Real effects of imperfect bank-firm matching *

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Abstract

We show that the characteristics of bank-firm matches affect firms' access to credit and real outcomes (investment and employment) during crises. We rely on granular, high-quality, firm-bank matched data over the period 2006-2016 from the Portuguese credit and firm registers. We identify a set of potential matches in a local credit market in pre-crisis years and estimate a model of bank-firm match formation showing that matches are more likely to form if banks are more capitalized and larger, firms have a lower probability of default, and local credit markets are less concentrated. We use this model to predict match formation in crisis times, and we identify a measure of "imperfect matches" given by the difference between realized and predicted matches. We document that in crisis times, imperfect matches lead to lower credit, investment, and employment. To address potential endogeneity of changes in bank-firm matches, we use as an instrument the banks' exposure to the EBA capital exercise. The negative effect of imperfect bank-firm matches on firm real outcomes also holds if firms keep the same number of bank relationships but change the identity of the banks with which they match.

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1 Introduction

Disruptions in credit markets have large consequences on economic activity. During the Great Depression and the Great Recession, as well as during the European sovereign debt crisis, a contraction in credit turned into a large decline in firms' investment and employment. One lesson from these extreme economic events is that relationship lending can mitigate the negative effects of a financial crisis by smoothing fluctuations in credit (Bolton, Freixas, Gambacorta and Mistrulli, 2016; Sette and Gobbi, 2015). When credit relationships terminate, the soft information dissipates and firms may struggle to start new relationships. Importantly, the new bank-firm matches may be less efficient than existing ones if the features of banks and firms matter for building bank-firm relationships. To the extent that individual bank-firm matches have different quality, substituting a bank relationship with one of lower quality may lead to restricted access to credit and lower firm growth.

This paper provides novel evidence on how the characteristics of bank-firm matches affect firms' access to credit and key real outcomes. Unlike other studies that focus on the existence or the break-up of bank-firm relationships, we study how firms and banks form matches. We explore the determinants of bank-firm matching formation in normal times, which we rely upon as a benchmark of stable bank-firm matches. We build on this foundation to develop a new index on the quality of the bank-firm matching that measures how matches in crisis times differ from those in normal times. Crucially, we explore how the matching quality index affects firms' access to credit, investment, and employment growth during the Global Financial and the Eurozone sovereign debt crises. Finally, we disentangle single and multiple banking relationships to better understand which types of firms are most affected by changes in the fundamentals of bank-firm matches.

Existing theories that identify the main determinants of bank-firm match formation, provide a useful framework for our empirical analysis. The first is the relative size of banks and firms. Bigger banks characterized by larger hierarchies may find it more difficult to monitor smaller borrowers (Stein, 2002). The second is bank capital and firm riskiness. Banks with higher capital are more likely to match with riskier and smaller firms, as they have higher incentives to monitor borrowers because of bigger skin-in-the-game (Holmstrom and Tirole, 1997). Other theories emphasize that higher leverage creates stronger incentives for monitoring (Diamond and Rajan, 2001), while models of risk-shifting (Keeley, 1990; Acharya and Naqvi, 2012) predict more frequent and stable matches between low-capital banks and risky firms. Finally, an additional potentially relevant determinant of bank-firm matches is competition in local credit markets (Allen, Carletti and Marquez, 2011).

Taking stock of these theories, our empirical approach proceeds as follows. First, relying on comprehensive microdata on the universe of loans from Portugal, we estimate a model to predict the determinants of realized bank-firm matches in the period before the global financial crisis. We find that a match between a bank and a firm is more likely to occur if the bank is large, is well capitalized, has a branch close to a firm, and the firm is less likely to default. These correlations are not causal and thus we cannot distinguish which party initiates the matching. However, they represent an important first glance at the bank and firm characteristics that are associated to the formation of bank-firm relationships. Importantly, they allow us to predict the bank-firm matching in normal times and therefore measure how existing or new matches in crisis times differ from normal times. We document that the years preceding the global financial crisis in Portugal are not characterized by excessive growth of credit based on Greenwood, Hanson, Shleifer and Sørensen (2020), and therefore represent a benchmark to evaluate the matches in a crisis.

Having the bank-firm formation as the starting point, we create an index for the quality of the bank-firm matching, which is the difference between the observed matches in the crisis period and those predicted by the model, estimated on the pre–crisis period. We document that the matching index deteriorates steadily between 2009 and 2015, and it improves somewhat afterward, without reverting to the pre–crisis levels. From a decomposition analysis, we observe that the main drivers of the evolution of the index arise from changes in bank and firm characteristics and from the termination of lending relationships, but changes in the shares of credit across banks play a limited role. Interestingly, small and midsize enterprises (SMEs), which typically suffer from borrowing constraints in crisis times, almost entirely drive the deterioration of the index.

Next, we document that the larger the difference between the observed and predicted matches (i.e, worse matching in crisis times relative to pre-crisis times), the lower the access to credit, investment, and employment at the firm-level. To address potential endogeneity concerns in match survival in crisis times, we exploit the shock created by the European Banking Authority's (EBA) capital exercise in 2011, which led selected banks to cut lending across the board, irrespective of firm characteristics (Blattner, Farinha and Rebelo, 2018; Gropp, Mosk, Ongena and Wix, 2019; Fraisse, Lé and Thesmar, 2020). This allows us to isolate exogenous variation in the supply–driven bank-firm matching quality that is is orthogonal to firm characteristics. Importantly, we document that the negative effect of deterioration in the bank-firm matching index occurs both when the number of matches falls, and when substituting banks keeps the number of relationships constant.

Our work relies on granular microdata from the Portuguese credit and firm registers. These data are ideal to study bank-firm formation, the quality of bank-firm matches, and how its changes have real effects on firms. First, the Portuguese credit registry has a very low reporting threshold, €50, which allows us to observe the entire population of bank-firm relationships. This is critical to obtain an accurate estimate of potential, observed and predicted bank-firm matches. Second, the dataset includes a large fraction of micro and small firms. These firms are heavily bank dependent–and typically cannot substitute bank credit with market financing when their access to credit worsens. Third, the Portuguese economy did not experience an unusual boom prior to the crisis, nor did it experience a housing bubble. We use the approach in Greenwood, Hanson, Shleifer and Sørensen (2020) to verify that between 2006 and 2008 Portugal was not in a credit boom (see Farinha, Spaliara and Tsoukas, 2019). This allows us to estimate predicted bank-firm match quality in pre–crisis times, which is a reasonable benchmark of how bank-firm relationships form.

Our findings contribute to several strands of the literature. Our work is most closely related to Schwert (2018) who shows, on syndicated loan data, that bank-dependent borrowers are more likely to form credit relationships with well–capitalized banks, as this allows bank–dependent firms to obtain a smoother flow of credit along the business cycle. We complement and extend these findings in several ways. We study the bank-firm matching to derive an index for the quality of the matching and analyze how the matching quality affects firms' access to credit, investment and employment growth. Importantly, we observe the whole population of borrowers and lenders from a comprehensive credit registry, which is critical to obtain a full picture of potential and realized matches, extending the evidence from syndicated loan data that typically include only large firms. We also study more broadly the drivers of match formation: capital in our set-up is one, albeit important, of several characteristics driving the creation of bank-firm matches. In this respect, we build on prior work showing that relative bank-firm size and distance affect the amount of loans, or their price, but do not look at the probability that a bank and a firm create a relationship. Small banks give SMEs better access to credit because they have a comparative advantage in producing soft information, which is a key input in lending to SMEs (Stein, 2002), while large banks in the U.S. are associated primarily with larger firms employing a transaction lending technology (Berger, Miller, Petersen, Rajan and Stein, 2005). Although our estimates aim at identifying predictors of a bank-firm match and warrant a causal interpretation only under rather strict assumptions, they are informative for theories of the drivers of bank-firm relationships.

We also contribute to the large literature on relationship lending. Several papers document that longer and stable bank-firm relationships support firms' access to credit (see for a summary Degryse, Kim and Ongena, 2009), especially in times of crises (Sette and Gobbi, 2015; Bolton, Freixas, Gambacorta and Mistrulli, 2016; Cohen, Hachem and Richardson, 2020). Our results contribute to this literature by showing that when matches break, the ensuing loss of soft information is amplified the more the new matching differs, in terms of bank-frim characteristics, from the matches prevailing in good times. This occurs also if bank-firm relationships are replaced and the total number of relationships remains constant: Credit access may be impaired depending on the quality of the new matching. Finally, even when matches are still in place, their quality may change because of changes in characteristics of banks and firms, and this affects access to credit and firm growth. Thus, the effectiveness of relationship lending in ensuring access to credit depends on the evolution of the bank and firm characteristics that matter for the quality of the match, and it is not sufficient to assess the length of the relationships or the distance between the borrower and the lender. We further contribute to the literature on relationship lending by documenting the determinants of the formation of bank-firm relationships.

Finally, the analysis of the real effects of the bank-firm match quality contributes more broadly to the literature on the real effects of financial shocks (Duchin, Ozbas and Sensoy, 2010; Cingano, Manaresi and Sette, 2016; DeJonghe, Dewachter, Mullier, Ongena and Schepens, 2020; Balduzzi, Brancati and Schiantarelli, 2018) and employment (Chodorow-Reich, 2014; Popov and Rocholl, 2018; Bentolila, Jansen, Jiménez and Ruano, 2018; Berton, Mocetti, Presbitero and Richiardi, 2018; Dwenger, Fossen and Simmler, 2020) by showing that the worsening of bank-firm matches that occurs in crises is a specific channel through which financial shocks affect credit access and impair firm growth. Moreover, we find that the real effects of worse bank-firm matches are stronger for firms with single bank relationships, which are disproportionately smaller firms. These results are related to recent work showing that small firms are more cyclical than larger firms (Crouzet and Mehrotra, 2020). Contrary to their findings, we document a potentially bigger relevance of financial frictions to explain firm growth in crisis times. Finally, our results on SMEs complement Chodorow-Reich, Darmouni, Luck and Plosser (2020), who document worse access to credit among SMEs relative to larger firms in U.S. data–and–tougher access to liquidity during the Covid-19 pandemic.

The paper is structured as follows. In section 2 we describe the empirical specifications and the estimation strategy. We present the data used in our empirical analysis in section 3. In section 4 we report the results. In section 5 we check the robustness of our findings, and we provide concluding comments in section 6.

2 Empirical specification

2.1 Bank-firm matching

As a first step, we model the determinants of the probability of a bank-firm match, as follows:

$$\begin{aligned} Prob(match_{b,f,l,t}) = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * Capital\ ratio_{b,t} \\ + \lambda_3 * HHI_{b,l,t} + \lambda_4 * Prob(default)_{f,t-1} + \alpha_0 + \epsilon_{b,f,l,t} \qquad (1) \end{aligned}$$

where the dependent variable *Match* is a dummy that takes the value one, if the bank (b) - firm (f) matching is in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. That is, there is potential matching due to firm location and the bank-branch location. Equation (1) features two main building blocks. The first involves the construction of bank-firm matches, which is key in identifying potential and observed matches. To this end, we need to define a relevant local credit market. According to existing theories and empirical evidence, geographical distance, particularly for small business, erodes banks' ability to acquire firm private (soft) information because it captures proximity to the information source in various guises. More specifically, for firms in distant locations it can be more costly to borrow because of information problems (Hauswald and Marquez, 2006) and transportation costs (Acharya, Hasan and Saunders, 2006). According to these theories, banks derive cost advantages ex-ante from being physically closer to the borrower.

