brier loss of the co-lenders' forecasts for affected firms rises by 0.0052 more than for comparison firms over the first year, an increase of 32 percent relative to its level before the

[20] Let π be the default probability given all relevant information, including the lender's. At the population level, with $p = \mathrm{E}[\pi]$, $S = \{\mathrm{Var}(\pi) - \mathrm{E}[(PD - \pi)^2]\}/[p(1-p)]$. Equation (11) of Murphy (1988) gives $S = 2G - \mathrm{Var}(PD)/[p(1-p)] - (\mathrm{E}[PD] - p)^2/[p(1-p)]$, where $G = \mathrm{Cov}(PD, \pi)/[p(1-p)]$ is the difference in average PD between firms that default and firms that do not. If the PD equals the default probability given the lender's information, then $\mathrm{E}[PD] = p$, $\mathrm{Cov}(PD, \pi) = \mathrm{Var}(PD)$ and $S = G$. Holding the lender's information fixed and updating these PDs accordingly, a common proportional increase in default probabilities weakly raises skill, whereas a common percentage-point increase weakly lowers it while the group's default rate stays below one half, provided all probabilities remain in $[0, 1]$.

exit. Where the closing bank was the only local lender, the loss rises by a further 0.0135. The total increase of 0.0187 amounts to 227 percent of the loss before the exit, so the co-lenders' forecast errors for these firms more than triple.

[Insert Figure 11 here]

The credit cut follows the same pattern. Column 3 shows that where another local lender remained, the co-lenders cut their credit to affected firms by €22,300 relative to comparison firms, or 3.3 percent of their credit to the firm before the exit. Where the closing bank was the only local lender, the cut is €16,800 larger. The total cut of €39,100 amounts to 8.5 percent of the co-lenders' credit to the firm. The difference is significant at the 5 percent level, and it does not come from larger relationships, since the co-lenders lend less to affected firms where the closing bank was the only local lender. Figure 11 shows both responses month by month. Nor is the contrast a matter of the co-lender's own presence in the municipality, which Section 5.3 examines: Appendix Figure A7 shows that among co-lenders without a branch in the municipality, too, the cut is larger where the closing bank was the only local lender. Where the firm loses its only local lender, its other lenders lose the most forecast accuracy and cut the most, consistent with the information channel.

5.3 Separating the Two Channels

To separate the two channels, we need lenders that are exposed to one channel but not to the other. Co-lenders with their own branch in the municipality are such lenders. They lend to the same firm, which becomes riskier when the closing bank leaves, but their own staff meet the firm and observe local conditions, so they keep producing local information about it. We therefore estimate equation (9) with $G_{be} = NonlocalB_{be}$, which equals one if co-lender b has no branch in the municipality at $T_e - 1$, with credit in euros and the Brier loss as outcomes. If the firm becomes equally riskier for both types of co-lender, the borrower-risk channel removes the same euro amount from their credit, and any difference in euros between them comes from the information channel. We compare the two groups in euros rather than in percent, because the same euro amount is a larger share of the smaller credit lines of nonlocal co-lenders.

[Insert Figure 12 here]

[Insert Table 6 here]

Local co-lenders keep their information, whereas nonlocal co-lenders lose it. Column 2 of Table 6 shows that over the first year, the Brier loss of local co-lenders' forecasts for

affected firms rises by only 0.0032 more than for comparison firms, and the increase is not statistically significant. For nonlocal co-lenders, the loss rises by a further 0.0113, so that the total increase of 0.0145 more than doubles the loss relative to its level before the exit. The credit response follows the same pattern. Local co-lenders, which keep their information, still cut their credit through the borrower-risk channel, but nonlocal co-lenders, which lose it, cut almost twice as much. Column 1 shows that local co-lenders reduce their credit to affected firms by €19,040 relative to comparison firms, or 2.8 percent of their credit to the firm before the exit. Nonlocal co-lenders cut €16,140 more. Their total cut of €35,180 amounts to 5.9 percent of their credit to the firm, and the difference between the two groups is significant at the 1 percent level. Figure 12 shows both responses month by month. The difference does not reflect differences in the riskiness of the firms that local and nonlocal co-lenders serve: Appendix Figure A8 shows that within groups of affected firms with similar PDs before the exit, nonlocal co-lenders also cut more than local ones.

This contrast lets us split the average co-lender cut between the two channels. Let $\bar{\beta}$ be the average co-lender cut of Table 3, column 1, and let $\bar{\beta}_L$ and $\bar{\beta}_N$ be the cuts at local and nonlocal co-lenders of Table 6, column 1. The average cut is a weighted average of the two,

$$\bar{\beta} = s_L\,\bar{\beta}_L + (1 - s_L)\,\bar{\beta}_N, \tag{10}$$

where s_L, the weight of local co-lenders in the estimate of $\bar{\beta}$, is their share of the identifying variation; Appendix C derives it, and in the basic sample $s_L = 0.512$. Each of the two cuts is the sum of a part due to the borrower-risk channel, F, and a part due to the information channel, I: $\bar{\beta}_L = F_L + I_L$ and $\bar{\beta}_N = F_N + I_N$. Two assumptions identify the parts: (A1) local co-lenders lose no information when the closing bank leaves, $I_L = 0$, because they keep producing their own local information about the firm; and (A2) the borrower-risk channel is the same at local and nonlocal co-lenders, $F_L = F_N = F$, because both lend to the same firms, which become riskier by the same amount. Under A1, the cut at local co-lenders is pure borrower-risk channel, and under A2 it measures the borrower-risk channel at all co-lenders, $F = \bar{\beta}_L$. The information channel then accounts for the extra cut at nonlocal co-lenders, $I_N = \bar{\beta}_N - \bar{\beta}_L$, and substituting both into equation (10) splits the average cut into the two channels:

$$\underbrace{\bar{\beta}}_{\text{average cut}} = \underbrace{\bar{\beta}_L}_{\text{borrower-risk channel}} + \underbrace{(1 - s_L)\left(\bar{\beta}_N - \bar{\beta}_L\right)}_{\text{information channel}}. \tag{11}$$

The information channel is thus the extra cut at nonlocal co-lenders, weighted by their share in the average cut.

In the basic sample, the local and nonlocal co-lenders cut €19,040 and €35,180, and equation (11) gives, in thousands of euros,

$$\underbrace{-26.91}_{\text{average cut}} = \underbrace{-19.04}_{\text{borrower-risk channel: 71\%}} + \underbrace{0.488 \times (-35.18 + 19.04)}_{\text{information channel: } -7.87\text{, or 29\%}}.$$

The information channel accounts for €7,900 of the €26,900 average cut, with a 95 percent confidence interval from €2,900 to €12,900, and the borrower-risk channel for the remaining €19,000. The matched sample attributes more of the cut to information. In this sample, local co-lenders cut their credit to affected firms by €6,700 relative to comparison firms, and nonlocal co-lenders cut €45,200 more, or €51,900 in total, as column 3 of Table 6 shows. Local co-lenders account for 69.6 percent of the identifying variation, so equation (11) attributes €13,700 of the €20,400 average cut, or 67 percent, to the information channel. Across the two samples, the information channel accounts for between 29 and 67 percent of the co-lender cut and the borrower-risk channel for the rest.

Each assumption errs in a known direction. If local co-lenders also lose some information, $I_L < 0$, their cut overstates the borrower-risk channel and the information share is larger than equation (11) gives; the small, insignificant rise in their Brier loss suggests that this loss is small. If the borrower-risk channel is larger at nonlocal co-lenders, $|F_N| > |F_L|$, the information share is smaller. Appendix C redoes the split with the borrower-risk channel at nonlocal co-lenders one and a half and two times that at local co-lenders. At one and a half times, the information channel accounts for 12 percent of the cut in the basic sample and 62 percent in the matched sample. If A2 fails in this direction, the basic sample's 29 percent overstates the role of lost information, whereas a failure of A1 would understate it. The matched sample gives firmer evidence: there, the information share stays above half even when the borrower-risk channel at nonlocal co-lenders is twice that at local ones.

5.4 Alternative Explanations

The co-lenders could cut for reasons that have nothing to do with the closing bank's local presence. The most obvious is that the closing bank had bad news about its local borrowers and left because of it. If the co-lenders learned the same news, they would cut even without losing any liquidity support or information. The evidence does not support this story. Exit timing follows bank-wide restructuring programs, and the PDs of a bank's local borrowers do not predict which of its last branches it closes (Section 2.1). The co-lenders' PDs for affected firms track those for comparison firms throughout the year before the exit (Figure 7), so the co-lenders see no deterioration before the closing bank leaves. And the closing bank does not

act as if it knew something bad about these firms: twelve months after the exit, 12.0 percent of its relationships with affected firms have zero credit, compared with 13.4 percent of the co-lenders' (Figure 4).

The co-lenders might instead simply follow the closing bank out, coordinating on its withdrawal without responding to the firm or to what they know about it. The timing of the cuts cannot settle this on its own. Appendix Table A7 shows that in about 40 percent of affected firms a co-lender cuts before the closing bank does or is the only lender that cuts, but a decline of more than 5 percent also captures amortization and depends on when each credit line comes up for renewal. What simple following does not explain is the difference between co-lenders: those without a branch in the municipality cut almost twice as much as those with one (Section 5.3).

The cut could also start with the firms. Affected firms might demand less credit after losing their local bank. Lower demand would reduce their borrowing, but it would not make them riskier or make the co-lenders' forecasts less accurate, and we observe both. Nor would it explain why co-lenders without a branch in the municipality cut almost twice as much as those with one. Alternatively, firms that need a branch might move their borrowing to co-lenders that keep one in the municipality, and those co-lenders might gain local market power from the exit. Either would raise credit at local co-lenders or concentrate the cut among them, yet local co-lenders cut as well, by about half as much as nonlocal ones (Section 5.3).

6 Conclusion

Technological transformation is reshaping the banking industry, leading banks across advanced economies to scale back their physical branch networks and retreat from local markets. What this transition means for firm financing depends not only on the banks that leave, but also on how a firm's other lenders respond. Although a firm's existing co-lenders already know the borrower and might be expected to step in as substitutes for a closing bank, this paper shows that they act as complements instead. Studying closures of a bank's last branch in Italian municipalities, we find that incumbent co-lenders cut credit rather than step in. One year after the exit, they account for 69 percent of the decline in affected firms' credit from their existing banks, cutting credit to affected firms by an extra 4.2 percent relative to their other borrowers in the same municipality.

We trace this complementary pullback to two roles that a local branch performs for the wider credit network. First, a local bank's close oversight and credit support help keep the borrower sound; once the bank leaves, affected firms default more often and co-lenders raise their default probabilities accordingly, especially where the firm depended heavily on the

closing bank. Second, a local bank's lending decisions transmit on-the-ground knowledge to other creditors through the credit register; after the exit, co-lenders' default forecasts become less accurate, most notably where the closing bank was the firm's sole local lender. By contrast, co-lenders with a branch of their own in the municipality lose little forecast accuracy and cut credit by about half as much as those without one, implying that lost information accounts for 29 percent of the co-lender cut.

Our results demonstrate that a local branch closure is not an isolated shock to the closing bank's own lending, but a shock across a firm's broader credit network. Because a local bank keeps the borrower sound and produces information that other creditors rely on, a bank's local presence complements the lending of a firm's other banks. Losing a local bank therefore imposes negative externalities on a firm's remaining lenders, prompting even informed co-lenders to cut back and undermining the insurance that borrowing from multiple banks is meant to provide. As banking becomes less local, a bank deciding to close a branch does not internalize these spillover losses across the firm's other creditors, which means that the broader impact of de-branching on firm credit reaches far beyond the credit withdrawn by the closing bank itself.

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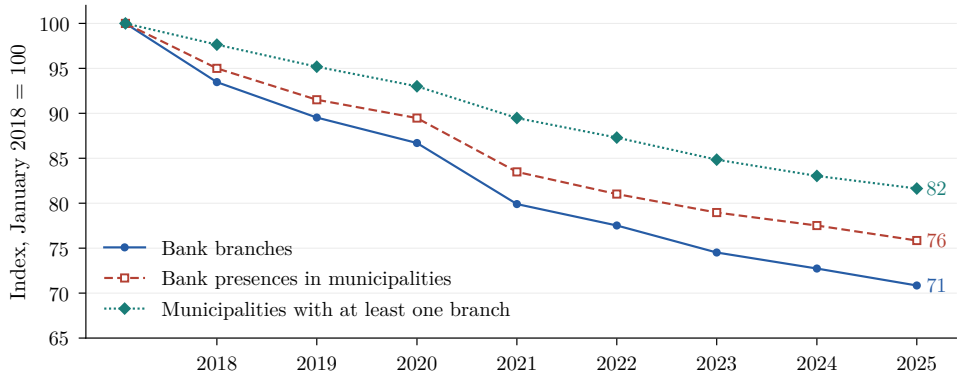
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Figures

Figure 2. Bank Branches and Last-Branch Exits in Italy

Panel A plots, at the end of each year, the number of branches of banks that lend to firms, the number of bank-municipality pairs in which the bank has at least one branch, and the number of municipalities with at least one bank branch, each as an index with January 2018 equal to 100. Representative offices and institutions without lending to firms are excluded; branches transferred to another bank count as continuing. In January 2018 the three series are 26,414 branches, 20,762 bank-municipality pairs, and 5,417 municipalities; in December 2025 they are 18,714, 15,748, and 4,422. Panel B plots the number of last-branch exits in each month between September 2018 and November 2025, by closing bank: 3,819 exits by 205 banks in 2,946 municipalities. A last-branch exit occurs when a bank closes its last branch in a municipality (in the 42 cities that span several postcodes, a postcode zone). The four banks with the most exits are shown separately, and the shaded area marks the exits we study. Source: Bank of Italy branch register.

