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Bank Loan Supply during Crises: The Importance of Geographic Diversification

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Bank Loan Supply during Crises: The Importance of Geographic Diversification*

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Abstract

We classify a large sample of banks according to the geographic diversification of their international syndicated loan portfolio. Our results show that diversified banks maintain higher loan supply during banking crises in borrower countries. The positive loan supply effects lead to higher investment and employment growth for firms. Diversified banks are stabilizing due to their ability to raise additional funding during times of distress, which also shields connected markets from spillovers. Further distinguishing banks by nationality reveals a pecking order: diversified domestic banks are the most stable source of funding, while foreign banks with little diversification are the most fickle. Our findings suggest that the decline in financial integration since the recent crisis increases countries' vulnerability to local shocks.

JEL classification: F30, G01, G15, G21, G32

Keywords: Diversification, Global Banking, Financial Stability, Syndicated Loan Market, Banking Crisis.

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1 Introduction

The last decades saw a steady increase in the importance of globally active banks. Banking integration peaked around 2007, but declined sharply during the global financial crisis. It has become a key objective for policy makers and academics to better understand the effects of integrated banks on financial stability and the real economy (BCBS, 2013). Several papers provide valuable evidence on the costs and benefits of lending by foreign banks.[1] However, an analysis of the consequences of banks' international portfolio diversification on financial stability is largely absent from the literature.

In this paper we provide first cross-country evidence on how internationally diversified banks adjust lending during banking crises in their borrower countries. We find that diversified banks stabilize loan supply and smooth shocks. On the bank-firm level, their loan supply during crises is 3.9 % higher, compared to banks with a concentrated portfolio. Higher loan supply has significant real effects on firm performance. Firms at the 75^{th} percentile in terms of loan exposure to diversified banks have 1.5 % higher loan growth during banking crises, relative to firms at the 25^{th} percentile. This translates into stronger investment (4.6 %) and employment (1.1 %) growth. As detailed bank-firm level data allow us to rigorously control for unobservable borrower characteristics through time-varying fixed effects on the firm level, the positive effects of diversification reflect banks' loan supply. Granular fixed effects at the bank-year level ensure that our results are not due to unobservable bank heterogeneity.

To measure the degree of geographic diversification of globally integrated banks, we

[1] For theoretical papers highlighting the importance of bank diversification, see Morgan, Rime and Strahan (2004), Cetorelli and Goldberg (2011, 2012), Kalemli-Ozcan, Papaioannou and Perri (2013a), Kalemli-Ozcan, Papaioannou and Peydró (2013b). For empirical evidence see De Haas and Van Lelyveld (2010; 2014), Buch and Goldberg (2015); Kerl and Niepmann (2016); Gilje, Loutskina and Strahan (2016); Goetz, Laeven and Levine (2016). Claessens (2017) provides an excellent summary on cross-border lending.

use disaggregated data on worldwide syndicated lending. For each bank we construct a Herfindahl-Hirschman Index of the geographic diversification of its international loan portfolio across countries, aggregated to the parent bank level. Banks with low portfolio concentration, i.e. those that lend to multiple countries, are classified as diversified. Banks that extend a large share of their loan portfolio to borrowers in few countries are classified as concentrated. Our classification of banks builds on recent literature that causally shows that geographically diversified banks have lower risk, because geographic expansion reduces exposure to idiosyncratic local shocks (Goetz, Laeven and Levine, 2016). Better diversification and lower risk thus provide better access to funding, especially during times of crises (Levine, Lin and Xie, 2016; Bord, Ivashina and Taliaferro, 2018). Based on these findings, we argue that banks that are geographically diversified across countries are financially less constrained during local shocks.

We provide evidence that diversified banks can better raise funding and are financially unconstrained, relative to their non-diversified counterparts. We show that diversified banks increase interbank borrowing on the syndicated loan market when faced with a local financial shock, relative to non-diversified banks. Using data on bank balance sheets from Bankscope, we also show that diversified banks increase their overall wholesale deposits during banking crises in borrower countries. In contrast, non-diversified banks see a decline in wholesale deposit growth during episodes of financial distress. These results are in line with the hypothesis that diversification ensures better access to funding.

For our full sample of banks active on the syndicated loan market, we provide further indirect evidence that geographically diversified banks are stabilizing due to their ability to raise new funds during times of distress. If banks are financially unconstrained when hit by a local financial shock, they can raise and distribute new funds to sustain loan supply in affected markets, but also in connected non-crisis countries. Banks that face financial constraints must trade off where to allocate existing funds (similar to Stein (1997)). Local shocks will then have spillover effects to non-crisis countries.[2] We show that, for highly diversified banks, maintaining loan growth in a crisis country has no spillover effects to non-crisis countries to which the same bank is lending. However, for banks with a concentrated portfolio, loan growth also falls in connected, but unaffected borrower countries. We interpret this as indirect evidence that diversified banks have looser 'financial constraints' and can raise new funds to sustain loan supply. Non-diversified banks are financially constrained and must cut back lending in affected and unaffected markets when faced with a shock.

We analyze systemic banking crises, i.e. crises that affect a whole country. Our argument hence rests on the assumption that diversification *across* countries allows for risk sharing during local (country-specific) systemic banking crises. To further investigate the link between diversification, risk, and access to funding, we show that the positive effects of diversification on loan supply and spillovers are significantly lower during episodes of global distress, when a significant share of banks' global portfolio is subject to shocks. In other words, when several borrower countries experience a crisis at the same time, the risk-sharing benefits of diversification with respect to local idiosyncratic shocks break down and diversified banks face tighter financial constraints.