From the Register of Exporters and Importers (*Registro Especial de Instituicoes*), we observe the list of bank-branches in Portugal with information about postal code and opening-closing dates for each branch. We restrict our analysis to active branches after 2006, which is the first year of our sample. Then, following Degryse and Ongena (2005) we obtain all bank-branches that operate in a four-digit post code. These represent all potential matches for firms with headquarters in the same post code.[1] Petersen and Rajan (2002) report that the distance between U.S. bank-firms increases over time, while Granja, Leuz and Rajan (2018) find a cyclical pattern in lending distances that widen in booms and shorten in downturns. However, Bonfim, Nogueira and Ongena (2021) show that the median distance between a firm and a bank in Portugal is 1.9 kilometres.

Importantly, approximately 70% of firms employ at least one bank that has branches in the same postal code, and the remaining firms are linked with bank-branches in different

[1] The first digit designates one of the nine postal regions: Lisbon (1), Estremadura e Ribatejo (2), Beira Litoral (3), Minho e Douro Litoral (4), Trás-os-Montes e Alto Douro (5), Beira Interior (6), Alentejo (7), Algarve (8), Madeira Islands, and Azores (9). The following two digits designate postal distribution centers within a region, and the fourth digit is a designated address.

post codes.[2] Next, we match these data using unique bank identifiers with credit registry data, and we geographically map the postal codes of bank-branches and firms to calculate the observed bank-firm matches.[3] Our data allow us to distinguish between potential and observed bank-firm matches, and therefore measure which bank and firm characteristics are correlated with a match realization out of the potential matches.

The second building block involves the selection of the potential drivers of bank firm matches. Prior literature highlights that the matching process depends on bank-firm size (Stein, 2002), bank capital (Holmstrom and Tirole, 1997), banking competition (Allen, Carletti and Marquez, 2011), and firms' riskiness (Keeley, 1990; Acharya and Naqvi, 2012). To capture size dependence, we use relative size and an interaction between the deciles of firm and bank size. We measure bank capital as the ratio of book equity to total assets. We include the Herfindahl-Hirschman index (HHI) of the branch concentration per bank at the four–digit post code. As for firms' riskiness, we incorporate the Banco de Portugal's estimation of the borrower's probability of default.[4] α_0 denotes different levels of time-varying and time-invariant fixed effects, and $\epsilon_{b,f,l,t}$ is a loan–level shock that captures the stochastic disturbances.

In equation (1) we are concerned with matching firms and banks, not with identifying a causal relationship from the drivers. We are mainly interested in reducing omitted-variable bias, as this might affect the predictions from the matching. The granularity of our dataset allows us to account for unobservables by including different sets of time-

[2] In unreported results for robustness, we define the relevant market at the seven-digit postcode. In doing so, we resort to a smaller geographical area compared to the four-digit postcode. Although the number of matches that we obtain is significantly smaller, the results are qualitatively unchanged.

[3] As we do not observe exactly which branch originates the loan, we aggregate all branches of a bank in a four–digit post–code, because this is our unit of analysis and final loan–approval occurs at the bank's headquarters.

[4] The Banco de Portugal calculates the probability that any given firm has a significant default episode vis-á-vis the banking system using information from the central credit register and comprehensive balance sheet data (Antunes, Goncalves and Prego, 2016). This variable measures the firm's probability of default on bank debt within a one-year horizon.

varying fixed effects (bank*year, firm*year, loan type, and location), because firms often have multiple bank relationships and lenders originate multiple loans within a year. Among these fixed effects, the bank*year and firm*year fixed effects are particularly important to control for time-varying demand and supply factors. Notably, we can compare how the coefficient of each driver of the bank-firm matching changes when we include different sets of fixed effects, indicating how each firm or bank observable characteristics correlates with unobservable characteristics.

In principle we could have used a structural model to identify the determinants of bank-firm formation. Yet, we decided to resort to a reduced-form matching model for the following reasons. First, we aim at obtaining a prediction of match quality, which can be flexibly obtained through a reduced-form approach. Second, there are potentially multiple matches between banks and firms on both sides, (i.e, both banks and firms form multiple matches). To date, there is no theory of multiple matching on both sides, which can guide us in obtaining an estimable model. Alternative approaches such as Berry, Levinsohn and Pakes (1995) require observing price data, and our data set does not include information on interest rates.

2.2 The imperfect-match index

We use the model in equation (1) in the pre-global financial crisis period (2006-2008) to predict matches out of sample in the post-crisis period.[5] This way, we can measure the extent to which matches formed in the crisis years differ from those formed in pre-crisis years, and then we can check whether this difference explains access to credit and firms' real outcomes.

[5]The crisis hit Portugal after the default of Lehman Brother which occurred in October 2008 and its effects on credit and real outcomes materialized from 2009 (Iyer, Peydro, da Rocha-Lopes and Schoar, 2013).

We construct the index through the following steps. First, we estimate equation (1) using a pre–crisis sample from 2006 until 2008 with different levels of fixed effects. Second, based on the estimated coefficients, we obtain out-of sample predicted bank-firm matches for the post–crisis period from 2009 to 2016. Finally, we take the difference between the observed and predicted matches. The difference ranges in the $[-1, 1]$ region, with larger deviations from zero to indicate a wider difference of realized matches from those prevailing in good times. As the difference approaches 1, the matching observed in crisis years is unlikely to occur in pre–crisis years. When the difference approaches -1, the matching is likely to occur in pre–crisis years, but it does not occur during the crisis. To define the index on the quality of the matching, we take the square of the difference between the realized matches and the predicted probability that the matching occurs. Hence, we interpret our match-quality index as a distance or proximity to the (predicted) bank-firm matching that would have occurred before the crisis, which we take as a benchmark for stable matches. Both positive and negative deviations from zero indicate that a match during the crisis is different from a match that would have occurred in pre-crisis times. The larger the index, the worse the match. For this reason we use the label "imperfect-match index" in the regressions.

We argue that the difference between matches in crisis times and those in normal times can affect access to credit and associated real effects. The rationale is that matches closer to those prevailing in normal times are associated with a better flow of information, improved management of the credit relationship, and other factors that alleviate lending frictions during bad times. In constructing the index, we implicitly assume that the matches estimated in the 2006-2008 period represent matches arising in a period of low financial constraints, in which both banks and firms form matches facing few constraints on their choices. Thus, these matches represent stable equilibrium matches arising in the credit market.

This is a reasonable assumption, because the pre-crisis period in Portugal is characterized by moderate economic growth (real GDP growth is 1.4% per year on average between 2004 and 2008; 1.5% between 2006 and 2008) and by the absence of a housing bubble. To support this hypothesis, we construct measures of credit booms following the approach in Greenwood, Hanson, Shleifer and Sørensen (2020). Figure 1 shows the indicator for non-financial business credit and asset prices boom[6]. The crisis period instead features a sharp contraction in GDP (-1.6% on average between 2009 and 2013, with especially large drops in 2009 and 2012 of -3.1% and -4.1%, respectively) and a strong rise in unemployment (to 16.1% in 2013, from an average of 7.5% in the five years between 2004 and 2008). Iyer, Peydro, da Rocha-Lopes and Schoar (2013) document a supply–driven drop in credit that increases credit constraints, especially for smaller and riskier firms. Finally, the absence of a household bubble in the Portuguese economy is depicted in figure 2.

2.3 Estimation of firm-level effects

In this section, we analyze the effect of the imperfect–match index on firms' real activities in the post-crisis period. To do so, we aggregate the data at the firm level.

As mentioned, the imperfect-match index is average predicted macthes minus the average realized matches across relationships, weighted by the share of credit in each relationship. In deriving the index, we saturate the empirical model from time-varying unobserved demand and supply factors (i.e., bank*year, firm*year, and location–fixed effects) and a broad range of control variables. However, determining a causal relation running from imperfect bank-firm matching to firms' decision-making poses an identification challenge

[6]The indicator signals that a country is in the "business red-zone" (i.e, it is in a period of financial over-heating), if non-financial business credit growth over the past three years is in the top quantile of the historical distribution and stock market returns over the same window are in the top tercile.

due to endogenous matching. Banks or firms may terminate matches of worse quality, thus creating a survivorship bias. In addition, the reason why a bank terminates a relationship, thus inducing a firm to seek a replacement, may correlate with firms' growth opportunities. This may be an especially relevant issue to the extent that banks with higher credit risk during good times are more likely to lend to firms with higher profit volatility (Iosifidi and Kokas, 2015). To address these concerns, we exploit an instrumental variables (IV) approach and estimate regressions of the following form:

$$Y_{f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t} \tag{2}$$

$$Imperfect\ Match_{b,f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{f,t} \tag{3}$$

where the outcome variables Y are the natural logarithm for the number of employees and tangible assets. Vector F denotes a set of firm control variables that are likely to influence firms' real decisions. First, we introduce firm size as the logarithm of the firms' real total assets. Next, we add return on assets (ROA) as a profitability indicator, which is a proxy for unlisted firms' Tobin's Q (Asker, Farre-Mensa and Ljungqvist, 2015). In addition, we control for firms' overall indebtedness using the leverage ratio, measured as long-term debt over total assets. We expect larger firms in better financial shape to be associated with higher levels of employment and tangible assets. Last, we incorporate firm and year fixed effects.

To yield exogenous variation in the imperfect-match index, we exploit variation in firms' dependence on credit from the European Banking Authority (EBA) capital exercise in October 2011. Specifically, we refer to the unexpected increase in bank capital requirements aimed at restoring confidence in the EU banking sector by ensuring that banks are adequately capitalized to mitigate unexpected losses. The EBA capital exercise was unexpectedly announced soon after the stress tests conducted in July 2011 (Mésonnier and Monks, 2015; Degryse, Karapetyan and Karmakar, 2020). This quasi-natural experiment required some banks to increase the minimum levels of the Core Tier 1 ratio to namely 9% by the end of 2011 and to 10% by the end of 2012. Banks were selected in a quasi-random fashion– based on size thresholds. Gropp, Mosk, Ongena and Wix (2019) show that banks reach the new required capital ratios by reducing their exposure to SME loans. In addition, Blattner, Farinha and Rebelo (2018) indicate that Portuguese banks involved in the capital exercise do not terminate relationships based on firm characteristics, but they cut credit across the board to meet the stringent requirements in a short time period.

We follow Gropp, Mosk, Ongena and Wix (2019) and construct an instrument using the EBA borrowing share:

$$EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}\ ,$$

where the numerator is the average amount of outstanding credit of firm f from EBA–exercised banks, and the denominator is the total amount of credit from all banks. Finally, regressions include firm and year fixed effects.