Panel A. Bank branches and bank presence in municipalities, end of year (January 2018 = 100)



Panel B. Last-branch exits per month, by closing bank

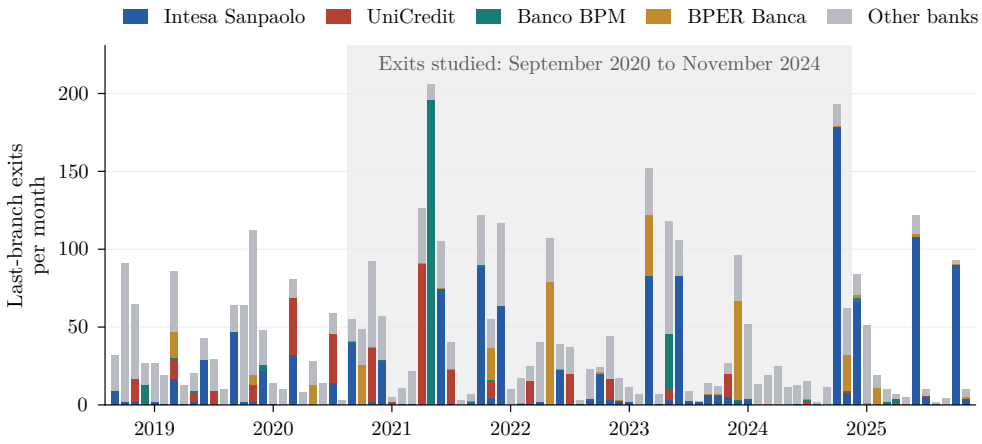


Figure 3. The Lending Network around a Last-Branch Exit

This figure shows the lending relationships around an exit. Bank A, the closing bank, closes its last branch in the municipality in month T_e. Firm X, an affected firm, borrows from bank A and from bank B, one of its incumbent co-lenders. Firm Y, a comparison firm, borrows from bank B in the same municipality but not from bank A. XA denotes the closing bank's relationship with the affected firm, XB an affected relationship, and YB a comparison relationship. All relationships are established: the bank lends to the firm in month $T_e - 1$ and already lent to it between months $T_e - 24$ and $T_e - 13$.

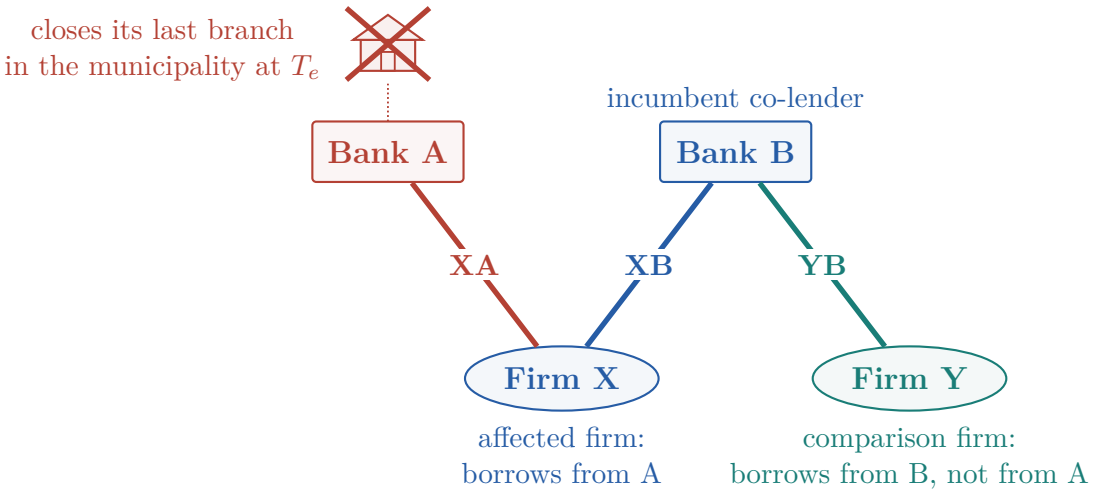


Figure 4. Relationship Status after the Exit: Closing Bank and Co-Lenders

This figure plots, by month relative to the exit, the share of the closing bank's relationships with affected firms (Panel A) and of the incumbent co-lenders' relationships with them (Panel B) with no material cut (credit above 95 percent of its level at $T_e - 1$), a partial cut (positive credit at most 95 percent of $T_e - 1$), and zero exposure. Each relationship with the closing bank has weight one and each co-lender relationship weight $1/K$, where K is the firm's number of incumbent co-lenders. Because no relationship is cut at $T_e - 1$, the share with a partial cut or zero exposure in each month is also the coefficient of equation (7) estimated with an indicator for such a cut as the outcome. Event-study sample. At $T_e + 12$, 12.0 percent of the closing bank's and 13.4 percent of the co-lenders' relationships have zero exposure, and 47.1 and 46.2 percent have been partially cut. Weighted by pre-exit credit, partial cuts account for 61 percent of the closing bank's and 54 percent of the co-lenders' exposure, and zero exposure for 5.8 and 6.8 percent. A decline of 5 percent also captures amortization.

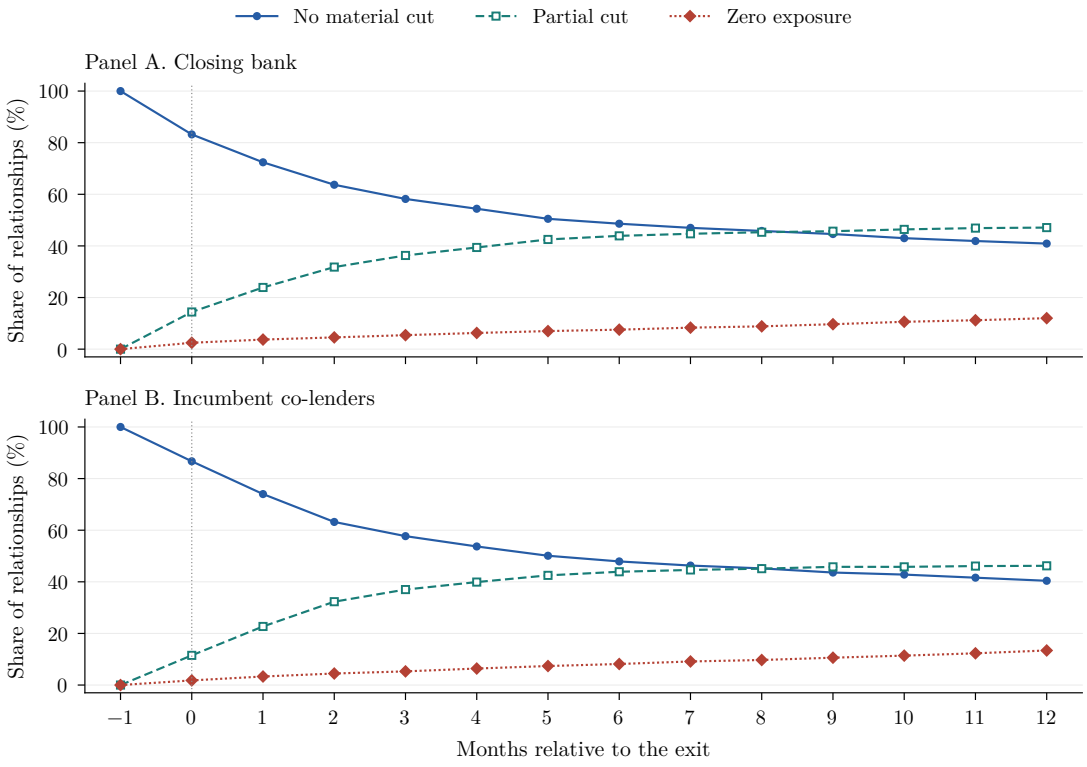


Figure 5. Co-Lenders' Credit to Affected Relative to Comparison Firms

This figure plots the coefficients β_k and their 95 percent confidence intervals from the regression of equation (8),

$$Credit_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the panel of the co-lenders' relationships from $T_e - 12$ to $T_e + 12$. $Credit_{ibet}$ is co-lender b's credit to firm i in month t of event e, in thousands of euros, winsorized at the 1st and 99th percentiles of its pre-exit distribution. $Treated_i$ equals one for affected firms and zero for comparison firms. α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect, so that β_k is the change since $T_e - 1$ in the co-lender's credit to affected firms minus the change in its credit to comparison firms in the same exit and month. Panel A: basic sample. Panel B: matched sample, in which comparison firms also borrow from a third bank and are matched to affected firms on industry and total assets. Standard errors are clustered by exit.

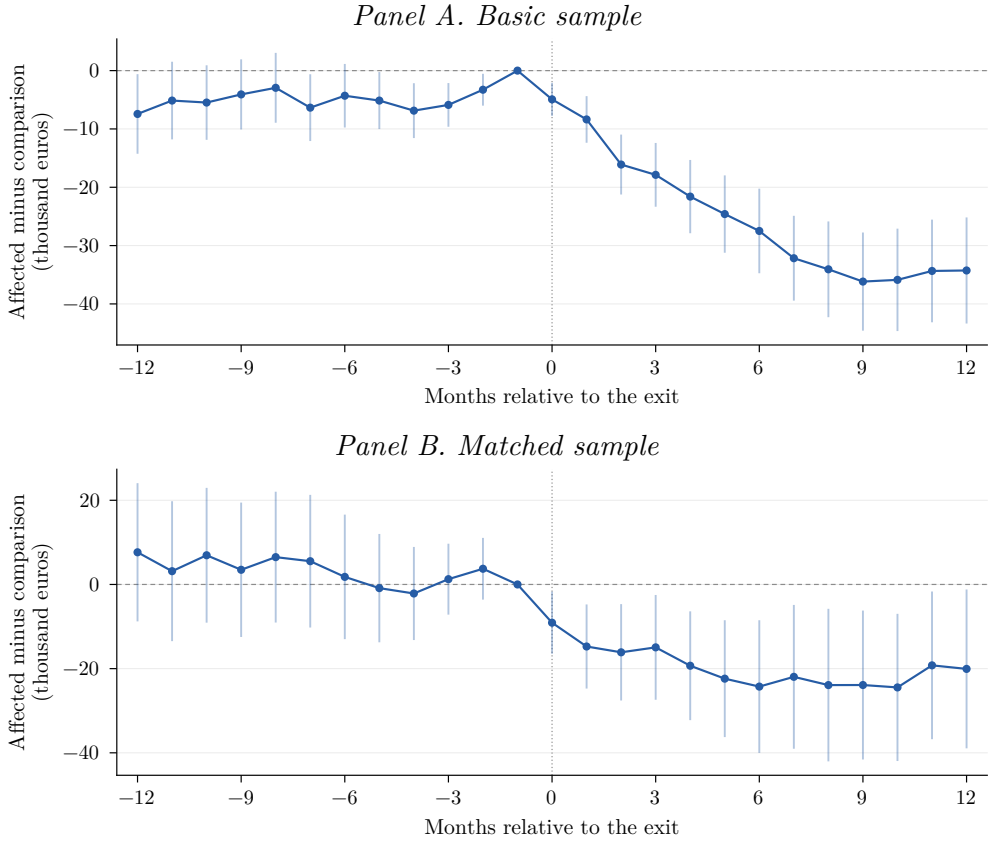


Figure 6. Co-Lenders' Credit to Affected Relative to Comparison Firms, in Percent

This figure plots the coefficients β_k and their 95 percent confidence intervals from equation (8) with the co-lender's credit in percent of the relationship's own level before the exit as the outcome, equation (2),

$$Credit^{\%}_{ibet} = 100 \times \frac{Credit_{ibet}}{Credit_{ibe,T_e-1}},$$

where $Credit_{ibe,T_e-1}$ is the same relationship's credit at $T_e - 1$, with credit winsorized as in Figure 5, on the panel of the co-lenders' relationships from $T_e - 12$ to $T_e + 12$. Each coefficient is the average change in credit to affected firms since $T_e - 1$ minus the average change in credit to comparison firms, each in percent of the relationship's own credit before the exit. Because every relationship is measured against its own level and counts equally, the larger size of affected relationships does not drive the comparison. Panel A: basic sample. Panel B: matched sample. Standard errors are clustered by exit.

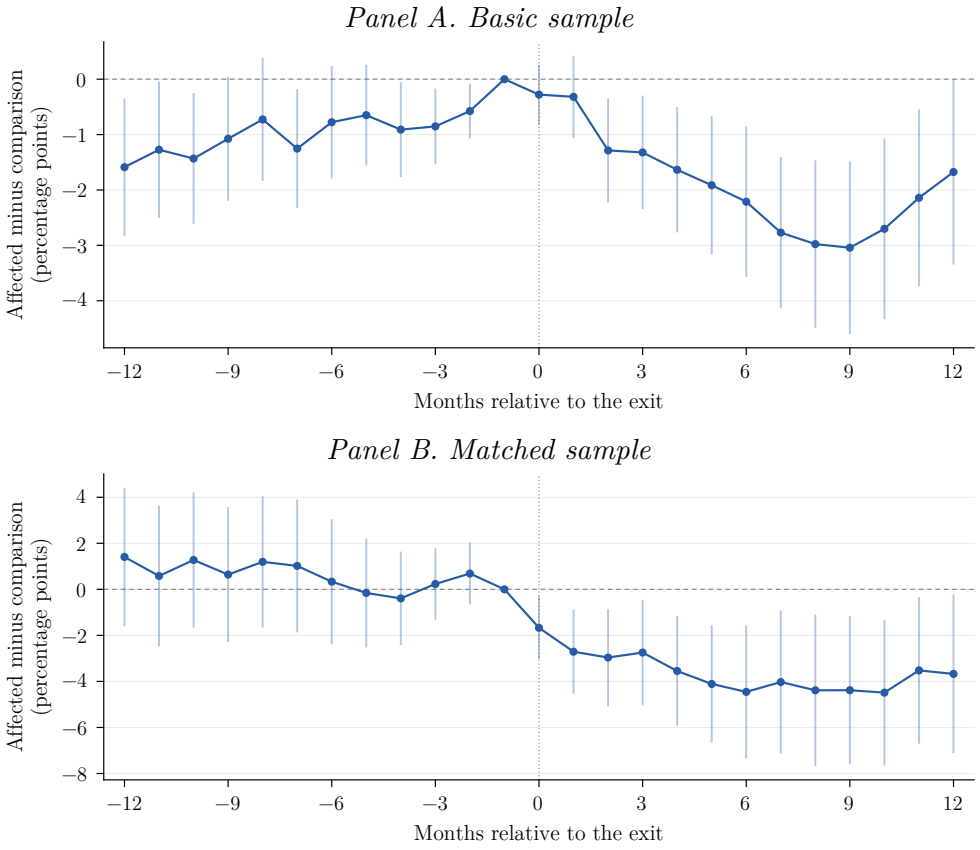


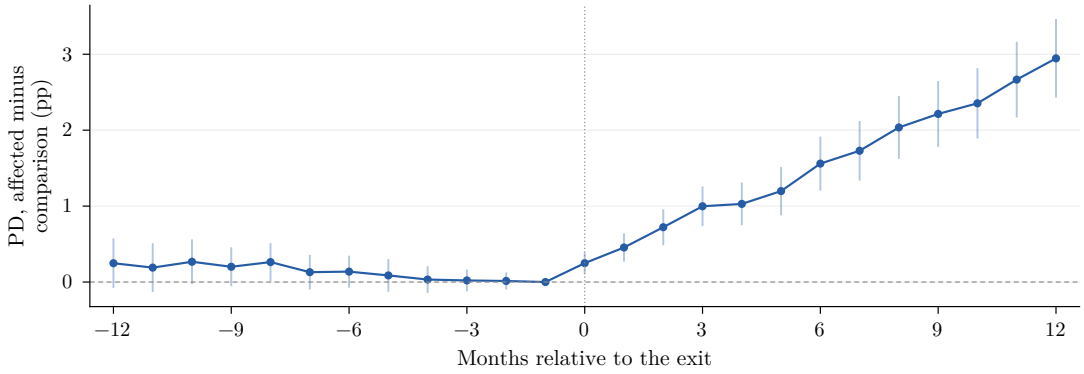
Figure 7. Co-Lenders' Assessments of Affected Firms and Their Defaults

This figure plots the coefficients β_k and their 95 percent confidence intervals from the regression of equation (8),

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the basic sample of the co-lenders' relationships in the months in which the co-lender reports for both its affected and its comparison firms. In Panel A, Y_{ibet} is co-lender b's reported one-year probability of default for firm i, in percentage points. In Panel B, it is an indicator, in percentage points, that the co-lender classifies firm i in default in month t. $Treated_i$ equals one for affected firms and zero for comparison firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect, so that β_k is the change since $T_e - 1$ for affected firms minus the change for comparison firms. Standard errors are clustered by exit.

Panel A. Co-lenders' PD for affected relative to comparison firms, percentage points



Panel B. Default status of affected relative to comparison firms, percentage points

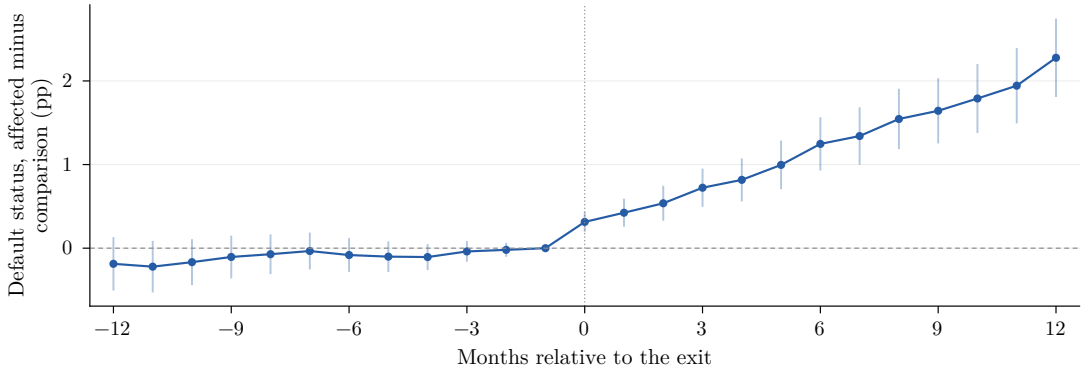


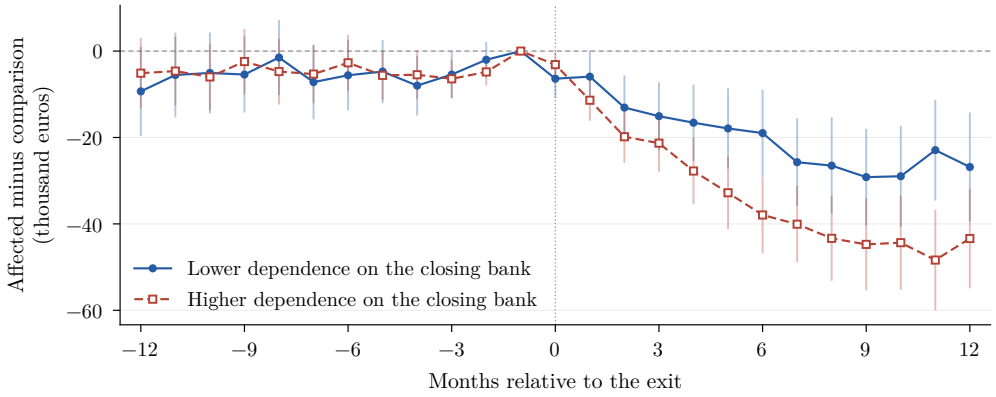
Figure 8. Co-Lenders' Response by the Affected Firms' Dependence on the Closing Bank

This figure plots the coefficients β_k (lower dependence) and $\beta_k + \delta_k$ (higher dependence) and their 95 percent confidence intervals from the regression of equation (9),

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, HighDep_{be}\right) Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the basic sample. $HighDep_{be}$ equals one if the closing bank held more than 25 percent of the credit of co-lender b's affected firms at $T_e - 1$. In Panel A, Y_{ibet} is the co-lender's credit to firm i in thousands of euros; in Panel B, its reported PD for firm i in percentage points, in the months in which it reports for both its affected and its comparison firms. $Treated_i$ equals one for affected firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Standard errors are clustered by exit.

Panel A. Co-lenders' credit to affected relative to comparison firms, thousands of euros



Panel B. Co-lenders' PD for affected relative to comparison firms, percentage points

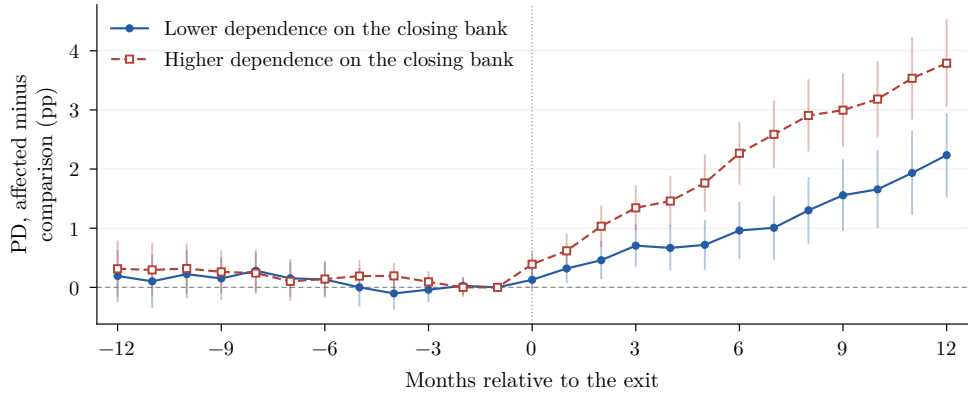


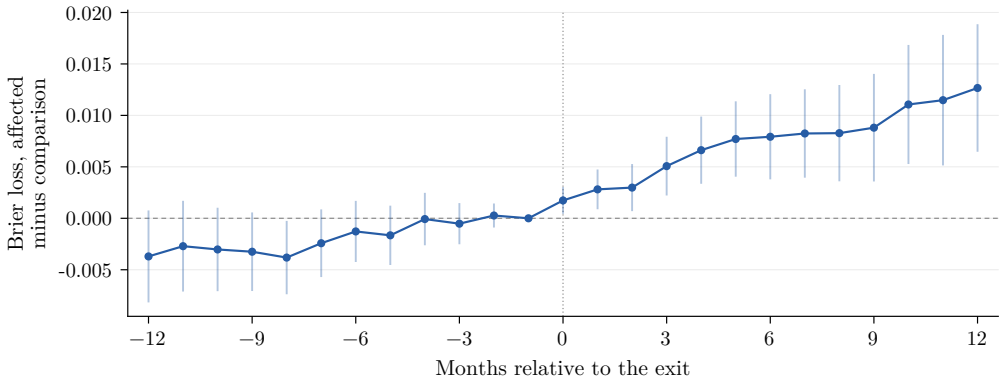
Figure 9. Accuracy of Co-Lenders' Default Forecasts for Affected Firms

Panel A plots the coefficients β_k and their 95 percent confidence intervals from the regression

$$Brier_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

where $Brier_{ibet} = (PD_{ibt} - Default^b_{i,t+1:t+12})^2$ is the squared error of co-lender b's default forecast for firm i (equation (3)), with the PD as a probability and $Default^b_{i,t+1:t+12}$ equal to one if the co-lender classifies the firm in default in any of the following twelve months, winsorized at the 1st and 99th percentiles of its pre-exit distribution. $Treated_i$ equals one for affected firms and zero for comparison firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Standard errors are clustered by exit. Panel B plots the change since $T_e - 1$ in the difference between affected and comparison firms in the co-lenders' forecast skill, $S = 1 - \overline{Brier}/[p(1-p)]$, where p is the group's observed default rate, so that $p(1-p)$ is the loss of a constant forecast at that rate. Basic sample, months in which the co-lender reports for both its affected and its comparison firms. Because the default window covers the twelve months after t, the loss in the months just before the exit already reflects defaults after it.