As an extension, we test for differential effects across single– versus multiple–relationship firms. It is common in the literature to disentangle the effects of single and multiple-relationship firms because the former group is less likely to switch lenders during extreme economic events. This is also borne out in our data, which we discuss below, as we show that approximately 70% of our firms rely on a single lender.

3 Data and summary statistics

3.1 Data description

We use proprietary administrative data from the Portuguese central bank containing detailed, high-quality, matched firm-bank information. We observe data on credit relationships and balance sheets for both firms and banks over the period 2006 to 2017. The dataset spans the period before and after the sovereign debt crisis and the EBA capital exercise and is made up by three main sources.

The first is the Central Credit Register (CRC) of Banco de Portugal, which includes monthly loan exposures for every firm-bank pair for 2006 to 2016. This comprehensive dataset records all commercial and industrial loans to non-financial publicly limited and limited liability companies by all banks operating in Portugal. The threshold for reporting loan information is €50; hence, the credit register records the universe of outstanding loans to corporations and individuals. It is a requirement for all financial institutions granting credit in Portugal to report all loans above 50 euros to CRC on a monthly basis. This is an appealing characteristic of the dataset for our analysis because we can effectively construct all potential matches and observe all realized matches. This database contains information about the amount of the loan and its status, namely if it is in a regular situation, renegotiated, overdue, or potential.

To match all loans with the corresponding bank-specific characteristics, we use the Monthly Financial Statistics data. This database reports balance sheet information for financial institutions operating in Portugal. The bank-level data are monthly in frequency.

Balance sheets and income statements are from the Informcao Empresarial Simplicada (IES), which covers the entire universe of Portuguese non-financial firms. The firm-level data are in annual frequency. We also use firms' probability of default computed by the

Banco de Portugal (Antunes, Goncalves and Prego, 2016).

As standard in the literature, we exclude companies that did not have complete records on our explanatory variables and firm-years with negative sales. To control for the potential influence of outliers, we remove observations in the one percent upper and lower tails of the distribution of the regression variables. Our panel includes 987,763 firm-bank observations with 512,446 firms. Finally, there are 453 banks active in the loan market.[7]

3.2 Summary statistics

Figure 3 gives a preliminary glimpse at the evolution of potential and realized matches over the sample period. The number of potential matches by postcode declines shortly after the European sovereign debt crisis in 2011 and remains low until 2017. The number of realized matches, however, drops at the same time with the sovereign debt crisis, but gradually increases after 2013.

Table 1 presents descriptive statistics about the bank-branch pairs over the sample period and their relevant post codes. We observe a modest reduction in the average number of branches after 2011. This echoes the pattern in figure 3, where we report potential and realized matches on a year-by-year basis. In addition, this dynamic pattern is in line with Bonfim, Nogueira and Ongena (2021), who document a significant number of branch closures during this period due to cost-cutting pressures. However, the number of branches for bank-post code remains relatively stable throughout the years.

Table 2 contains descriptive statistics of the variables in the empirical models. The firm-level statistics highlight that our sample includes a large fraction of SMEs.[8] The average outstanding loan is €27,300, and the average default probability within one year

[7] Our sample of banks contains "caixas agricola", which have local importance for small firms in Portugal.

[8] A large percentage of Portuguese firms are small according to the European Commission's criteria: only 1% are large and 85% are micro.

is 6%. In table 3, we delve deeper into the data by examining the distribution of the realized firm-bank matches. Interestingly, approximately 70% of the firms in our sample match with only one bank, confirming previous findings for Portugal (Farinha and Santos, 2002).[9]

4 Results

4.1 Bank-firm matches

We begin our analysis by examining the probability of bank-firm match. Table 4 shows estimates of equation (1) using different sets of fixed effects. The findings point to a strong increase in the probability of a match as banks become larger. The coefficients on all models are positive and highly statistically significant, suggesting that both small and large firms are more likely to match with a large bank. This finding is not just a mechanical effect driven by large banks having more branches. That is, we compute the set of potential matches on banks active in a given post code and we assign the same weight to all active banks in a postcode, irrespective of the number of branches they have in the area. This is a new result in the literature; previous work conjectures an advantage of small banks in lending to small firms (Berger, Miller, Petersen, Rajan and Stein, 2005). Interestingly, the result that larger banks are more likely to form matches holds when we progressively saturate the model with combinations of firm, bank, and period fixed effects, although it drops in magnitude.[10]

Moving to bank characteristics, the capital ratio is negatively related with the prob-

[9]There is variability across Europe in the prevalence of single as opposed to multiple banking. Portugal appears to be more similar to Belgium (DeJonghe, Dewachter, Mullier, Ongena and Schepens, 2020), and different from Italy, where multiple banking is more common (Detragiache, Garella and Guiso, 2000; Sette and Gobbi, 2015).

[10]Of course, the interpretation of the model with bank-firm fixed effects in column VII changes somewhat, in that the parameters estimate the effect of switches among firms or banks across size classes.

ability of matching. However, when we include bank fixed effects, the coefficient turns positive and significant. This is in line with previous studies (Schwert, 2018) suggesting that bank capital is a measure of risk–bearing capacity. Banks that are better capitalized are more likely to form credit relationships. In addition, we show that the concentration of the local credit market is negatively associated with the probability that matches form between banks and firms. This finding, which holds when we control for location fixed effects, is consistent with expectations that firms are less likely to match with banks in more concentrated markets. Access to credit in highly concentrated markets is presumably more costly–because of higher interest rates or collateral requirements.

In terms of riskiness, firms assigned a higher probability of default are less likely to form matches. Once again, this is consistent with the notion that high-risk firms have limited access to external financing and thus are more credit constrained (Jiménez, Ongena, Peydró and Saurina, 2014). Overall, the controls in the model to predict bank-firm matches that occur in normal times have the expected signs.

In principle, the determinants of matches may change if firms have a single or multiple bank relationships. We explore this issue and report results when we disentangle single relationships from multiple relationships in table 5. Column II displays estimates for the subsample of firms with single bank relationships (column I reports the baseline for convenience). For firms with single bank relationships, matches occur more frequently with large banks, irrespective of firm size. Matches are also more frequent with banks that are highly capitalized. Interestingly, local market concentration correlates positively with the probability of matching for single-bank firms. This is in line with the literature on relationship lending, showing that banks are more willing to invest in single relationships in less competitive markets because the relationship-specific investment they make in acquiring information is more likely to pay off (Boot and Thakor, 2000). As for the probability of default, it is insignificant and quantitatively small for single-bank firms.

Regarding firms with multiple bank relationships, relative size matters only for large firms, which are more likely to match with large banks. The capital ratio has a negative correlation with the probability of a match. This finding concurs with previous theoretical and empirical work that documents greater use of multiple-bank lending when banks have lower equity, firms are less profitable, and monitoring costs are high (Detragiache, Garella and Guiso, 2000).

We dig further into the baseline results to look for heterogeneous effects across firm size, which is an important dimension of the lending technology banks choose (Degryse, Kim and Ongena, 2009). Specifically, in table 6 we report results from specifications including an interaction between the dummy for small firms and bank capital and firms' probability of default. We observe that the point estimate on the interaction between small firms and bank capital is positive and significant (at the 1% level).

Bank capital is positively correlated with the probability of a match in particular for small firms, and with riskier firms, irrespective of firm size. This is important, as it suggests that stronger banks are more likely to match with riskier firms, pointing to an allocation of risk toward banks that have a higher risk–bearing capacity. These findings are consistent with Schwert (2018), who works on a very different sample of syndicated loans, that typically go to large firms, from U.S. based banks and borrowers.

4.2 Imperfect-match index

In this section we construct the index of predicted matches, conditional on the bank and firm characteristics that correlate with the probability of bank-firm formation. As discussed in sub-section 2.2, the index of imperfect matching is the difference between observed matches in the pre-crisis period and predicted matches out of sample in the subsequent years (2009-2016). Our approach is novel and enables us to classify the quality of matching consistently based on two assumptions. First, banks and firms are less constrained to formulate matches in good economic times compared to crisis times. Second, pre-crisis years are not characterized by an unusual growth in credit to non-financial firms. The former assumption is reasonable, while the latter is, overall, satisfied based on the evidence we show in sub-section 2.2. Finally, the goodness of fit of the estimated models suggests that our prediction is good, as we can explain 50% of the variation in the probability of forming a match.

Figure 4 shows the evolution of the index using the global financial crisis and the subsequent Eurozone sovereign debt crisis as the shock period. We observe that the index worsens over time, especially between 2010 and 2012, reaching a peak in 2015, before improving somewhat in 2016. In figure 5, we also break down the index for small and large firms.[11] Small (large) firms are those whose assets are in the lower (upper) quartile of the total assets distribution. Interestingly, we show that the index for large firms remains relatively stable over time, but it deteriorates for their smaller counterparts from 2010 onward.

For the purpose of the empirical analysis, we predict matches during the crisis period using estimates computed over 2006-2008.[12] In a robustness check we also estimate match formation using variables between 2006 and 2011 and predict matches out of sample from 2012 onward (see table A8).

It is important to explore the drivers of the variation in the imperfect–match index. To this aim, we use the approach in Baily, Hulten and Campbell (1992) to decompose the change in the imperfect–match index at the firm-level into four main components. The first is the contribution of the bank and firm fundamentals, (i.e, the change in the

[11] Higher index values mean larger deviation from the predicted match, and thus a worse match.

[12] Hence, the imperfect match 2009 refers to the indicator computed using parameters over 2006-2008.

predicted match) at the bank-firm level (block 1), the second is the change in the share of credit, keeping the index constant (block 2), the third is the contribution of new lending relationships (block 3), and the fourth is the contribution of the termination of existing ones (block 4). Formally:

$$
\begin{aligned}
\Delta MI_{ft} = \sum_b (MI_{f,b,t} - MI_{f,b,t-1}) * sharecredit_{f,b,t} \\
+ \sum_b MI_{f,b,t-1} * (sharecredit_{f,b,t} - sharecredit_{f,b,t-1}) \\
+ \sum_b (MI_{f,b,t} * sharecredit_{f,b,t}) \\
- \sum_b (MI_{f,b,t-1} * sharecredit_{f,b,t-1})
\end{aligned}
$$

where MI_{ft} is the matching index aggregated at the firm-level and $MI_{f,b,t}$ is the index at the bank-firm level. The first two terms are computed on relationships that are in place in consecutive periods ("incumbents"). The term $\sum_b (MI_{f,b,t} - MI_{f,b,t-1}) * sharecredit_{f,b,t}$ is the "within" component as it measures the effect of changing the characteristics of banks and firms, keeping the share of credit constant (as of time t). The term $\sum_b MI_{f,b,t-1} * (sharecredit_{f,b,t} - sharecredit_{f,b,t-1})$ is the "between" component as it measures the effect of changing the share of credit, keeping the quality of the index constant (as of time t-1). The final blocks correspond to the extensive margin. The term $\sum_b (MI_{f,b,t} * sharecredit_{f,b,t})$ captures the contribution of new relationships, which is computed for relationships in place at t ("new entrants")– but that were not in place in t-1. Finally, the term $\sum_b (MI_{f,b,t-1} * sharecredit_{f,b,t-1})$ stands for the contribution of exit, which is only for relationships in place at t-1 that are not in place in t.