Panel A. Brier loss of co-lenders' forecasts for affected relative to comparison firms



Panel B. Forecast skill of co-lenders' forecasts for affected relative to comparison firms

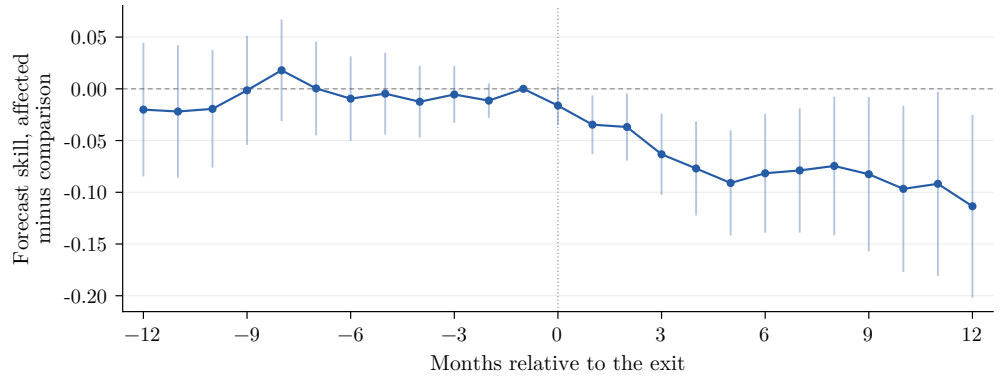


Figure 10. Accuracy of Co-Lenders' Default Forecasts for Non-Defaulting Firms

This figure plots the coefficients β_k and their 95 percent confidence intervals from the relationship-level regression

$$Brier_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the co-lenders' relationships with non-defaulting firms, defined as firms that do not default in our analysis period. $Brier_{ibet}$ is the squared error of co-lender b's default forecast for firm i (equation (3)), winsorized using the same pre-exit thresholds as in the full sample. $Treated_i$ equals one for affected firms and zero for comparison firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. The omitted month is $T_e - 1$. Panel A reports the basic sample and Panel B the matched sample, in which comparison relationships are weighted by their matching weights. Standard errors are clustered by exit.

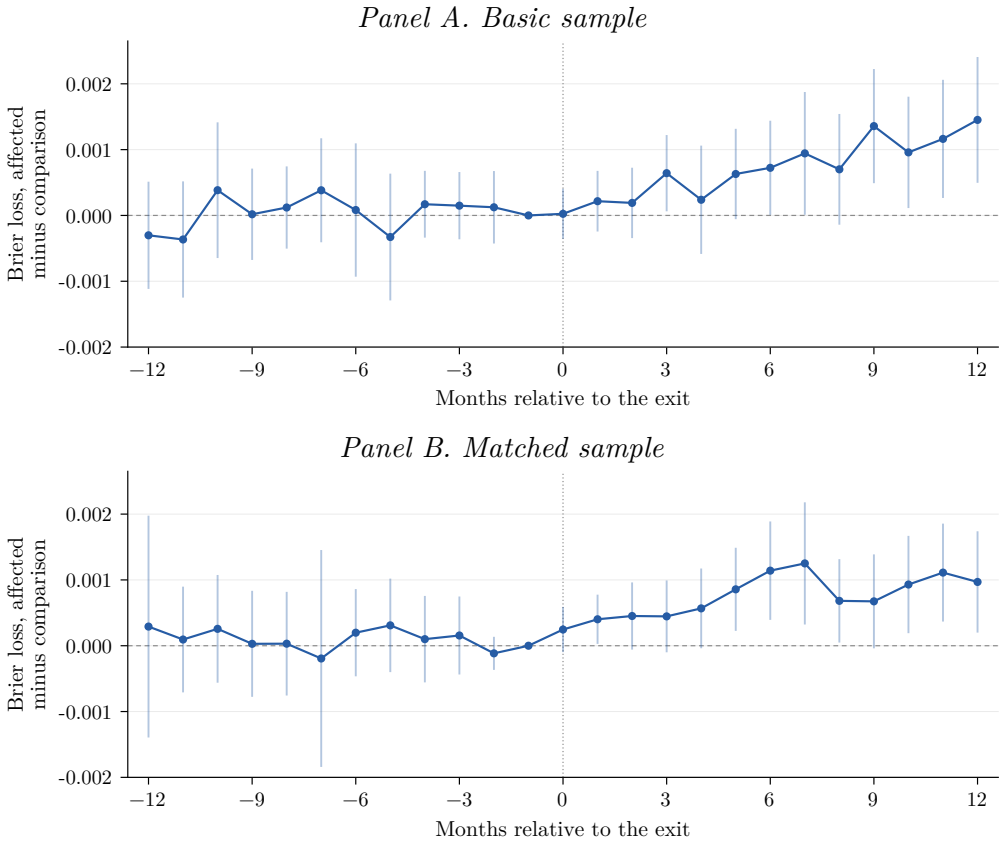


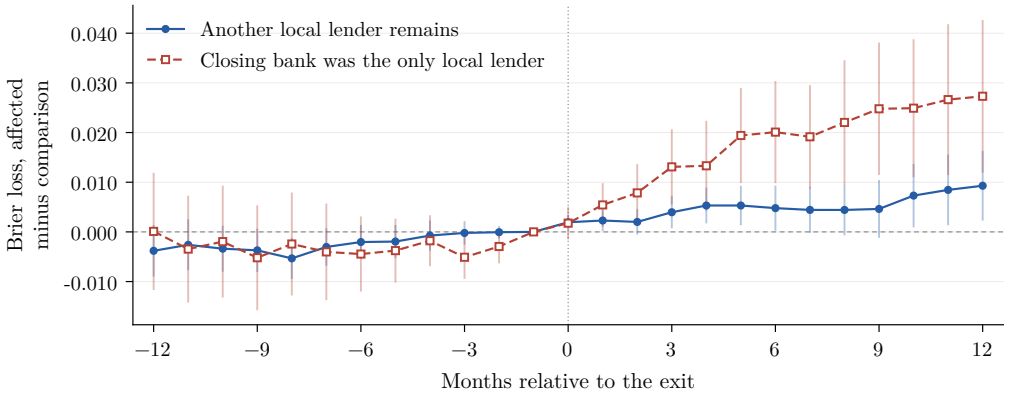
Figure 11. Co-Lenders' Response When the Closing Bank Was the Firm's Only Local Lender

This figure plots the coefficients β_k (another lender of the affected firms has a branch in the municipality) and $\beta_k + \delta_k$ (the closing bank was the only local lender) and their 95 percent confidence intervals from the regression of equation (9),

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, OnlyLocal_{be}\right) Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the basic sample. $OnlyLocal_{be}$ equals one if the closing bank was the only lender with a branch in the municipality among the lenders of co-lender b's affected firms at $T_e - 1$. In Panel A, Y_{ibet} is the Brier loss of the co-lender's default forecast for firm i, in the months in which it reports for both its affected and its comparison firms; in Panel B, its credit to firm i in thousands of euros. $Treated_i$ equals one for affected firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Standard errors are clustered by exit.

Panel A. Brier loss of co-lenders' forecasts for affected relative to comparison firms



Panel B. Co-lenders' credit to affected relative to comparison firms, thousands of euros

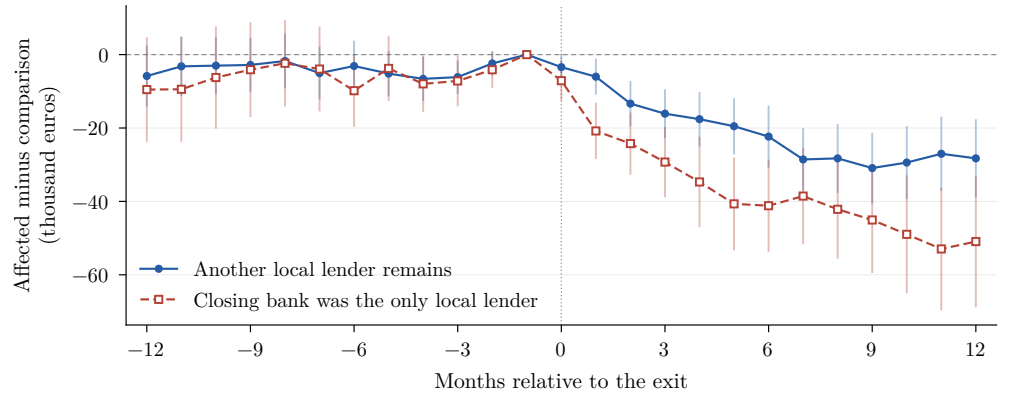


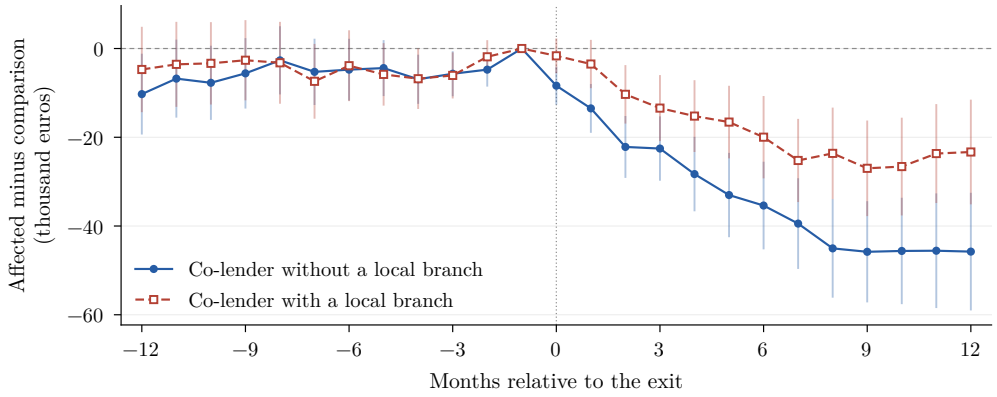
Figure 12. Co-Lenders' Response by the Co-Lender's Own Presence in the Municipality

This figure plots the coefficients β_k (co-lender with a branch in the municipality) and $\beta_k + \delta_k$ (co-lender without one) and their 95 percent confidence intervals from the regression of equation (9),

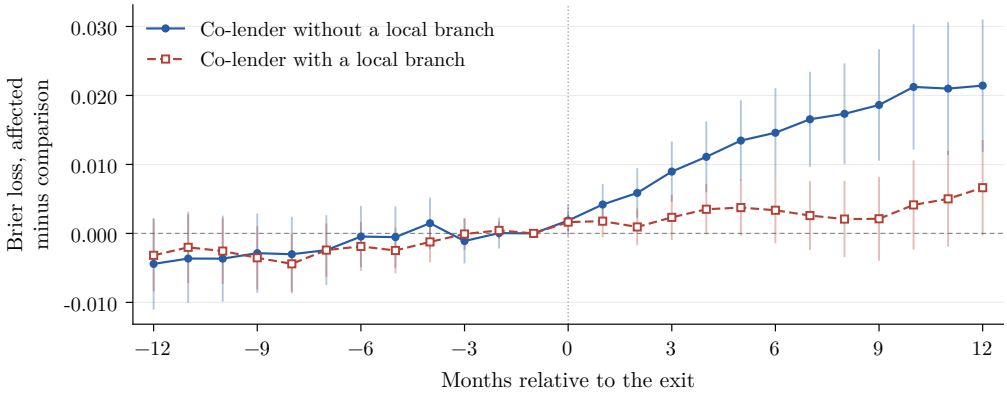
$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, NonlocalB_{be}\right) Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the basic sample. $NonlocalB_{be}$ equals one if co-lender b has no branch in the municipality at $T_e - 1$. In Panel A, Y_{ibet} is the co-lender's credit to firm i in thousands of euros; in Panel B, the Brier loss of its default forecast for firm i, in the months in which it reports for both its affected and its comparison firms. $Treated_i$ equals one for affected firms; α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Standard errors are clustered by exit.

Panel A. Co-lenders' credit to affected relative to comparison firms, thousands of euros



Panel B. Brier loss of co-lenders' forecasts for affected relative to comparison firms



Tables

Table 1. Which Banks Leave Which Municipalities, and When?

This table reports branch-level regressions of last-branch exits. Panel A estimates the linear probability model

$$Exit_{kmt} = \phi_{g(k,m,t)} + \varepsilon_{kmt}$$

on the 1.56 million bank-municipality-months in which bank k has a branch in municipality m, with one set of fixed effects g at a time; $Exit_{kmt}$ equals one if the bank closes its last branch in the municipality in month t, which happens in 0.29 percent of bank-municipality-months. The last column reports the R^2 when each month's exits are reassigned at random across the bank-municipalities at risk, averaged over ten draws, which measures the fit that the number of groups alone produces. Panel B estimates

$$Close_{jkmt} = \beta' Z_{km,t-6:t-1} + \alpha_{kt} + \gamma_{mt} + \theta' W_{jkmt} + \varepsilon_{jkmt},$$

where $Close_{jkmt}$ equals 100 if branch j, bank k's last branch in municipality m, closes in month t. $Z_{km,t-6:t-1}$ contains six-month averages of the bank's local loan book: its number of borrowers, the average PD of its local borrowers, the mean squared error of its own default forecasts, and the distance of its PDs from those of the borrowers' other lenders. W_{jkmt} contains exposure per borrower, pricing, branch age, and merger indicators. α_{kt} are bank-by-month and γ_{mt} municipality-by-month fixed effects, so that the comparison is between a bank's last branches in different municipalities in the same month. Standard errors clustered by bank are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

Panel A. Share of the variation in exits fitted by each set of fixed effects

Fixed effects	Groups	R^2	R^2, exits reassigned
Month	87	0.004	0.004
Bank	715	0.008	0.000
Region × month	1,740	0.007	0.005
Province × month	9,570	0.014	0.010
Bank × month	47,991	0.214	0.033

Panel B. Which of a bank's last branches close

	Last branch closes
Number of borrowers (per 10)	−0.033***
	(0.008)
Average borrower PD	0.265
	(0.185)
Own forecast error (mean squared error)	0.037
	(0.141)
Distance of own PDs from the other lenders' PDs	0.588
	(0.921)
Bank × month fixed effects	Yes
Municipality × month fixed effects	Yes
Within-R^2 of the local loan book	0.0004
Mean closure rate (pp)	0.30
Observations	251,137

Table 2. Summary Statistics

This table describes the data. Panel A reports the size of the analysis sample and of the two samples of the co-lender comparison. Panels B to E describe the exits, the affected firms, and the co-lenders' relationships with affected and comparison firms in the month before the exit, $T_e - 1$. Panel B covers all last-branch exits between September 2020 and November 2024 in which the closing bank has at least one borrower in the municipality in AnaCredit. Panels C to E cover the affected firms and the affected and comparison relationships that meet the sample rules at $T_e - 1$, of which the estimation samples are subsets; rows marked † use the relationships of the basic estimation sample for which the co-lender reports a PD and the firm's default status over the next twelve months is known. Monetary variables and employees are winsorized at the 1st and 99th percentiles. PDs are reported by banks that rate the firm with internal models and equal 100 percent for firms in default.

Panel A. Analysis sample and co-lender comparison

	Exits	Affected firms	Comparison firms	Affected relationships	Comparison relationships	Relationship-months
Basic	1,829	9,823	91,824	17,322	121,453	3,387,046
Matched	847	2,851	4,016	4,146	5,432	239,059

	N	Mean	SD	P10	Median	P90
Panel B. Last-branch exits						
Closing bank's borrowers in the municipality	2,124	19.5	23.2	3	12	43
Population of the municipality (thousands)	2,079	160.2	489.0	1.6	6.9	358.1
Other banks in the municipality	2,124	3.5	5.9	0	2	9
No other bank in the municipality (%)	2,124	24.4				
Panel C. Affected firms						
Revenue (€ million)	14,961	8.6	24.1	0.3	2.1	19.0
Total assets (€ million)	14,283	10.7	32.1	0.4	2.6	21.5
Employees	15,174	24.5	54.1	1	9	60
Firm age (years)	15,174	25.7	14.5	8.5	24.0	43.9
Number of lenders	15,174	3.8	2.2	2	3	7
Credit from all lenders (€ thousand)	15,174	2,233	4,074	137	755	5,637
Closing bank's share of the firm's credit (%)	17,322	26.2				
Panel D. Affected relationships: incumbent co-lender and affected firm						
Credit (€ thousand)	32,359	652	1,134	50	270	1,543
Co-lender's share of the firm's credit (%)	32,359	26.6	22.1	4.4	20.0	60.1
Co-lender's PD for the firm, if reported (%)	20,750	7.9	22.6	0.2	1.1	10.3
Default in the next twelve months (%)†	8,979	5.8				
Brier loss of the co-lender's forecast†	8,979	0.0154				
Interest rate (%)	31,750	3.67	2.39	0.85	3.46	6.72
Remaining maturity (years)	27,497	2.9	2.6	0.2	2.4	5.9
Secured share of instruments (%)	32,359	69.6	40.8	0.0	100.0	100.0
Co-lender has a branch in the municipality (%)	17,322	44.1				
Panel E. Comparison relationships: incumbent co-lender and comparison firm						
Credit (€ thousand)	219,669	419	1,058	31	115	863
Co-lender's share of the firm's credit (%)	115,331	41.0	26.0	8.9	37.5	80.0
Co-lender's PD for the firm, if reported (%)	150,950	13.5	30.6	0.2	1.3	100.0
Default in the next twelve months (%)†	62,411	10.0				
Brier loss of the co-lender's forecast†	62,411	0.0217				
Interest rate (%)	216,668	3.72	2.60	0.75	3.30	7.09
Remaining maturity (years)	187,580	3.9	3.1	0.4	3.4	8.1
Secured share of instruments (%)	219,669	80.6	34.4	0.0	100.0	100.0
Co-lender has a branch in the municipality (%)	121,453	76.4				
Comparison firm's number of lenders	170,859	1.7	1.3	1	1	3

Table 3. Co-Lenders' Credit to Affected Relative to Comparison Firms

This table reports the first-year average of the coefficients $\beta_1, \ldots, \beta_{12}$ from the regression of equation (8),

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

estimated on the co-lenders' relationships from $T_e - 12$ to $T_e + 12$. In columns 1 and 2, Y_{ibet} is co-lender b's credit to firm i in month t of event e, in thousands of euros, winsorized at the 1st and 99th percentiles of its pre-exit distribution. In columns 3 and 4, Y_{ibet} is the same credit in percent of the relationship's own credit at $T_e - 1$, $Credit^{\%}_{ibet}$ of equation (2), so that every relationship counts equally regardless of its size. $Treated_i$ equals one for affected firms and zero for comparison firms. α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect for the co-lender. Columns 1 and 3 use the basic sample and columns 2 and 4 the matched sample, in which comparison relationships are weighted by their matching weights. Observations are relationship-months. The mean of the dependent variable is the affected relationships' mean credit at $T_e - 1$ in columns 1 and 2; in columns 3 and 4 it is the comparison relationships' average first-year change in credit, in percent of their credit at $T_e - 1$. Standard errors clustered by exit are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

	Credit (€ thousand)		Credit (percent of pre-exit level)	
	(1) Basic	(2) Matched	(3) Basic	(4) Matched
Treated × *Post*	−26.91***	−20.44***	−2.00***	−3.75***
	(3.03)	(6.62)	(0.56)	(1.21)
Relationship-event FE	Yes	Yes	Yes	Yes
Bank-event-time FE	Yes	Yes	Yes	Yes
Observations	3,387,046	239,059	3,387,046	239,059
R^2	0.90	0.90	0.90	0.90
Mean of dependent variable	638	544	−4.7	−3.2

Table 4. The Borrower-Risk Channel: Co-Lenders' PDs and Dependence on the Closing Bank

This table reports the tests of the borrower-risk channel. Columns 1 and 2 report estimates of equation (8) with the co-lender's reported PD as the outcome, and columns 3 and 4 estimates of equation (9) with $G_{be} = HighDep_{be}$:

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, HighDep_{be}\right) Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

where columns 1 and 2 omit the δ_k terms. The table reports the first-year averages of β_k, the response where $G_{be} = 0$, and of δ_k, the additional response where $G_{be} = 1$; the response where $G_{be} = 1$ is their sum. Y_{ibet} is co-lender b's reported one-year probability of default for firm i in percentage points (columns 1, 2, and 4), in the months in which the co-lender reports for both its affected and its comparison firms, or its credit to firm i in thousands of euros (column 3). $Treated_i$ equals one for affected firms and zero for comparison firms. $HighDep_{be}$ equals one if the closing bank held more than 25 percent of the credit of the co-lender's affected firms at $T_e - 1$. α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Columns 1, 3, and 4 use the basic sample and column 2 the matched sample. Observations are relationship-months. The mean of the dependent variable is the affected relationships' mean at $T_e - 1$. Standard errors clustered by exit are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

	(1) PD (pp) Basic	(2) PD (pp) Matched	(3) Credit (€k)	(4) PD (pp)
			By dependence on the closing bank	
Treated × *Post*	1.66***	0.73***	−20.64***	1.13***
	(0.16)	(0.26)	(4.11)	(0.22)
Treated × *Post* × *HighDep*			−13.97***	1.16***
			(5.08)	(0.32)
Relationship-event FE	Yes	Yes	Yes	Yes
Bank-event-time FE	Yes	Yes	Yes	Yes
Observations	2,051,613	148,821	3,387,046	2,051,613
R^2	0.77	0.77	0.90	0.77
Mean of dependent variable	7.3	6.7	638	7.3

Table 5. The Information Channel: Forecast Accuracy and the Firm's Only Local Lender

This table reports the information-channel tests. Columns 1 and 2 report estimates of equation (8) with the Brier loss of equation (3) as the outcome, and columns 3 and 4 estimates of equation (9) with $G_{be} = \mathit{OnlyLocal}_{be}$:

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, \mathit{OnlyLocal}_{be}\right) \mathit{Treated}_i \times \mathit{Event}_{t-T_e=k} + \varepsilon_{ibet},$$

where columns 1 and 2 omit the δ_k terms. The table reports the first-year averages of β_k, the response where $G_{be} = 0$, and of δ_k, the additional response where $G_{be} = 1$; the response where $G_{be} = 1$ is their sum. Y_{ibet} is the Brier loss of co-lender b's default forecast for firm i, $(PD_{ibt} - \mathit{Default}^{b}_{i,t+1:t+12})^2$, winsorized at the 1st and 99th percentiles of its pre-exit distribution, in the months in which the co-lender reports for both its affected and its comparison firms (columns 1, 2, and 4), or its credit to firm i in thousands of euros (column 3). $\mathit{OnlyLocal}_{be}$ equals one if the closing bank was the only lender with a branch in the municipality among the lenders of the co-lender's affected firms at $T_e - 1$. α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. Columns 1, 3, and 4 use the basic sample and column 2 the matched sample. Observations are relationship-months. The mean of the dependent variable is the affected relationships' mean at $T_e - 1$. Standard errors clustered by exit are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

	(1) Brier loss Basic	(2) Brier loss Matched	(3) Credit (€k) Closing bank only local lender?	(4) Brier loss
Treated × *Post*	0.0078***	0.0085***	−22.28***	0.0052***
	(0.0018)	(0.0027)	(3.50)	(0.0020)
Treated × *Post* × *OnlyLocal*			−16.85**	0.0135***
			(6.56)	(0.0049)
Relationship-event FE	Yes	Yes	Yes	Yes
Bank-event-time FE	Yes	Yes	Yes	Yes
Observations	1,647,647	123,718	3,122,391	1,531,365
R^2	0.83	0.85	0.90	0.83
Mean of dependent variable	0.0147	0.0097	642	0.0152

Table 6. Co-Lenders' Response by Their Own Presence in the Municipality

This table reports estimates of equation (9) with $G_{be} = NonlocalB_{be}$,

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \left(\beta_k + \delta_k \, NonlocalB_{be}\right) Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

where $NonlocalB_{be}$ equals one if co-lender b has no branch in the municipality at $T_e - 1$, α_{ibe} is a relationship-event fixed effect, and λ_{bet} is a bank-event-time fixed effect. The table reports the first-year averages of β_k, the response of local co-lenders, and of δ_k, the additional response of nonlocal co-lenders; the response of nonlocal co-lenders is their sum. Y_{ibet} is the co-lender's credit to firm i in thousands of euros (columns 1 and 3) or the Brier loss of its default forecast (columns 2 and 4). Columns 1 and 2 use the basic sample and columns 3 and 4 the matched sample. Observations are relationship-months. The mean of the dependent variable is the affected relationships' mean at $T_e - 1$. Standard errors clustered by exit are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

	(1)	(2)	(3)	(4)
	Credit (€k)	Brier loss	Credit (€k)	Brier loss
	Basic		Matched	
Treated × *Post* (local co-lender)	−19.04***	0.0032	−6.72	0.0049
	(3.79)	(0.0020)	(8.20)	(0.0030)
Treated × *Post* × *NonlocalB*	−16.14***	0.0113***	−45.15***	0.0176***
	(5.22)	(0.0032)	(13.26)	(0.0066)
Relationship-event FE	Yes	Yes	Yes	Yes
Bank-event-time FE	Yes	Yes	Yes	Yes
Observations	3,387,046	1,647,647	239,059	123,718
R^2	0.90	0.83	0.90	0.85
Mean of dependent variable	638	0.0147	544	0.0097

Appendix

A Data and Sample Construction

A.1 Data Sources

Table A1 lists the data. The branch register identifies the exits and the local presence of every lender; AnaCredit gives the credit, the PDs, and the defaults of each lender-firm pair, and the characteristics of the firms. The two are linked through the banks' identifiers: AnaCredit identifies lenders by legal entity, and each legal entity is linked to the bank that operates the branches in the register.

Table A1. Data Sources

This table lists the data sources, their coverage, and the variables that we take from each.