Table 7 reports the contribution of each of the four components in explaining the variation in the imperfect-match index. Overall, the index changes from 0.160 in 2009 to 0.190 in 2016 (see the top panel of table 7), indicating a worsening of match quality during the crisis years (see also figure 4). Changes in the index come mainly from changes in bank and firm characteristics (block 1) and from the opening of new bank-firm relationships (block 3). The contribution of changes in the shares of credit (block 2) and of the termination of existing relationships is marginal (block 4). This suggests that new relationships opened during the crisis period are on average worse (i.e, less similar to those prevailing in normal times), than existing ones, leading to a deterioration in the index. The small contribution of the termination of existing relations suggests that the credit relationships that end during the crisis are similar to those that remain in place or are characterized by smaller shares of credit (as of 2009), leading to a marginal contribution of the termination of relationships to the overall change in the match quality index.

4.3 Matching quality and access to credit: Bank-firm evidence

Next, we explore the real effects of imperfect bank-firm matching. As a starting point, we validate the economic rationale of the matching index by analyzing how it affects the access to credit, and relationship survival at the bank-firm level. In table 8 we report estimates of a model where we regress the matching index on the outstanding loan amounts. We find evidence that the matching index negatively affects the supply of bank credit across all models. This finding is robust to including different combinations of fixed effects. In other words, higher values of the index, which imply larger deviations from the pre-crisis match, lead to a significant deterioration in credit that firms obtain during a downturn at the credit–relationship level. Importantly, this finding, at the bank-firm level does not depend on the composition of bank lending to firms, rather, it is solely affected by the characteristics of the match. Based on the reported specifications, we control for time-varying unobservable supply factors (bank*year fixed effects), demand factors (firm*year fixed effects), and more restrictive bank-firm unobserved characteristics (bank*firm fixed effects). For example, in column III of table 8, we compare the same bank lending to different firms (within variation), but we control for location and common shocks. The effect is economically significant: a one–standard–deviation deterioration in match quality is associated with a drop in credit of between 0.2 and 0.6 percentage points, depending on the specification. This is a sizable effect because it corresponds to between 1/10 and 1/4 of a standard deviation in the outstanding loan amount. This corresponds to a drop of between 263,000 and 657,000 euros.

In table 9, we examine whether and how the matching quality influences the probability of switching lenders or terminating a lending relationship. For the definition of firms switching lenders, we follow closely Ioannidou and Ongena (2010) and Bonfim, Nogueira and Ongena (2021). Specifically, we define a new credit relationship as a *switch* when we observe in the firm's credit registry a new loan from a bank with which it does not have a lending relationship during the previous twelve months. However, this does not differentiate between firms that replace banks keeping the number of lenders constant and those that add a new banking relationship. To disentangle the former group from the latter, we create *termination of lending*. This is a dummy that equals one if the bank terminates an existing relationship, and zero otherwise. Columns I to III present results for switching lenders, followed by termination of lending in columns IV to VI. The results show that higher quality matches are less likely to be associated with either a switch or an outright termination. This is a sanity check for the imperfect–match index, which indeed identifies as imperfect matches those more likely to end.

4.4 Real effects of imperfect matching

We now explore the real effects of the imperfect firm-bank matching quality. To carry out this test, we aggregate the credit registry data at the firm-year level. As mentioned, changes in the match index may be endogenous to firm or bank developments. To address this concern, we use an IV approach based on exogenous variation from the EBA capital exercise initiated in 2011 and affecting a subset of banks in Portugal. Specifically, following the strategy detailed in sub-section 2.3, we use the share of credit from capital–exercised banks over the credit from other non-affected banks (Gropp, Mosk, Ongena and Wix, 2019) as a plausible exogenous instrument for the matching index.[13] We identify banks that affected by the EBA exercise and link this information to the credit registry.[14] In this manner, we exploit only variations in the match-quality index that are due to the EBA borrowing share. The intuition is that the EBA capital exercise leads affected banks to reach the new capital requirements by reducing SMEs' lending. This reduction likely hits harder firms that are attached to EBA-affected banks. Gropp, Mosk, Ongena and Wix (2019) and Fraisse, Lé and Thesmar (2020) show that increasing capital requirements reduces bank lending.[15]

Table 10 shows the results of the IV model. The first-stage estimates in panel A are statistically significant and in line with our expectations. In particular, we show that following the EBA capital exercise the imperfect-match index deteriorates. In addition, we verify the validity and relevance of the instrument using two diagnostic tests, reported at the bottom of the table. In panel B, we show the second-stage estimates, where the

[13]The minimum Core Tier 1 ratio increased to 10% in 2012 and banks had to comply until the end of that year. At the same time, banks subject to the EBA stress tests were also subject to stricter capital requirements. These additional capital requirements were offset by curtailing lending.

[14]In Portugal, the EBA's rules affected four banking groups (containing seven banks), namely CGD, Banco BPI, BCP, and ESFG.

[15]We find consistent results in our sample. Table A9 shows that firms borrowing from EBA banks experience a lower credit growth relative to other firms.

main outcome variables are the natural logarithm of the number of employees (columns I to III) and natural logarithm of tangible assets (columns IV to VI). Given that we conduct our analysis at the firm level, we incorporate firm and year fixed effects to control for time-invariant characteristics and macroeconomic effects, respectively.[16] We run the tests on the whole sample and on sub-samples accounting for both single and multiple bank relationships.

Starting with column I, we observe that imperfect matches exert a negative and highly significant effect on firm employment. The point estimate suggests that worsening a standard deviation in the matching quality is associated with a drop in firms' employment of 0.9 percentage points, which is about 90 per cent of a standard deviation. When we split our sample to distinguish between firms with single and multiple relationships (columns II and III), we find that the former entirely drives the effect. Match quality matters for determining employment decisions of single bank firms, but firms with multiple relationships remain unaffected by changes in match quality. In the following columns of table 10, we rerun the same regressions but use firms' fixed tangible assets as the outcome variable and find that the main results persist. Specifically, a one-standard-deviation worsening in the imperfect-match index is associated with a reduction in firms' tangible assets of 2.7 percentage points, which is 1.2 times a standard deviation, again an economically significant effect.

We also estimate the model with OLS estimates. The results are in table A6 and are both quantitatively and qualitatively similar to the baseline IV estimates. We continue to find that large deviations from the perfect match are associated with declines in both employment and tangible assets. Interestingly, the OLS coefficients are somewhat larger in

[16] As the imperfect-match index is a generated fitted regressor, we alleviate possible measurement bias in the construction of the standard errors by replicating table 8 with bootstrap standard errors with 300 replications (see table A7 in the online appendix).

absolute value than the ones obtained using IV, suggesting that match quality deteriorates, especially for firms with worse investment and growth opportunities.

A key question to understand better the impact of match quality on firms' activities is the following. To what extent does a change in the total number of lenders or a substitution of banks drive the variation in match quality, keeping the number of lenders constant? In the former scenario, it would be difficult to disentangle the effect of a change in the imperfect-match index from that of a contraction in credit stemming from the termination of a credit relationship. In principle, firms may be negatively affected by the termination of credit relationships if they cannot promptly substitute them by increasing credit from other banks or by starting new relationships, which may prove difficult during economic downturns. We explore this question by estimating the same IV model on the sample of firms that switch lenders, keeping the total number of lenders constant. This is a powerful test because it allows us to examine the effect of the quality of the match controlling for the total number of credit relationships, and thus, in principle, credit availability. We show the results of this exercise in table 11. As it is evident in panel A, our instrument is valid, powerful, and in line with the first-stage results in table 10. In the second stage (panel B), the estimated coefficient on the instrumented imperfect-match index is negative and statistically significant at 1% across all specifications. The point estimates are somewhat smaller than those in the baseline models, but statistical significance in stronger in the case of investment for multiple lenders (column VI).

Focusing on the differential role of relationship lending, we show that firms with single relationships remain strongly affected. However, we also find, in contrast to table 11, a negative and significant effect on the level of employment and investment rate for firms with multiple relationships that switch to new lenders during the crisis. This finding sheds light on the real effects of switching banks during adverse economic events. For instance, Ioannidou and Ongena (2010), among others, document the loan-pricing advantage of switching lenders. We show that, in crisis times, switching lenders may come at the cost of forming a worse match, leading to lower credit access with associated negative real effects on investment and employment.

5 Robustness

We conduct a series of robustness tests for the results in the previous section. The results of these tests are summarized below but are not reported due to space constraints. They are in the online appendix.

5.1 Alternative specifications

To begin with, we check whether the results of the baseline specification hold when we modify the specification as follows. First, we estimate the models on a year-by-year basis to inspect the dynamic evolution of the point estimates; second, we remove all control variables. We report the results in tables A3 and A2, respectively. We find that our main results are confirmed.

We also examine whether our baseline results remain unchanged when we employ an additional set of fixed effects, a different estimation method, and further firm- and bank-specific variables. We re-estimate the empirical models from table 4 and report the results in table A1. Column I includes industry-location-size and year fixed effects, column II shows results from a probit model, column III clusters standard errors at the bank-firm level, column IV includes further firm characteristics, and column V incorporates additional bank characteristics. In summary, the results of the baseline model are qualitatively and quantitatively the same.

5.2 Removing Lisbon and Porto

In order to confirm that our results are not driven by how we define the geographical area of potential and realized matches, we remove Lisbon and Porto from the sample. The rationale is that these are the two largest cities in Portugal, for which the definition of postcodes at the four-digit level may yield excessively small areas. We reproduce the baseline model that predicts bank-firm matching after removing the two cities from our sample and report the estimates in table A4. Next, we run all other tests excluding Lisbon and Porto; the results are in table A5 and hold.

5.3 Examining the extensive margin

We shift our attention to an alternative dimension of firm outcomes, namely firms' survival prospects. The objective of this exercise is to establish the importance of the imperfect-match quality index on the extensive margin. Given that firm closures are a major concern during the recent financial crisis, we replicate the models from tables 10 and 11 in table A10, using the probability of default as the dependent variable. We find that the probability of default is positively associated with the imperfect-match index. Moreover, this finding is stronger for firms with single bank relationships. Hence, we conclude that the real effects of the imperfect-match index hold not only for employment and growth, but also for firms' chances of survival.

6 Conclusion

This paper studies the drivers of bank-firm matches and how changes in match characteristics affect firms' access to credit and firm growth, as measured by investment rate and employment growth. The paper defines a set of potential matches based on banks active in the local credit market where a firm is based. Next, it estimates a model to study the drivers of bank-firm matches using data from the years preceding the global financial crisis. This period is characterized by moderate credit growth and the absence of credit or housing bubbles (Greenwood et al., 2020); it can thus represent bank-firm match formation in normal times. This allows us to study how bank-firm matches in crisis times differ from model predictions and test whether these differences translate into lower credit growth, firm investment, and employment.

We find that observed matches between banks and firms are more frequent if banks are large (irrespective of firm size), bank capital is higher, the local credit market is less concentrated, and firms are less likely to default. Next, we document that in crisis times, matches that differ from predicted ones (i.e, matches that involve firms and banks with characteristics different from those that correlate with match formation in good times) are associated with lower credit growth, firm investment, and employment growth. Importantly, these findings hold controlling for the potential endogeneity of match-quality changes, and they also hold keeping the number of bank relationships constant. This indicates that the effect of imperfect matches on firm outcomes is not just due to a drop in the number of lending relationships. Our results extend the findings of the literature on relationship lending, opening up the black box of bank-firm matches. We find that the relative characteristics of banks and firms that lead to match formation matter for the efficiency of lending relationships in bad times. When matches are broken and substituted with new ones, the ensuing loss of soft information is amplified the more the new matches differ in terms of relative characteristics, from the matches prevailing in good times. Even when matches are still in place, their quality may change because of changes in characteristics of banks and firms. This affects access to credit and firm growth.

Our results are also important to understand why disruptions in credit markets have such large and pervasive effects on economic growth. Even if firms are able to substitute banks in downturns, there is a loss in terms of access to credit and firm growth, when the relative characteristics of matched banks and firms differ from those that lead to match formation in good times. Finally, our findings suggest that policy interventions targeting bank and firm characteristics that lead to stable matches in lending relationships are critical to ensure a steady flow of credit to the real economy in crises times.

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Figure 1: Business credit and asset prices growth

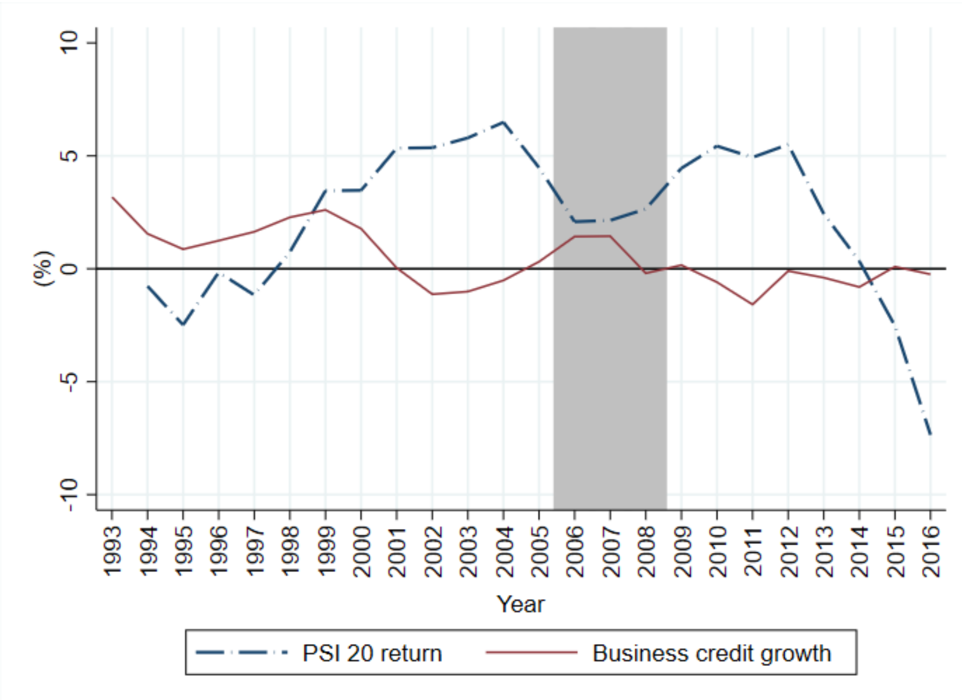


Figure 2: Household credit and household prices growth

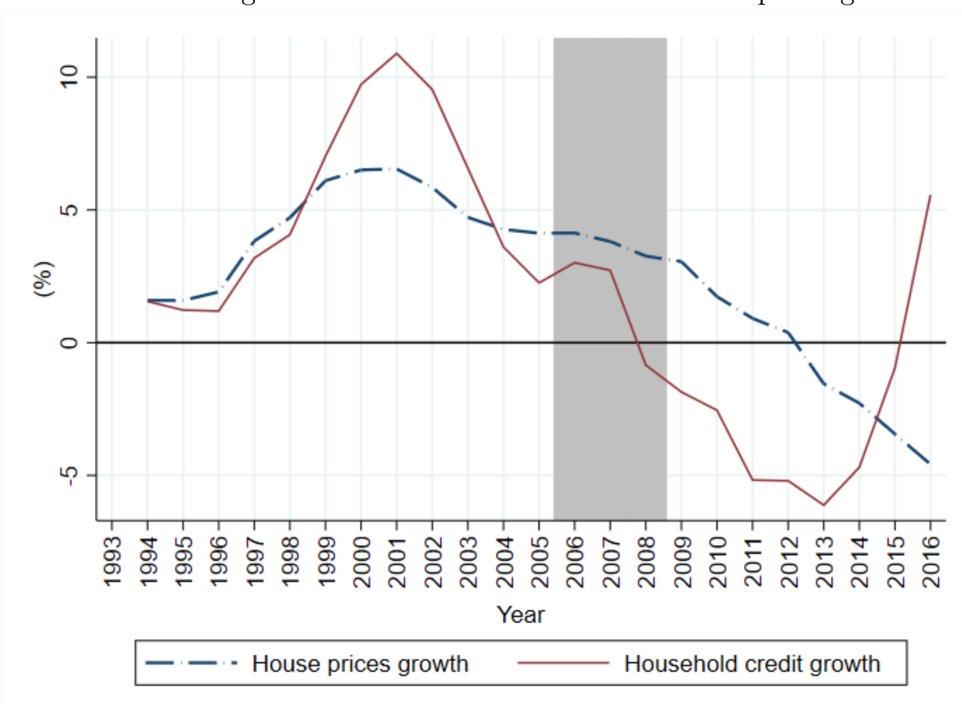


Figure 3: Realized and potential bank-firm matches

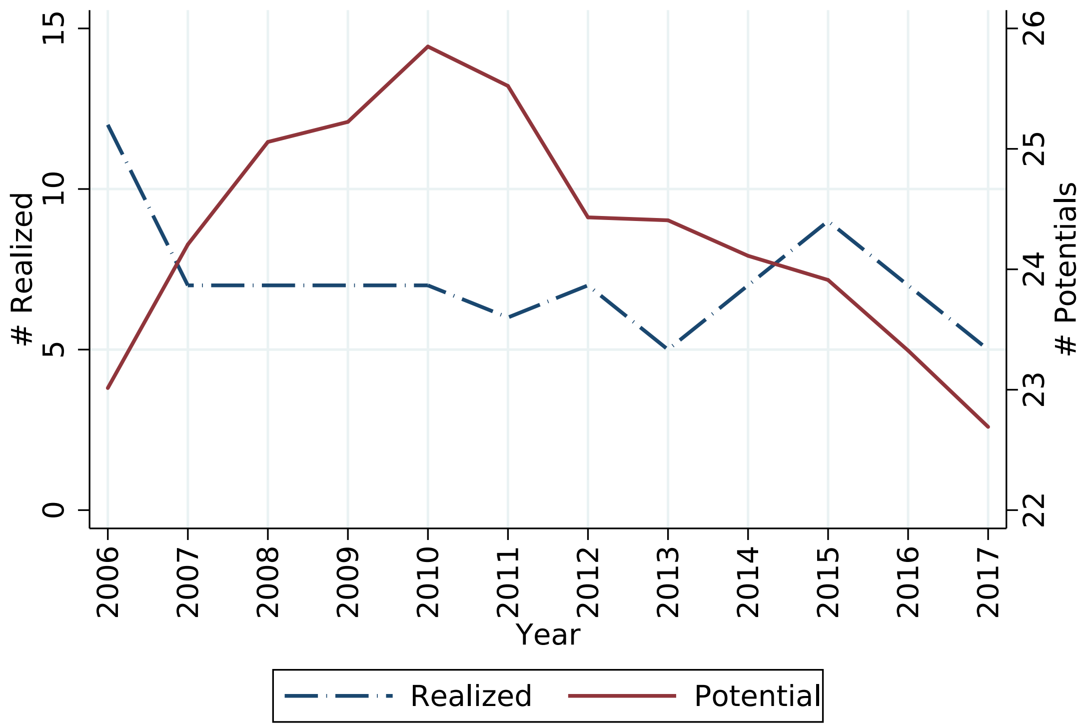


Figure 4: Imperfect-match index

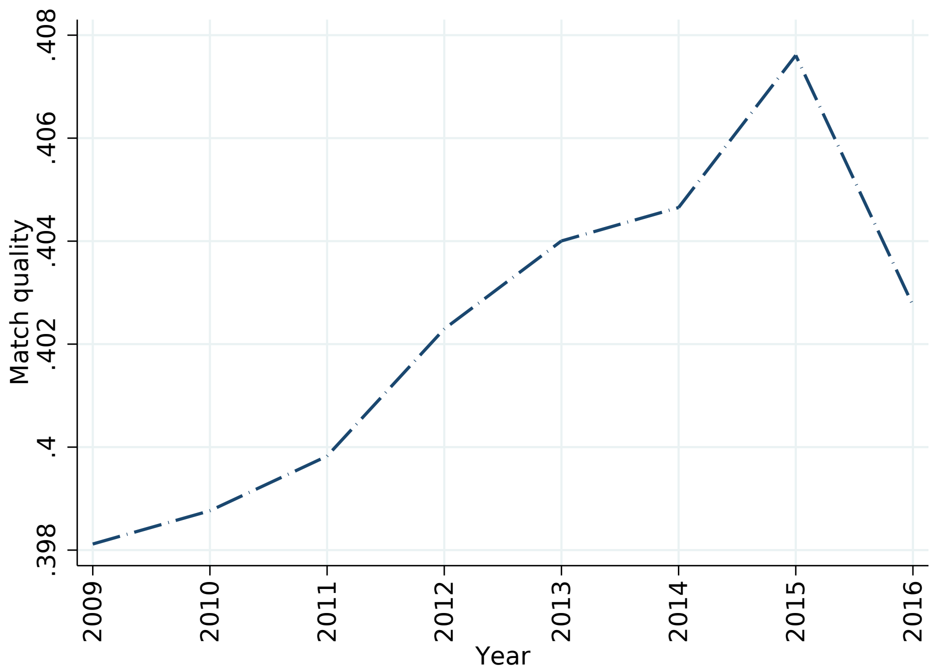
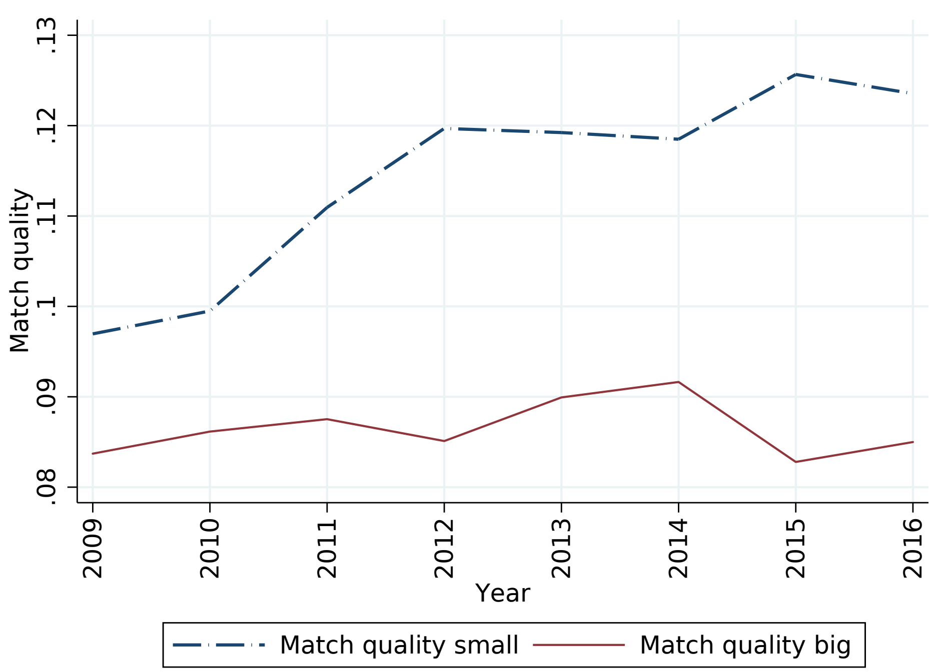