Source	Coverage	Variables used
Branch register (Bank of Italy)	Every bank branch in Italy; monthly snapshots, January 2018 to December 2025	Bank operating the branch, address, municipality and postcode, type of office, opening and closing dates. Used to identify last-branch exits, whether a co-lender has a branch in the municipality, and the number of banks in the municipality.
AnaCredit (European Central Bank and Bank of Italy)	Every loan of a euro-area bank to a legal entity whose total commitment with the bank reaches €25,000; monthly from September 2018	Outstanding and off-balance-sheet amounts, type of instrument, collateral and guarantees, interest rate, maturity; the lender's one-year PD and default status (banks with internal ratings); the firm's revenue, total assets, employees, age, and industry.
ISTAT	Italian municipalities	Municipality codes, population, and provinces.

A.2 Identifying Last-Branch Exits

A last-branch exit occurs when a bank closes its last branch in a municipality. Table A2 sets out how each kind of branch event is treated. A branch that continues under another bank is not a closure, and a closure counts as an exit only if the bank itself continues to operate after it. Because AnaCredit identifies lenders by legal entity, a co-lender that stops reporting as a separate legal entity during the event window is not observed afterwards, and its relationships leave the sample.

Table A2. Treatment of Branch Events

This table sets out how branch events in the branch register are treated in identifying last-branch exits and in following the lenders' relationships.

Event	Treatment
A bank closes a branch and keeps another branch in the municipality	Not an exit.
A bank closes its last branch in the municipality	Last-branch exit in the month of the closure, T_e.
A branch continues under another bank	Not a closure.
A branch closes in the month in which its bank stops operating as a separate bank	Not an exit.
A co-lender stops reporting as a separate legal entity during the event window	Its relationships are not observed afterwards and leave the sample.
Representative offices; institutions that do not lend to firms	Excluded.
City spanning several postcodes (42 cities, such as Rome and Milan)	Each postcode zone is treated as a separate municipality.

A.3 Relationships and Samples

Table A3 shows how the sample is built. Panel A starts from all last-branch exits in which the closing bank has a borrower in the municipality in AnaCredit and follows the closing bank's local borrowers to the affected firms of the analysis. The largest step is the requirement that the firm also borrow from another bank: a firm that borrows only from the closing bank has no co-lender whose response we could study. Requiring that both the closing bank's and the co-lender's relationships with the firm be established, so that both banks know the firm, and that their credit be observed throughout the window gives the event-study sample. An exit drops out of it when none of the closing bank's local borrowers is a small or medium-sized firm with established relationships with the closing bank and with a co-lender.

Panel B reports the samples of the co-lender comparison, which holds fixed the co-lender, the municipality, and the month. The basic sample of the comparison contains 17,322 affected and 121,453 comparison relationships.

Comparison relationships are smaller than affected relationships, and comparison firms often borrow from the co-lender alone, whereas every affected firm borrows from at least two banks. The matched sample therefore restricts comparison firms to firms that also borrow from a third bank with an established relationship, so that, like affected firms, they borrow from several banks. For each affected firm, it keeps up to three comparison firms of the same co-lender in the same exit and broad industry section (NACE section) whose average total assets before the exit are closest to the affected firm's in logs, with a ratio of total assets

between 0.5 and 2. A comparison firm can be matched to several affected firms, in which case its relationship enters with the sum of its matching weights. Matches are fixed with pre-exit data. The matched sample contains 4,146 affected and 5,432 comparison relationships in 847 exits, and Table A5 compares the matched affected and comparison firms.

Table A3. Sample Construction

This table shows how the analysis sample is built. Panel A starts from all last-branch exits in the branch register between September 2018 and November 2025 in which the closing bank has at least one borrower in the municipality in AnaCredit at $T_e - 1$, and follows the closing bank's local borrowers to the affected firms of the analysis; each row adds one requirement. The last row also requires that the closing bank's and the co-lender's credit to the firm be at least €25,000 at $T_e - 1$ and be observed from $T_e - 12$ to $T_e + 12$, which restricts it to exits between September 2020 and November 2024; it is the analysis sample. Panel B reports the samples of the co-lender comparison: established affected and comparison relationships with credit observed for both groups in every month from $T_e - 12$ to $T_e + 12$. Risk outcomes use the months in which the co-lender reports for both its affected and its comparison firms. The matched sample is a subset of the basic sample.

Panel A. From the closing bank's local borrowers to affected firms

	Exits	Firm-exits
Closing bank's local borrowers at $T_e - 1$	3,303	63,345
Small and medium-sized firms	3,245	51,505
that also borrow from another bank	3,043	29,401
with established relationships with both banks	2,298	17,905
with credit observed in every month of the window	1,829	11,902

Panel B. Co-lender comparison

	Basic	Matched
Affected relationships	17,322	4,146
Comparison relationships	121,453	5,432
Comparison relationships per affected relationship (p25 / p50 / p75)	3 / 9 / 24	1 / 3 / 5
Relationship-months, credit	3,387,046	239,059
Relationship-months, PD	2,051,613	148,821
Relationship-months, Brier loss	1,647,647	123,718

A.4 Variables

Table A4 defines the variables.

A.5 Estimation

All regressions are estimated on the relationship-level panel of stacked exits. Each observation is a relationship between a co-lender and a firm in month t of an exit window, from $T_e - 12$ to $T_e + 12$. Equations (8) and (9) include a relationship-event fixed effect and a bank-event-

Table A4. Variable Definitions

This table defines the variables used in the analysis. T_e is the month of exit e.

Variable	Definition
Last-branch exit	A bank closes its last branch in a municipality (in the 42 cities that span several postcodes, a postcode zone), with the rules of Table A2. The exit month is T_e.
Affected firm	A small or medium-sized firm in the municipality with an established relationship with the closing bank.
Incumbent co-lender	Another bank with an established relationship with the affected firm that does not exit the municipality.
Comparison firm	A firm in the municipality with an established relationship with the co-lender that does not borrow from the closing bank.
Established relationship	Positive credit at $T_e - 1$, and lending by the same bank at some point between $T_e - 24$ and $T_e - 13$ (equation (5)).
Credit	Outstanding plus off-balance-sheet amount, summed over the lender's instruments with the firm, in euros (equation (1)); winsorized at the 1st and 99th percentiles of its pre-exit distribution.
Credit, percent of pre-exit level	$Credit^{\%}_{ibet} = 100 \times Credit_{ibet} / Credit_{ibe,T_e-1}$, the co-lender's credit to the firm in percent of the same relationship's credit at $T_e - 1$ (equation (2)).
PD	The lender's reported one-year probability of default for the firm, in percent; equal to 100 when the lender classifies the firm in default. Reported by banks that use internal ratings for the firm.
Default status	Equal to one if the lender reports the firm in default in month t (Article 178 of the Capital Requirements Regulation: unlikely to pay or more than 90 days past due).
Brier loss	$\left(PD_{ibt} - Default^{b}_{i,t+1:t+12}\right)^2$, with PD as a probability and $Default^{b}_{i,t+1:t+12}$ equal to one if co-lender b reports firm i in default in any of months $t+1$ to $t+12$ (equation (3)); winsorized at the 1st and 99th percentiles of its pre-exit distribution.
Forecast skill	$S = 1 - \overline{Brier}/[p(1-p)]$, where p is the group's observed default rate: one minus the loss relative to that of a constant forecast at the observed default rate (equation (4)).
Dependence, $HighDep_{be}$	One if the closing bank held more than 25 percent of the credit of the co-lender's affected firms at $T_e - 1$.
Only local lender, $OnlyLocal_{be}$	One if the closing bank was the only lender with a branch in the municipality among the lenders of the co-lender's affected firms at $T_e - 1$.
Nonlocal co-lender, $NonlocalB_{be}$	One if the co-lender has no branch in the municipality at $T_e - 1$.

time fixed effect, so that each coefficient compares the co-lender's affected and comparison relationships in the same exit and month. The tables report the first-year average of the monthly coefficients, $\bar{\beta} = \frac{1}{12}\sum_{k=1}^{12}\beta_k$, with its standard error. The number of observations is the number of relationship-months from $T_e - 12$ to $T_e + 12$ in which the outcome is observed. In the matched sample, comparison relationships are weighted by their matching weights. Credit and the Brier loss are winsorized at the 1st and 99th percentiles of their pooled pre-exit distributions, with the same caps in all samples. Standard errors are clustered by exit.

A.6 Balance of the Matched Sample

Table A5 compares affected and comparison firms in the matched sample. Matching on industry and total assets balances revenue, employees, age, the co-lender's credit and PD, and the secured share of the relationship; the gaps in total assets and remaining maturity are statistically significant but small.

Table A5. Balance of Affected and Comparison Firms in the Matched Sample

This table compares affected firms and their relationships with the co-lenders with matched comparison firms and their relationships with the same co-lenders before the exit. Comparison firms are weighted by their matching weights. The credit sample is the matched sample of Table 3, column 2; the PD sample is the matched sample of Table 4, column 2. "Compar." denotes matched comparison firms. Gap is the difference between the means of affected and comparison firms, and p is the p-value of a test that the gap is zero, with standard errors clustered by exit. In the basic sample, affected firms have mean revenue of €14.8 million, total assets of €17.2 million, and 41 employees, the co-lenders lend them €777,800 at $T_e - 1$, and the co-lenders' PD for them is 7.5 percent.

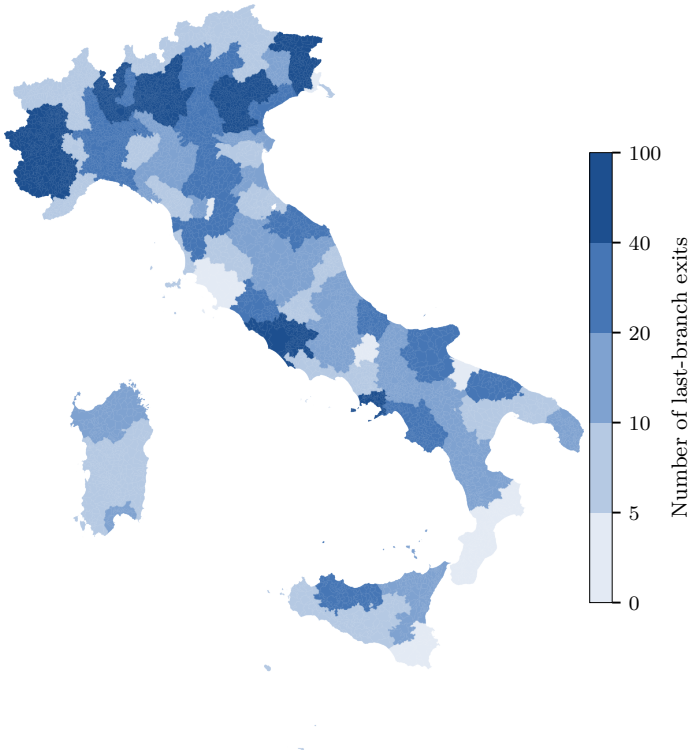
	Matched, credit sample				Matched, PD sample			
	Affected	Compar.	Gap	p	Affected	Compar.	Gap	p
Revenue (€ million)	8.71	7.84	0.87	0.409	9.00	8.70	0.30	0.475
Total assets (€ million)	7.72	7.03	0.69	<0.001	8.75	7.93	0.81	<0.001
Employees	24.92	23.60	1.31	0.223	26.69	25.86	0.83	0.410
Firm age (years)	26.65	26.58	0.07	0.862	27.29	27.23	0.06	0.893
Co-lender's credit at $T_e - 1$ (€ thousand)	552.80	545.63	7.17	0.806	635.66	631.82	3.84	0.932
Co-lender's pre-exit credit (€ thousand)	553.83	543.37	10.46	0.724	635.96	628.04	7.92	0.860
Co-lender's PD at $T_e - 1$ (%)	6.94	7.07	−0.13	0.847	6.70	6.87	−0.17	0.801
Remaining maturity (years)	2.93	3.08	−0.15	0.017	2.52	2.63	−0.11	0.109
Secured-instrument share (%)	70.79	69.82	0.97	0.256	67.80	66.34	1.45	0.179

B The Geography of Last-Branch Exits

This appendix shows where banks leave and asks whether they choose where to leave. Figure A1 maps the number of last-branch exits that we study by province, and Figure A2 scales them by the number of bank presences in each province, where a bank presence is a bank with at least one branch in a municipality. Every one of the 107 provinces has exits. The number of exits is largest in the large provinces of the north and in Rome and Naples, where banks have the most branches; scaled by bank presences, the exits are spread much more evenly. Nationally, 11 percent of bank presences end in an exit between September 2020 and November 2024, and in half of the provinces the share lies between 8 and 14 percent.