Figure 5: Imperfect-match index for small (25^{th}) and large (75^{th}) firms



Tables

Table 1: Bank-branch information

Year	# of banks	# of branches	# of branches per bank	# of branches per bank-zipbase
2006	410	3,184	653	4
2007	415	3,357	673	4
2008	429	3,457	690	4
2009	423	3,492	692	4
2010	412	3,492	689	4
2011	402	3,328	600	3
2012	393	3,279	590	3
2013	387	3,235	570	3
2014	379	3,117	535	3
2015	362	3,041	512	3
2016	338	2,977	490	3
2017	328	2,921	469	3

The table reports the evolution of bank-branch level information.

Table 2: Summary statistics

	Level	Obs.	Mean	Std.	Min.	Max.
Panel A: Credit registry dataset for new relationships						
Year	Loan	1,626,578			2006	2017
Ln(amount outstanding)	Loan	1,626,578	10.813	14.628	0.000	24.091
# of new relations	Loan	1,626,578	2.02	1.760	1.000	61.000
Panel B: Dataset on active bank branches						
Year	Branch	104,675			2006	2017
# banks	Branch	104,675			1.000	460
# branches	Branch	104,675			1.000	3,605
# branches per zip code	Branch	104,675	41.386	35.996	1.000	191.000
Banks' branches	Branch	104,675	3.587	3.525	1.000	31.000
Banks' branches shares	Branch	104,675	0.131	0.129	0.005	1.000
Panel C: Dataset used in the regression analysis						
New relationship (0,1)	Loan	5,647,211	0.127	0.333	0.000	1.000
# of possible matches	Loan	5,647,211	20.935	14.664	1.000	74.000
# of realized matches	Loan	5,647,211	1.241	0.652	1.000	12.000
Ln(outstanding amt)	Loan	418,535	8.048	2.630	0.000	20.500
Imperfect match (2009)	Loan	2,937,273	0.151	0.148	0.010	0.811
Large_large	Loan	5,647,211	0.242	0.428	0.000	1.000
Small_small	Loan	5,647,211	0.247	0.431	0.000	1.000
Small_large	Loan	5,647,211	0.258	0.438	0.000	1.000
Large_small	Loan	5,647,211	0.252	0.434	0.000	1.000
Switching (0,1)	Loan	802,049	0.229	0.420	0.000	1.000
Termination of lending (0,1)	Loan	802,049	0.279	0.449	0.000	1.000
Small firm (0,1)	Firm	5,647,211	0.505	0.500	0.000	1.000
Large firm (0,1)	Firm	5,647,211	0.495	0.500	0.000	1.000
Ln(turnover)	Firm	5,190,398	12.080	1.832	-4.605	22.988
Ln(total expenses)	Firm	5,584,081	12.081	1.818	-4.605	23.000
Prob(default)	Firm	5,635,477	0.055	0.065	0.000	0.905
Ln(# of employees)	Firm	4,919,955	1.427	1.178	0.000	9.624
Ln(fixed tangible assets)	Firm	4,987,923	10.376	2.272	-4.605	22.257
Ln(total assets)	Firm	5,647,211	12.190	1.929	-4.605	23.262
Ln(ROA)	Firm	3,305,770	-3.528	1.802	-43.185	14.181
Ln(sales)	Firm	3,041,740	11.776	2.400	-4.605	22.981
Ln(leverage)	Firm	5,598,134	-.319	.945	-17.658	16.559
EBA borrowing share (0,1)	Firm	424,062	3.995	19.453	0.000	100
Small bank (0,1)	Bank	5,647,211	0.500	0.500	0.000	1.000
Large bank (0,1)	Bank	5,647,211	0.500	0.500	0.000	1.000
Capital ratio	Bank	5,023,981	0.106	0.164	0.000	5.017
EBA bank (0,1)	Bank	5,647,211	0.029	0.168	0.000	1.000
Ln(bank assets)	Bank	5,647,211	12.187	1.561	2.778	13.916
Ln(deposits)	Bank	5,639,453	10.841	1.785	-0.607	13.063
Bank cash	Bank	5,647,211	1,460	1,089	0.000	3,835
HHI	Branch-Zipbase	5,647,211	0.544	0.384	0.070	9.000

The table provides basic descriptive statistics. See online appendix A1 for precise definitions of the variables.

Table 3: Total number of realized matches within firm-year

#	Freq.	Percent	Cum.
1	690,488	69.83	69.83
2	178,496	18.05	87.89
3	65,424	6.62	94.5
4	29,012	2.93	97.44
5	14,250	1.44	98.88
6	6,840	0.69	99.57
7	2,814	0.28	99.85
8	944	0.10	99.95
9	297	0.03	99.98
10	130	0.01	99.99
11	44	0.00	100
12	24	0.00	100
Total	988,763	100	
Unique number of banks: 453			
Unique number of firms : 512,446			

The table reports the distribution of the total number of realized matches in the final sample.

Table 4: Bank-firm matching

	I	II	III	IV	V	VI	VII
Large_large	0.119***	0.102***	0.031***	0.031***	0.033***	0.017***	0.013***
	[267.193]	[209.097]	[31.051]	[31.051]	[32.985]	[16.247]	[8.096]
Small_large	0.089***	0.083***	0.012***	0.012***	0.026***		0.012***
	[210.030]	[80.384]	[8.797]	[8.797]	[26.676]		[6.973]
Small_small	-0.025***	-0.015***	-0.015***	-0.015***		-0.018***	-0.038***
	[-68.130]	[-15.093]	[-14.801]	[-14.801]		[-17.806]	[-33.249]
Capital ratio	-0.024***	-0.012***	0.003***	0.003***	0.004***		0.012***
	[-58.586]	[-26.859]	[2.762]	[2.762]	[3.178]		[6.326]
HHI	-0.016***	-0.014***	-0.012***	-0.012***		-0.008***	-0.014***
	[-37.826]	[-8.225]	[-7.470]	[-7.470]		[-4.817]	[-8.602]
Prob(default)	0.044***	-0.060***	-0.060***	-0.060***		-0.060***	-0.060***
	[18.452]	[-10.751]	[-10.864]	[-10.864]		[-10.974]	[-11.122]
Observations	5,013,829	5,011,739	5,011,739	5,011,739	5,010,697	5,011,739	3,049,146
R-squared	0.038	0.082	0.099	0.099	0.118	0.111	0.467
Year FE	Y	Y	Y	Y			Y
Firm FE		Y	Y	Y		Y	
Bank FE			Y	Y	Y		
Locations FE				Y	Y	Y	Y
Firm*Year FE					Y		
Bank*Year FE						Y	
Firm*Bank FE							Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total capital). To avoid the dummy trap, we exclude the "Large_small" interaction. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Bank-firm matching : Single versus multiple lending

	I	II	III
	Full sample	Single lending	Multiple lending
Large_large	0.031***	0.031***	0.042***
	[31.051]	[30.592]	[12.322]
Small_large	0.012***	0.039***	-0.009
	[8.797]	[27.487]	[-1.099]
Small_small	-0.015***	-0.009***	-0.002
	[-14.801]	[-8.032]	[-0.289]
Capital ratio	0.003***	0.013***	-0.018***
	[2.762]	[10.920]	[-3.527]
HHI	-0.012***	0.004**	-0.019*
	[-7.470]	[2.412]	[-1.789]
Prob(default)	-0.060***	0.005	-0.070**
	[-10.864]	[0.817]	[-2.031]
Observations	5,011,739	4,173,031	838,653
R-squared	0.099	0.061	0.175
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Bank FE	Y	Y	Y
Locations FE	Y	Y	Y
Cluster SE	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) match is identified in the credit registry within a 4-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total capital). To avoid the dummy trap we exclude the "Large_small" interaction. Columns II and III are estimated on single and multiple lending relationships, respectively. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Bank-firm matching: Heterogeneous effect

	I	II	III
Large_large	0.032***	0.032***	0.023***
	[31.892]	[31.837]	[22.864]
Small_large	0.011***	0.003**	-0.009***
	[8.186]	[1.970]	[-5.720]
Small_small	-0.016***	-0.024***	-0.026***
	[-15.644]	[-21.245]	[-22.064]
Capital ratio	-0.001	0.003**	-0.029***
	[-1.107]	[2.433]	[-23.619]
HHI	-0.013***	-0.012***	-0.012***
	[-7.602]	[-7.454]	[-7.150]
Prob(default)	-0.061***	-0.134***	0.084***
	[-11.066]	[-18.457]	[10.038]
Small_firm * Capital_ratio	0.008***		
	[9.440]		
Small_firm * Prob(default)		0.172***	
		[16.924]	
Large_firm * Prob(default)			-0.185***
			[-16.120]
Large_firm * High_capital			-0.005***
			[-5.757]
High_capital * Prob(default)			-0.082***
			[-12.514]
Large_firm * High_capital * Prob(default)			0.025**
			[2.414]
Observations	5,011,739	5,011,739	5,011,739
R-squared	0.099	0.099	0.099
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Bank FE	Y	Y	Y
Locations FE	Y	Y	Y
Cluster SE	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets) for firms with single and multiple lending relationships. We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) match is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total bank assets). To avoid the dummy trap we exclude the "Large_small" interaction. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Decomposition of the changes in the imperfect-match index

Decomposition of the change in the imperfect-match index between 2009 and 2016		
Mean of imperfect-match index (Year=2009): 0.160		
Mean of imperfect-match index (Year=2016): 0.190		
Components	Absolute difference	Proportion (%)
Firm and bank characteristics (Block 1)	0.0272	87.37
Changes in the share of credit (Block 2)	-0.0000	-0.09
New relationships opened (Block 3)	0.0042	13.52
Relationships closed (Block 4)	-0.0002	-0.80
Overall	0.0312	100

The table reports the decomposition of the change in the imperfect-match index between 2009 and 2016. Each line reports the average of each block across firms.