Figure A1. Number of Last-Branch Exits by Province, September 2020 to November 2024

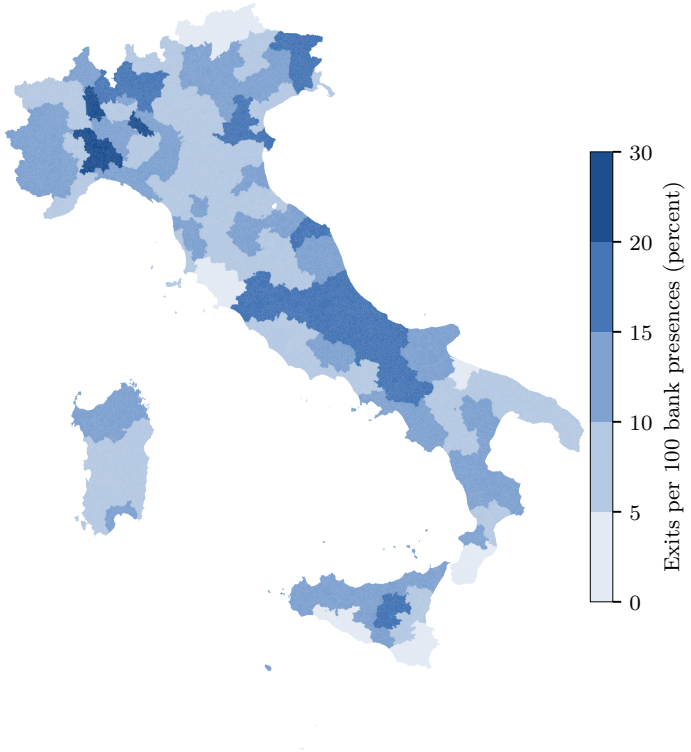
This figure maps, for each Italian province, the number of last-branch exits between September 2020 and November 2024 in which the closing bank had at least one borrower in the municipality in AnaCredit: 2,124 exits in all 107 provinces. The median province has 13 exits and the largest 100. Exits in the postcode zones of a large city are counted in the city's province. Source: Bank of Italy branch register, AnaCredit, and ISTAT.



Do banks pick where to leave? Banks close branches in programs that run across their whole networks. A wave of ten or more exits by the same bank in the same month, which together account for 1,617 of the 2,124 exits, reaches a median of 10 regions and 18 provinces.

Figure A2. Last-Branch Exits as a Share of Bank Presences, by Province

This figure maps, for each Italian province, the number of last-branch exits of Figure A1 divided by the number of bank presences in the province at the end of August 2020, in percent. A bank presence is a bank with at least one branch in a municipality (in the 42 cities that span several postcodes, a postcode zone); representative offices and institutions that do not lend to firms are excluded. The map covers 2,124 exits and 18,792 bank presences. The province shares range from 3 to 28 percent; the median is 10 percent. Source: Bank of Italy branch register, AnaCredit, and ISTAT.

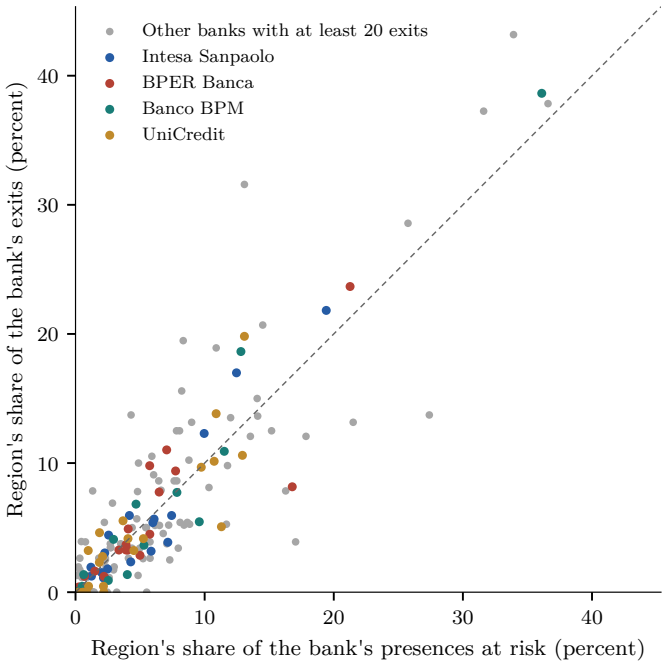


Banco BPM's wave of May 2021 closed its last branch in 179 municipalities in 12 regions and 45 provinces, and Intesa Sanpaolo's wave of October 2024 in 172 municipalities in 18 regions and 69 provinces.

To ask whether banks choose where to leave, we compare where each bank's exits occur with where the bank had branches when it decided to close them. For each wave, the bank's presences at risk are its presences at the end of the month before the wave. If the bank picked the municipalities of a wave at random among its presences, the share of the wave's exits in each region would equal, in expectation, that region's share of the bank's presences at risk. Summing over a bank's waves gives, for each region, the share of the bank's exits that random choice would put there. Figure A3 plots, for each bank with at least 20 exits and each region, the region's actual share of the bank's exits against this benchmark. The points lie close to the 45-degree line: across banks and regions, the correlation between the two shares is 0.90. Each bank's exits follow the geography of its own network.

Figure A3. Regional Distribution of Each Bank's Exits and of Its Branches

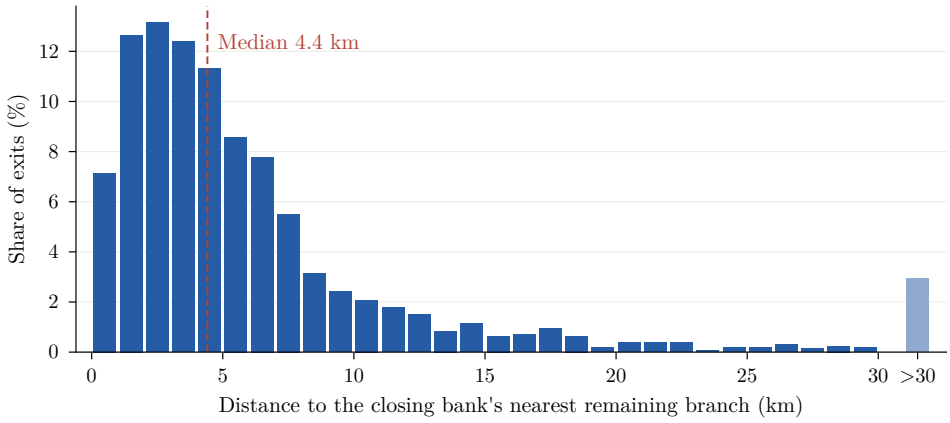
This figure plots, for each bank with at least 20 last-branch exits between September 2020 and November 2024 and each region, the region's share of the bank's exits against the region's share of the bank's presences at risk. A bank's presences at risk for a wave of exits (all its exits in one month) are its bank-municipality presences at the end of the previous month; the expected share sums each wave's number of exits times the region's share of the presences at risk, over the bank's waves. The dashed line is the 45-degree line. The four banks with the most exits are shown in color. Banco di Sardegna, whose presences and exits are almost all in Sardinia, is not shown. Source: Bank of Italy branch register.



Distance to the closing bank's nearest branch. Figure A4 shows how far the closing bank's nearest remaining branch is from the branch it closes. The median exit leaves the bank's nearest branch 4.4 kilometers away, and in 16 percent of exits more than 10 kilometers away.

Figure A4. Distance to the Closing Bank's Nearest Remaining Branch

This figure plots the distribution of the distance between the closing branch and the closing bank's nearest remaining branch, for the 2,124 last-branch exits between September 2020 and November 2024 in which the closing bank had at least one borrower in the municipality in AnaCredit. The distance is the great-circle distance to the nearest geocoded branch of the same bank that is open in the month of the exit and does not itself close that month; for exits that close several branches, the distances are averaged. It is measured for 2,016 exits; for the others, the branches lack coordinates or the bank keeps no other branch. Bars show the share of exits in one-kilometer bins; the last bar pools distances above 30 km. The median is 4.4 km, the 25th and 75th percentiles are 2.4 and 7.3 km, 57 percent of the exits are within 5 km, 16 percent are more than 10 km away, and 5.5 percent more than 20 km. Source: Bank of Italy branch register.



C Splitting the Co-Lender Cut

This appendix shows how the split of Section 5.3 follows from the estimates in Tables 3 and 6, and how it changes when either of its two assumptions fails.

The average cut as a weighted average. Table 3 estimates the average co-lender cut $\bar{\beta}$ over all co-lender-exit pairs. Table 6 estimates the cut $\bar{\beta}_L$ at local co-lenders and the additional cut $\bar{\delta}$ at nonlocal co-lenders, so that nonlocal co-lenders cut $\bar{\beta}_N = \bar{\beta}_L + \bar{\delta}$. Both fixed effects of equation (8) are specific to a co-lender and an exit, and so is the indicator $NonlocalB_{be}$. Each co-lender-exit pair therefore enters $\bar{\beta}$ in proportion to its identifying variation, the variation of $Treated_i \times Post_t$ that remains after the fixed effects are removed, and $\bar{\beta}$ is a weighted average of the two group estimates,

$$\bar{\beta} = s_L\,\bar{\beta}_L + (1 - s_L)\,\bar{\beta}_N, \qquad s_L = \frac{\sum_{ibet}(1 - NonlocalB_{be})\,\tilde{Z}^2_{ibet}}{\sum_{ibet}\tilde{Z}^2_{ibet}},$$

where $\tilde{Z}_{ibet}$ is $Treated_i \times Post_t$ after removing the fixed effects. The weight s_L is 0.512 in the basic sample and 0.696 in the matched sample. It differs from the local co-lenders' share of affected relationships, 44 and 67 percent, because a pair contributes more variation the more balanced its numbers of affected and comparison relationships are. With these weights, the group estimates reproduce the average cut up to rounding: $0.512 \times (-19.04) + 0.488 \times (-35.18) = -26.92$ in the basic sample, against -26.91 in Table 3, and $0.696 \times (-6.72) + 0.304 \times (-51.87) = -20.45$ in the matched sample, against -20.44.

The two channels. Each group's cut is the sum of a borrower-risk part and an information part, $\bar{\beta}_L = F_L + I_L$ and $\bar{\beta}_N = F_N + I_N$. Under A1, local co-lenders lose no information, $I_L = 0$, and under A2, the borrower-risk part is the same euro amount in both groups, $F_L = F_N$. The additional cut at nonlocal co-lenders is then their information part, $\bar{\delta} = I_N$, and equation (11) attributes to the information channel the share of it that enters the average cut, $(1 - s_L)\,\bar{\delta}$. This is -7.87 thousand euros, or 29 percent of the average cut, in the basic sample and -13.71 thousand euros, or 67 percent, in the matched sample. Because $\bar{\delta}$ is estimated directly in Table 6, the confidence interval of the information channel is $1 - s_L$ times that of $\bar{\delta}$, taking s_L as given: from -12.9 to -2.9 thousand euros in the basic sample and from -21.6 to -5.8 in the matched sample. The borrower-risk channel is the rest of the average cut, $\bar{\beta}_L$.

If local co-lenders also lose information. A1 fails if the exit also costs local co-lenders some information, $I_L < 0$. Their cut then contains an information part, so $\bar{\beta}_L$ overstates the

borrower-risk channel and the information share is larger than the split gives. Column 2 of Table 6 suggests that this part is small: the Brier loss of local co-lenders' forecasts rises by an insignificant 0.0032 relative to comparison firms, against 0.0145 at nonlocal co-lenders.

If the borrower-risk channel differs between the two groups. A2 fails if the borrower-risk channel removes more euros from the credit of nonlocal co-lenders, for example because their affected firms become riskier or because they react more strongly to the same rise in risk. Appendix Figure A8 shows that nonlocal co-lenders cut more than local ones also among affected firms with similar PDs before the exit, so the gap does not come from differences in the firms' risk before the exit. Suppose nevertheless that the borrower-risk part at nonlocal co-lenders is τ times that at local co-lenders, $F_N = \tau F_L$, with A1 maintained. The borrower-risk channel in the average cut is then $[s_L + (1 - s_L)\tau]\,\bar{\beta}_L$, and the information channel is the rest,

$$\bar{\beta} - \left[s_L + (1 - s_L)\,\tau\right]\bar{\beta}_L.$$

Table A6 reports the split for $\tau = 1$ (A2) and for $\tau = 1.5$ and 2. The information channel remains a cut as long as $\tau < (\bar{\beta}/\bar{\beta}_L - s_L)/(1 - s_L)$: about 1.8 in the basic sample and 7.7 in the matched sample. In the matched sample, the borrower-risk channel at nonlocal co-lenders would have to be almost eight times that at local co-lenders before lost information played no role.