Table 8: Imperfect-match index and credit supply

	I	II	III	IV	V
Imperfect match	-4.563***	-0.340***	-0.706***	-1.429***	-1.427***
	[-130.159]	[-4.642]	[-4.755]	[-6.258]	[-6.251]
# of bank-branches					0.058
					[0.537]
Observations	258,627	130,398	31,043	38,698	38,698
R-squared	0.108	0.651	0.704	0.708	0.708
Year FE	Y	Y		Y	Y
Bank FE	Y	Y			
Firm FE		Y			
Locations FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bank*Year FE			Y		
Firm*Bank FE				Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Y_{b,f,t} = \alpha_0 + \beta_1 * Imperfect - match_{b,f,t} + mu_0 \epsilon_{b,f,t}$. In all specifications the dependent variable is the outstanding amount of credit of the realized firm (f) - bank (b) matches that operate in the same four-digit postcode (l) at time (t). The main explanatory variable is the imperfect-match index. For the index, larger deviations from zero indicate a wider difference of observed matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Switching lenders and terminating relationships: Loan-level evidence

	I	II	III	IV	V	VI
Dependent variable		Switching lender			Termination of lending	
Imperfect match	0.019***	0.054***	0.053***	0.057***	0.101***	0.100***
	[5.810]	[14.242]	[14.039]	[17.187]	[25.928]	[25.608]
Capital ratio	-0.048***	-0.040***		-0.051***	-0.044***	
	[-4.410]	[-3.149]		[-4.612]	[-3.332]	
HHI branch	-0.039***	-0.045***	-0.020	-0.043***	-0.051***	-0.022
	[-3.817]	[-3.630]	[-1.466]	[-4.062]	[-3.983]	[-1.580]
Prob(default)	0.149***			0.159***		
	[6.513]			[6.848]		
Ln(firm assets)	0.013***			0.016***		
	[6.089]			[7.579]		
Ln(bank assets)	0.022***	0.036***		0.025***	0.038***	
	[4.195]	[5.657]		[4.596]	[5.752]	
Observations	297,301	252,610	252,567	297,301	252,610	252,567
R-squared	0.443	0.452	0.455	0.435	0.444	0.448
Year FE	Y			Y		
Firm FE	Y			Y		
Bank FE	Y	Y		Y	Y	
Locations FE	Y	Y	Y	Y	Y	Y
Firm*Year FE		Y	Y		Y	Y
Bank*Year FE			Y			Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Y_{b,f,t} = \alpha_0 + \beta_1 * Imperfect - match_{b,f,t} + mu_0 \epsilon_{b,f,t}$. We estimate all specifications using a linear probability model, where the dependent variables are switching lenders (columns I to III) and termination of lending (columns IV to VI). The main explanatory variable is the imperfect-match index that is calculated as the difference between the observed and predicted matches. For the index, larger deviations from zero indicate a wider difference of realized matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: The real effects of the imperfect-match index: Firm-level evidence

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.003***	0.004***	-0.009	0.001***	0.001**	-0.003
	[4.352]	[4.390]	[-1.455]	[4.096]	[2.465]	[-0.969]

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{Imperfect\ Match}$	-5.300***	-5.339***	0.292	-16.318***	-16.767***	-0.407
	[-10.105]	[-9.996]	[0.033]	[-14.892]	[-14.890]	[-0.014]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	134,267	115,359	21,297	131,204	112,528	20,967
R-squared	0.936	0.935	0.254	0.908	0.908	-258.8
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
LM-test for under identification	974	952	5.771	903	882	1.29
P-value for under identification	0.000	0.000	0.016	0.000	0.000	0.256
F-stat for weak identification	116.85	983	3.018	114.3	909	0.668
Weak identification 10% CR	16.38	16.38	16.38	16.38	16.38	16.38
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in parenthesis) using a 2SLS regression. We estimate the following IV set-up: $Y_{f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$, with the first step: $Imperfect\ Match_{b,f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{b,f,t}$. In both steps, we include basic firm-level controls for firm size, ROA, and leverage. For our instrument, we follow Gropp, Mosk, Ongena and Wix (2019) and construct it as $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$, where the numerator is the average amount of outstanding credit of firm f from EBA exercised banks, and the denominator is the total amount of credit from all banks. We report the first-stage regressions in panel A. The LM statistic is distributed as chi-square under the null that the equation is unidentified. The F-stat is distributed as chi-square under the null of exogeneity. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: The real effects of the imperfect-match index:: Firm-switcher-level evidence

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.003***	0.003***	0.001***	0.002***	0.003***	0.001***
	[6.155]	[4.863]	[5.876]	[3.234]	[4.607]	[5.550]

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{Imperfect\ Match}$	-3.441***	-3.380***	-5.313***	-6.932***	-7.465***	-6.242**
	[-5.346]	[-4.502]	[-3.648]	[-5.543]	[-5.039]	[-2.567]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	57,909	50,149	7,734	58,071	50,325	7,723
R-squared	0.292	0.313	0.202	0.247	0.269	0.249
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
LM-test for under identification	162.8	141.6	38.66	162.5	155.3	24.18
P-value for under identification	188.6	148.4	34.17	166.3	129.7	30.61
F-stat for weak identification	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification 10% CR	191.6	151	34.53	168.5	131.6	30.81
Cluster SE	16.38	16.38	16.38	16.38	16.38	16.38

The table reports coefficients and t-statistics (in parenthesis) using a 2SLS regression only for firms that switch banks. We estimate the following IV set-up: $Y_{f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$, with the first step: $Imperfect\ Match_{b,f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{b,f,t}$. In both steps, we include basic firm-level controls for firm size, ROA, and leverage. For our instrument, we follow Gropp, Mosk, Ongena and Wix (2019) and construct it as $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$, where the numerator is the average amount of outstanding credit of firm f from EBA exercised banks, and the denominator is the total amount of credit from all banks. We report the first-stage regressions in panel A. The LM statistic is distributed as chi-square under the null that the equation is unidentified. The F-stat is distributed as chi-square under the null of exogeneity. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Online appendix

A1 Definition of the variables used

- *New relationship*: is a dummy that equals one if the firm has a loan from a bank that it had no relationship and zero otherwise.
- *Match*: is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match.
- *Imperfect match*: is an index made up by the average predicted match - the average realized match, weighted by the share of credit in each relationship.
- *Termination of Lending*: is a dummy that equals one if the bank has terminated an existing relationship and zero otherwise.
- *Large firm*: is a dummy that equals one if the firm's real total assets are above the median size of all firms, and zero otherwise.
- *Small firm*: is a dummy that equals one if the firm's real total assets are below the median size of all firms, and zero otherwise.
- *Large bank*: is a dummy that equals one if the bank's total assets are above the median assets of all banks, and zero otherwise.
- *Small bank*: is a dummy that equals one if the bank's total assets are below the median assets of all banks, and zero otherwise.
- *ROA*: denotes the firm's return on assets.
- *Leverage*: is the firm's ratio of long term debt to total assets.

- $Prob\,default$: is measured as the probability that any given firm will have a significant default episode vis-á-vis the banking system using information from the central credit register and comprehensive balance sheet data.

- *Capital ratio*: is the bank's ratio of book equity to total assets.

- *Switching*: is a dummy that equals one if we observe in the firm's credit registry a new loan from a bank with which it did not have a lending relationship during the previous twelve months, and zero otherwise.

- *EBA bank*: is a dummy that equals one for all banks in Portugal included in the 2011 EBA capital exercise, and zero otherwise.

- $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$; where the numerator is the average amount of outstanding credit of firm f from EBA exercised banks, and the denominator is the total amount of credit from all banks.

- HHI: denotes the Herfindahl-Hirschman index.

Table A1: Bank-firm matching: Alternative tests

	I	II	III	IV	V
Large_large	0.032***	0.114***	0.031***	0.031***	0.023***
	[37.742]	[28.096]	[30.983]	[29.326]	[22.830]
Small_large	0.023***	0.003	0.012***	0.015***	0.004***
	[28.400]	[0.858]	[9.002]	[10.536]	[3.175]
Small_small		-0.196***	-0.015***	-0.012***	-0.015***
		[-74.567]	[-15.271]	[-10.861]	[-14.803]
Capital ratio		0.149***	0.003***	0.004***	0.006***
		[13.841]	[2.787]	[3.003]	[5.016]
HHI		-0.032***	-0.012***	-0.013***	-0.013***
		[-15.603]	[-8.018]	[-7.715]	[-7.727]
Prob(default)		0.197***	-0.060***	-0.057***	-0.060***
		[17.281]	[-11.248]	[-9.020]	[-10.868]
Ln(turnover)				-0.001**	
				[-1.980]	
Ln(total expenses)				0.008***	
				[9.250]	
Ln(deposits)					0.006*
					[1.901]
Bank cash					0.000***
					[23.257]
Observations	5,645,040	4,977,513	5,011,739	4,616,007	5,011,739
R-squared	0.097		0.099	0.100	0.099
X-sq (Probit)		203174			
Year FE	Y	Y	Y	Y	Y
Firm FE	Y		Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Locations FE	Y	Y	Y	Y	Y
Industry*Location*Size*Year FE	Y				
Cluster SE	Robust	Robust	Bank*Firm	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) match is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total capital). To avoid the dummy trap we exclude the "Large_small" interaction. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A2: Bank-firm matching: Year-by-year analysis

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Large_large	0.080***	-0.013*	-0.012*	-0.006	-0.012*	0.001	-0.013**	-0.003	0.011*	-0.001	0.002
	[16.089]	[-1.904]	[-1.898]	[-0.931]	[-1.724]	[0.157]	[-2.001]	[-0.461]	[1.751]	[-0.082]	[0.250]
Small_large	-0.026***	-0.006	-0.008	-0.009	-0.005	-0.001	-0.005	0.004	0.009	-0.002	-0.009
	[-5.200]	[-0.871]	[-1.339]	[-1.407]	[-0.773]	[-0.088]	[-0.682]	[0.526]	[1.397]	[-0.349]	[-1.371]
Small_small	-0.056***	-0.013***	-0.012***	0.002	-0.010***	-0.004***	-0.017***	-0.030***	-0.024***	-0.016***	0.004***
	[-84.906]	[-11.977]	[-11.943]	[1.390]	[-8.835]	[-3.633]	[-12.575]	[-19.971]	[-14.139]	[-11.495]	[2.938]
HHI	-0.009***	-0.004***	-0.005***	-0.003***	-0.003**	-0.000	0.001	0.004*	0.004*	0.004*	0.007***
	[-15.151]	[-3.838]	[-4.944]	[-3.191]	[-2.372]	[-0.008]	[0.447]	[1.765]	[1.871]	[1.932]	[2.759]
Prob(default)	0.064***	0.021***	0.015***	0.020***	0.018***	0.010*	0.006	0.002	0.001	0.011	0.012
	[13.990]	[3.352]	[2.653]	[3.493]	[3.164]	[1.807]	[1.091]	[0.325]	[0.187]	[1.496]	[1.532]
Observations	1,878,062	596,771	586,453	528,706	500,559	440,835	344,407	346,626	375,074	401,790	328,868
R-squared	0.140	0.062	0.062	0.058	0.0577	0.0684	0.0522	0.0450	0.0471	0.063	0.049
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) match is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total capital). To avoid the dummy trap we exclude the "Large_small" interaction. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A3: Bank-firm matching and relative size

	I	II	III	IV	V	VI	VII
Large_large	0.130***	0.107***	0.029***	0.029***	0.032***	0.017***	0.014***
	[315.867]	[235.489]	[35.140]	[35.140]	[37.331]	[18.017]	[9.932]
Small_large	0.101***	0.088***	0.010***	0.010***	0.023***		0.012***
	[260.145]	[94.729]	[8.614]	[8.614]	[27.888]		[8.282]
Small_small	-0.019***	-0.013***	-0.013***	-0.013***		-0.016***	-0.033***
	[-64.505]	[-14.857]	[-14.989]	[-14.989]		[-18.050]	[-34.193]
Observations	5,647,211	5,645,121	5,645,121	5,645,121	5,644,074	5,645,120	3,426,707
R-squared	0.044	0.086	0.106	0.106	0.123	0.118	0.470
Year FE	Y	Y	Y	Y			Y
Firm FE		Y	Y	Y		Y	
Bank FE			Y	Y	Y		
Locations FE				Y	Y	Y	Y
Firm*Year FE					Y		
Bank*Year FE						Y	
Firm*Bank FE							Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Prob(match)_{b,f,l,t} = \lambda_1 * (Firm\ Size_{f,l,t} * Bank\ Size_{b,l,t}) + \lambda_2 * X_{b,f,l,t} + a_0 + \epsilon_{b,f,l,t}$. We estimate all specifications using a linear probability model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) match is identified in the credit registry within a four-digit post code (l) at time t, and zero if they do not match. To capture size dependence, we use interactions between firm and bank size. For instance, "Large_large" is the interaction between a large firm (above the median of the distribution of total assets) and a large bank (above the median of the distribution of total capital). To avoid the dummy trap we exclude the "Large_small" interaction. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A4: Imperfect-match index and credit supply: Excluding Lisbon and Porto

	I	II	III	IV	V
Imperfect match	-4.409***	-0.279***	-0.744***	-1.328***	-1.3270***
	[-118.74]	[-3.58]	[-4.69]	[-5.49]	[-5.48]
# of bank-branches					0.115
					[0.543]
Observations	218,083	110,594	26,267	32,708	32,708
R-squared	0.106	0.653	0.705	0.711	0.711
F-stat	20.411	12.84	22.000	30.11	15.20
Year FE	Y	Y		Y	Y
Bank FE	Y	Y			
Firm FE		Y			
Locations FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bank*Year FE			Y		
Firm*Bank FE				Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Y_{b,f,t} = \alpha_0 + \beta_1 * Imperfect\ match_{b,f,t} + \mu_f + \mu_t + \epsilon_{b,f,t}$. We estimate all specifications using OLS, where the dependent variable is the outstanding amount of credit of the realized firm (f) - bank (b) matches that operate in the same four-digit postcode (l) at time (t). The main explanatory variable is the imperfect match index that is calculated as the difference between the realized and predicted matches. For the index, larger deviations from zero indicate a wider difference of realized matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A5: Imperfect-match index and real effects: Firm-level evidence excluding Lisbon and Porto

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.002***	0.002***	0.000	0.002***	0.002***	0.000
	[13.759]	[13.920]	[0.462]	[12.790]	[13.006]	[0.273]

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{Imperfect\ Match}$	-8.470***	-8.742***	-59.992	-32.894***	-34.067***	-107.162
	[-6.547]	[-6.768]	[-0.483]	[-10.489]	[-10.885]	[-0.256]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	115,346	99,243	18,056	112,683	96,799	17,777
R-squared	0.933	0.255	-10	0.911	0.91	-28.93
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
LM-test for under identification	194.1	198.5	0.217	167.8	173.4	0.075
P-value for under identification	0.000	0.000	0.641	0.000	0.000	0.783
F-stat for weak identification	189.3	193.8	0.213	163.6	169.2	0.074
Weak identification 10% CR	16.38	16.38	16.38	16.38	16.38	16.38
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in parenthesis) using a 2SLS regression. We estimate the following IV set-up: $Y_{f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$, with the first step: $Imperfect\ Match_{b,f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{b,f,t}$. In both steps, we include basic firm-level controls for firm size, ROA, and leverage. For our instrument, we follow Gropp, Mosk, Ongena and Wix (2019) and construct it as $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$, where the numerator is the average amount of outstanding credit of firm f from EBA exercised banks, and the denominator is the total amount of credit from all banks. We report the first stage regressions in Panel A. We drop Lisbon and Port from the sample. The LM statistic is distributed as chi-square under the null that the equation is unidentified. The F-stat is distributed as chi-square under the null of exogeneity. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6: Imperfect-match index and real effects: Firm-level OLS estimates

	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
Imperfect match	-5.581***	-6.074***	-4.394***	-11.736***	-12.816***	-8.026***
	[-136.321]	[-136.138]	[-36.860]	[-143.236]	[-141.528]	[-37.357]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	279,000	257,691	21,309	267,530	246,548	20,982
R-squared	0.119	0.136	0.085	0.146	0.164	0.109
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in parenthesis) using a 2SLS regression. We estimate the following IV set-up: $Y_{f,t} = \alpha_0 + \beta_1 * Imperfect\ Match_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$. In both steps, we include basic firm-level controls for firm size, ROA, and leverage. The main explanatory variable is the imperfect match index that is calculated as the difference between the observed and predicted matches. For the index, larger deviations from zero indicate a wider difference of realized matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A7: Imperfect match index: Bootstrap SE

	I	II	III	IV	V
Imperfect match	-4.563***	-0.340***	-0.760**	-1.429***	-1.427***
	[-96.576]	[-2.911]	[-2.310]	[-4.008]	[-3.862]
# of bank-branches					0.058
					[0.386]
Observations	258,627	130,398	31,043	38,698	38,698
R-squared	0.104	0.651	0.704	0.708	0.708
Wald (P-value)	0.000	0.004	0.002	0.000	0.001
Year FE	Y	Y		Y	Y
Bank FE	Y	Y			
Firm FE		Y			
Locations FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bank*Year FE			Y		
Firm*Bank FE				Y	Y
Cluster SE	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

The table reports coefficients and t-statistics (in brackets). The dependent variable is the outstanding amount for the realized firm (f) - bank (b) matches that operate in the same four-digit postcode (l) at time (t). The main explanatory variable is the imperfect match index that is calculated as the difference between the observed and predicted matches. For the index, larger deviations from zero indicate a wider difference of realized matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A8: Imperfect match index and loan outstanding amount: EU sovereign debt crisis

	I	II	III	IV	V
Imperfect match (2011)	-4.861***	-0.125***	-0.761***	-1.394***	-1.387***
	[-103.527]	[-3.984]	[-3.984]	[-4.140]	[-4.115]
# of bank-branches					0.304
					[1.029]
Observations	179,923	77,304	20,524	20,549	20,549
R-squared	0.106	0.681	0.717	0.730	0.730
F-stat	10.718	1.539	15.871	17.141	9.041
Year FE	Y	Y		Y	Y
Bak FE	Y	Y			
Firm FE		Y			
Locatios FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bak*Year FE			Y		
Firm*Bak FE				Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Y_{b,f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{b,f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{b,f,t}$. We estimate all specifications using OLS, where the dependent variable is the outstanding amount of credit of the realized firm (f) - bank (b) matches that operate in the same four-digit postcode (l) at time (t). The main explanatory variable is the imperfect match index that is calculated as the difference between the observed and predicted matches. For the index, larger deviations from zero indicate a wider difference of realized matches from those prevailing in good times. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A9: EBA exercise and outstanding credit

	I	II
EBA exercise	-0.571***	-0.614**
	[-2.951]	[-2.653]
Capital ratio	0.493	1.965***
	[0.955]	[8.186]
HHI	-0.024	-0.008
	[-1.334]	[-0.442]
Ln(deposits)	-0.000	-0.001*
	[-0.013]	[-1.975]
Bank size	-0.336**	0.020
	[-2.593]	[0.118]
Observations	407,556	407,553
R-squared	0.020	0.046
F-stat	24.11	27.03
Year FE	Y	Y
Bank FE		Y
Cluster SE	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression: $Y_{b,f,t} = \alpha_0 + \beta_1 * EBAexercise_{b,f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{b,f,t}$. We estimate all specifications using OLS, where the dependent variable is the outstanding amount of credit of the realized firm (f) - bank (b) matches that operate in the same four-digit postcode (l) at time (t). We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table A10: Imperfect-match index and the probability of default: Firm-level evidence

	Panel A: First stage					
	I	II	III	IV	V	VI
	All firms			Only for firms that switched lenders		
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.001***	0.001***	0.000	0.001***	0.001***	0.001
	[8.443]	[32.648]	[1.431]	[29.620]	[29.964]	[1.431]

	Panel B: Second stage					
	I	II	III	IV	V	VI
	All firms			Only for firms that switched lenders		
Dependent variable	Prob(default)					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{Imperfect\ Match}$	0.274***	0.269***	-0.854	0.203***	0.194***	3.113
	[7.377]	[6.972]	[-0.688]	[5.118]	[4.823]	[0.611]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	148,238	128,056	22,543	55,172	47,092	9,736
R-squared	0.697	0.685	0.0647	0.708	0.719	-11.898
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
LM-test for under identification	198.8	110.3	40.65	142.6	192.4	0.395
P-value for under identification	0.000	0.000	0.000	0.000	0.000	0.530
F-stat for weak identification	114.8	62.42	40.99	81.19	108.8	0.382
Weak identification 10% CR	16.38	16.38	16.38	16.38	16.38	16.38
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

The table reports coefficients and t-statistics (in parenthesis) using a 2SLS regression. We estimate the following IV set-up: $Y_{f,t} = \alpha_0 + \beta_1 * \widehat{Imperfect\ Match}_{f,t} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$, with the first step: $Imperfect\ Match_{b,f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{b,f,t}$. In both steps, we include basic firm-level controls for firm size, ROA, and leverage. For our instrument, we follow Gropp, Mosk, Ongena and Wix (2019) and construct it as $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$, where the numerator is the average amount of outstanding credit of firm f from EBA exercised banks, and the denominator is the total amount of credit from all banks. We report the first stage regressions in Panel A. The LM statistic is distributed as chi-square under the null that the equation is unidentified. The F-stat is distributed as chi-square under the null of exogeneity. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,**,*** marks denote the statistical significance at the 10%, 5%, and 1% level, respectively.