Table A6. The Split of the Co-Lender Cut under Alternative Assumptions

This table splits the average co-lender cut, $\bar{\beta} = s_L\bar{\beta}_L + (1 - s_L)\bar{\beta}_N$, into the borrower-risk channel and the information channel, in thousands of euros. Local co-lenders lose no information (A1), and the borrower-risk channel at nonlocal co-lenders is τ times that at local co-lenders; $\tau = 1$ is A2. The responses $\bar{\beta}_L$ and $\bar{\beta}_N$ are those of Table 6, columns 1 and 3, and s_L is the local co-lenders' share of the identifying variation. Under A2, the 95 percent confidence interval of the information channel, in brackets, is $1 - s_L$ times that of the additional cut at nonlocal co-lenders in Table 6.

τ	Borrower-risk channel	Information channel	Information share
Basic sample: $\bar{\beta} = -26.91$, $s_L = 0.512$			
1	−19.04	−7.87	29%
		[−12.9, −2.9]	
1.5	−23.68	−3.23	12%
2	−28.32	+1.41	−5%
Matched sample: $\bar{\beta} = -20.44$, $s_L = 0.696$			
1	−6.72	−13.71	67%
		[−21.6, −5.8]	
1.5	−7.74	−12.69	62%
2	−8.77	−11.67	57%

Why the split is in euros. A2 is a statement about euros: if the firm becomes equally riskier for both types of co-lender, the borrower-risk channel removes the same euro amount from their credit. In percent of each co-lender's credit, the same euro amount is larger for the smaller credit lines of nonlocal co-lenders, so A2 does not carry over to percentage changes. The same algebra applied to the percentage change of credit gives information shares of 152 percent in the basic sample and 43 percent in the matched sample, and we report the split in euros.

D Additional Results

D.1 Co-Lenders' Credit

Figure A5. Exits in Which the Closing Bank Had More than 50 Local Borrowers

This figure plots the coefficients β_k and their 95 percent confidence intervals from equation (8),

$$Credit_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

in thousands of euros, estimated on the exits in which the closing bank had more than 50 borrowers in the municipality before the exit. α_{ibe} is a relationship-event fixed effect and λ_{bet} a bank-event-time fixed effect. First-year average: −€32,910, 5.0 percent of the co-lenders' pre-exit credit to affected firms (€655,000). Standard errors are clustered by exit.

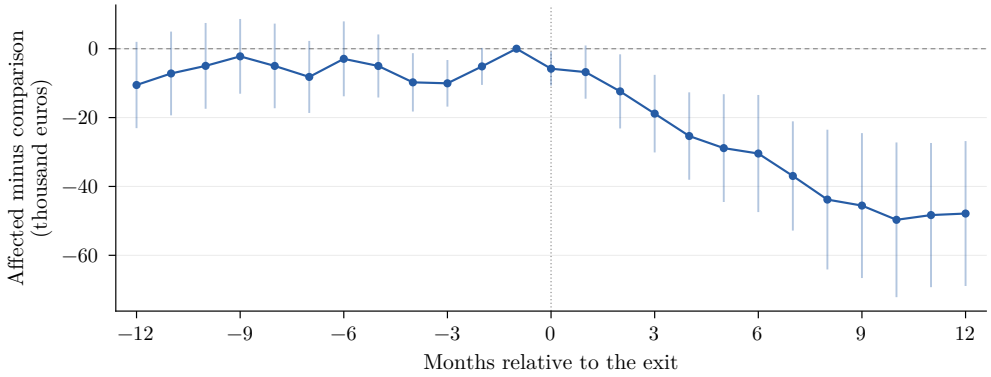


Table A7. Does the Co-Lender Cut Only When the Closing Bank Cuts?

This table relates the co-lenders' cuts to the closing bank's. Panel A groups firm-exits by the closing bank's credit to the firm at $T_e + 12$. For each group, it reports the number of firm-exits, the weighted share of co-lender relationships with a credit cut at $T_e + 12$, and the share of firm-exits in which at least one co-lender cuts credit in any month from T_e through $T_e + 12$. The relationship share weights each relationship by $1/K$, where K is the firm's number of incumbent co-lenders. Panel B reports the share of firm-exits in which each lender cuts credit first over the same window. A cut is a decline of more than 5 percent from the lender's credit to the firm at $T_e - 1$ and can reflect ordinary amortization. Both panels use the event-study sample.

Panel A. Co-lender cuts by the closing bank's credit at $T_e + 12$

Closing bank at $T_e + 12$	Firm-exits	Co-lender relationships cut	Firms with a co-lender cut
No material cut	5,062	53.9%	70.8%
Partial cut	5,827	63.5%	77.7%
Zero exposure	1,481	63.6%	76.0%

Panel B. Who cuts first between T_e and $T_e + 12$ (share of firm-exits)

Only a co-lender cuts 17.0%; neither cuts 8.1%; the closing bank cuts first 25.7%; same month 9.3%; a co-lender cuts first 23.0%; only the closing bank cuts 16.9%.

D.2 Co-Lenders' Assessments and Forecasts

Table A8. Risk Outcomes on Relationships Reported in Every Month

This table compares the first-year averages of the monthly coefficients of equation (8),

$$Y_{ibet} = \alpha_{ibe} + \lambda_{bet} + \sum_{k \neq -1} \beta_k \, Treated_i \times Event_{t-T_e=k} + \varepsilon_{ibet},$$

across two samples of reports. "Months with a report" uses the months in which the co-lender reports for both its affected and its comparison firms, as in the main estimates. "Reported in every month" keeps only relationships for which the co-lender reports in every month from $T_e - 12$ to $T_e + 12$. The outcomes are the Brier loss, the co-lender's reported PD in percentage points, and an indicator, in percentage points, that the co-lender classifies the firm in default.

Sample	Outcome	Months with a report	Reported in every month
Basic	Brier loss	+0.0078	+0.0082
Basic	PD (pp)	+1.66	+1.74
Basic	Default status (pp)	+1.27	+1.29
Matched	Brier loss	+0.0085	+0.0054
Matched	PD (pp)	+0.73	+0.90
Matched	Default status (pp)	+0.34	+0.35

Figure A6. Co-Lenders' Reported PDs in the Matched Sample

This figure plots the coefficients β_k and their 95 percent confidence intervals from equation (8) with the co-lender's reported PD, in percentage points, as the outcome, estimated on the matched sample in the months in which the co-lender reports for both its affected and its comparison firms. First-year average: +0.73 points, 11 percent of the co-lenders' pre-exit PD for affected firms (6.7 percent); their PD for affected firms rises by 0.54 points and their PD for comparison firms falls by 0.19 points. Standard errors are clustered by exit.

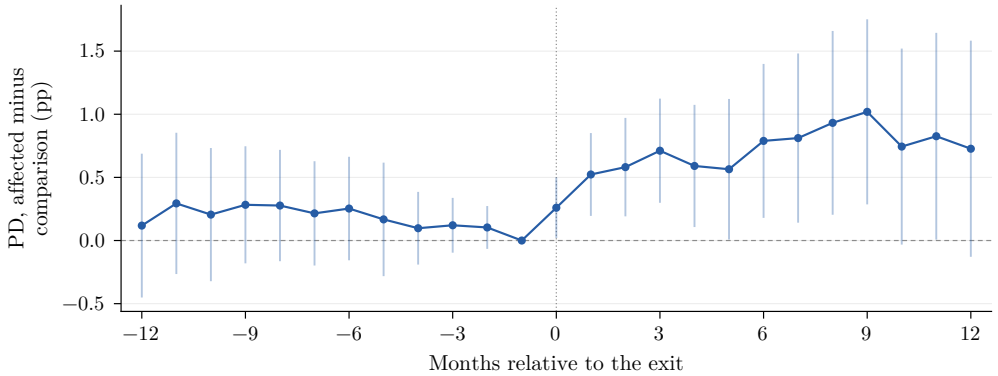


Figure A7. Closing Bank as the Only Local Lender, among Nonlocal Co-Lenders

This figure plots the coefficients of equation (9) with $G_{be} = OnlyLocal_{be}$ and the co-lender's credit to affected relative to comparison firms, in thousands of euros, as the outcome, with 95 percent confidence intervals, estimated on co-lenders without a branch in the municipality. The two lines compare exits in which another of the affected firms' lenders kept a branch in the municipality with exits in which the closing bank was the only local lender. First-year averages: −€30,290 (4.5 percent of the co-lenders' pre-exit credit to affected firms) where another local lender remained and −€39,130 (8.5 percent) where the closing bank was the only local lender, a difference of −€8,840. Standard errors are clustered by exit.

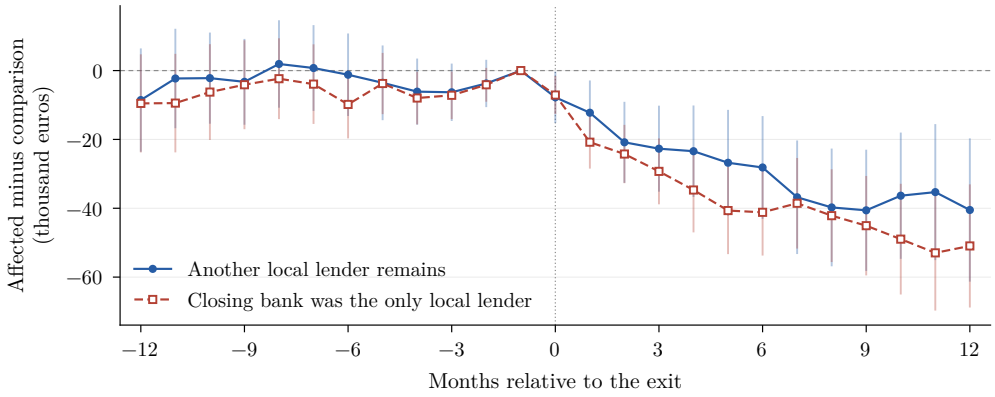


Figure A8. Local and Nonlocal Co-Lenders within Groups of Similar Borrower Risk

This figure plots the gap between the credit response of local and nonlocal co-lenders, local minus nonlocal, in thousands of euros, with 95 percent confidence intervals, within groups of affected firms defined by the co-lender's PD before the exit (fixed cutoffs), basic sample. The gaps are estimated within each group from equation (9) with $G_{be} = NonlocalB_{be}$, where $NonlocalB_{be}$ equals one if the co-lender has no branch in the municipality at $T_e - 1$. The equal-weight average of the gaps across groups is €23,110.

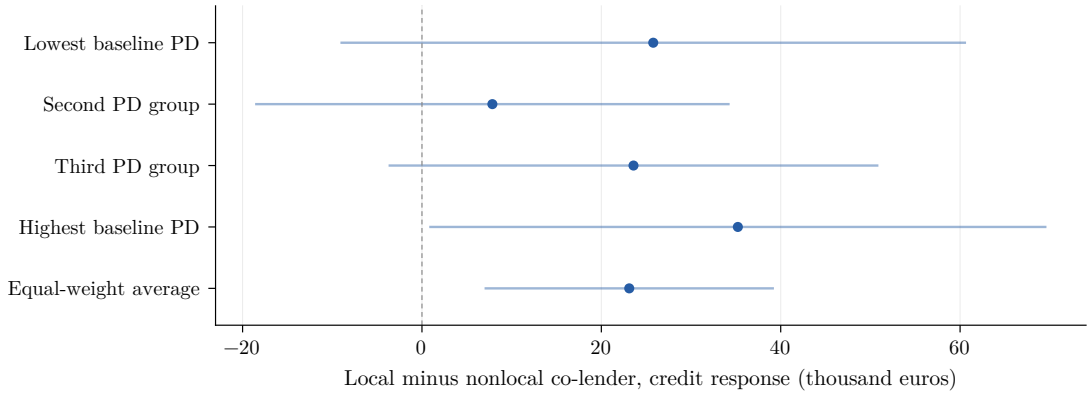


Table A9. Brier Loss, Default Rate, and Forecast Skill

This table reports, for affected and comparison relationships, the mean Brier loss of the co-lenders' default forecasts, the observed default rate p, the loss of a constant forecast at that rate, $p(1-p)$, and forecast skill $S = 1 - \overline{Brier}/[p(1-p)]$, in the month before the exit and twelve months after it. All rows use the relationships that support the $T_e + 12$ skill contrast, and the Brier loss is winsorized. These levels reproduce the $T_e + 12$ contrast and are not first-year averages. The first-year average difference in skill between affected and comparison firms is -0.077 (delta-method standard error 0.026).

Group	Month	Brier loss	Default rate (%)	Constant-forecast loss	Skill
Affected	$T_e - 1$	0.0127	5.38	0.0509	0.750
Affected	$T_e + 12$	0.0237	6.74	0.0629	0.623
Comparison	$T_e - 1$	0.0186	9.43	0.0854	0.782
Comparison	$T_e + 12$	0.0169	7.94	0.0731	0.768