We contrast our categorization by diversification with the common classification in the literature by nationality into foreign and domestic banks. Diversified banks can be foreign or domestic, and foreign banks diversified or non-diversified. We find that classifying banks by diversification instead of nationality uncovers strikingly different lending behavior. While diversified banks maintain higher loan supply than concentrated banks during banking crises, foreign banks reduce their loan supply by more than domestic

[2] For example, during a banking crisis in Canada, diversified banks can maintain lending in Canada and Mexico, because they can raise new funds. Constrained banks have to trade off where to allocate existing funds and cut lending in at least one country.

banks. Further analysis reveals the following pecking order: diversified domestic banks are the most stable source of funding, while foreign banks with little diversification are the most fickle. Foreign, but diversified banks occupy an intermediate position between both extremes. The ordering speaks to findings on the flight home effect (Giannetti and Laeven, 2012) and behavior of gross capital flows during crises (Broner, Didier, Erce and Schmukler, 2013).[3]

For robustness, we address alternative explanations to the argument that diversified banks smooth local shocks through better access to funding. First, we exclude that differences in borrower risk, in terms of volatility of borrower sales growth, explain results. While diversified banks have lower portfolio risk on average, we show that the positive effect of diversification remains stable once we control for portfolio risk. Second, we rule out the possibility that diversified banks extend a lower share of their total loans to countries in crisis. Including the share of loans in crisis shows that, if anything, diversification becomes more important when a larger share of loans is in distress. Third, we create alternative measures of diversification and specialization that capture potentially correlated aspects of banks' business models. We group banks by the share of loans extended to foreign borrowers; by their country and industry specialization; and control for firms' diversification across lenders. Across specifications, bank diversification maintains its positive and significant effect on loan supply.

The key identification issue for cross-country studies using aggregate data is to control for loan demand. If diversified banks lend to different firms than banks with a concentrated portfolio, any observed differential change in loan volume reflects both demand and supply effects. Disaggregated data allow us to overcome this challenge. Our bank-firm

[3]We find a similar pecking order when we distinguish banks by whether they have a local affiliate in a borrower country or not. This suggests that distance – and local information – matter when making lending decisions during crises (Degryse and Ongena, 2005; De Haas and Van Lelyveld, 2014; Bolton, Freixas, Gambacorta and Mistrulli, 2016).

level analysis employs firm*bank and firm*time fixed effects to absorb all time-varying unobservable firm fundamentals.[4] The combination of both fixed effects allows shocks to affect each firm at each point in time heterogeneously and accounts for any change in borrower characteristics. For example, time-varying fixed effects on the firm level absorb changes in firm sales, management, or productivity, while bank*firm fixed effects control for distance between borrowers and lenders. On the firm level, we combine firm with country*industry*time fixed effects to control for time-varying industry demand. The identifying assumption is that loan demand by all firms within the same industry and country changes equally. While in principle firm demand could exhibit heterogeneity within industries, we run bank-firm level regressions to confirm that this is of second order importance. The positive effect of diversification on credit hence reflects loan supply factors.

Our results increase in magnitude when we include bank*year fixed effects that control for unobservable time-varying bank characteristics, for example bank size, risk taking, or capital ratios. In essence, we are comparing lending by the same bank to the same firm during a crisis at different levels of diversification − this is, we hold all unobservable bank characteristics constant. The increase in coefficient size suggests that diversification has a stabilizing effect on lending above and beyond other balance sheet characteristics. Additionally, we match a sub-sample of banks in Dealscan with bank balance sheet data in Bankscope. This allows us to directly control for the marginal effects of several bank characteristics on loan supply during local crises. We show that diversification remains an important and significant explanatory variable for loan supply during crises after controlling for marginal effects of bank size (log assets), tier 1 capital ratio, share of wholesale deposits, leverage ratio, and return on assets.

[4]See Khwaja and Mian (2008); Jiménez, Mian, Peydró and Saurina (2014a); Jiménez, Ongena, Peydró and Saurina (2014b); Morais, Peydró and Ruiz (2019).

Our paper contributes to the literature in two ways. First, and to the best of our knowledge, we are the first paper to study the consequences of banks' geographic diversification in a cross-country setting. Due to data limitations, so far most studies distinguish banks by headquarter location into foreign and domestic and look at cross-border lending.[5] While bank nationality has been shown to be an important determinant of loan supply, our approach reflects the related, but distinct dimension of banks' integration into the financial system, captured by their portfolio allocation. This allows us to shed new light on banks' role during crises. Note that both categorizations need not be mutually exclusive. Diversified banks can be foreign, but domestic banks also diversified, depending on the country in which the shock originates. We find that grouping banks by diversification instead of nationality uncovers new patterns that complement existing findings in the literature on banking integration and the behavior of foreign and domestic banks.[6] The global scope of our detailed bank-firm level data allows for clean identification of credit supply effects as well as external validity.

Second, while the effect of shocks to banks' home markets and consequent spillovers are well explored, few papers investigate the role of banks during distress in their host markets.[7] Many crises over the last two decades were shocks to borrower countries and globally integrated banks were usually heavily involved. During the Asian crisis, Japanese and European banks were exposed to markets in Thailand, the Philippines, or South Korea; and during Argentina's woes, American banks had a strong presence in Latin Amer-

[5]See, for example, Peek and Rosengren (1997, 2000); Cetorelli and Goldberg (2011, 2012); Schnabl (2012); Correa, Sapriza and Zlate (2016); De Haas and Van Horen (2013); De Haas and Van Lelyveld (2014); Ongena, Peydró and Van Horen (2015); Bremus and Neugebauer (2018).

[6]For example, Claessens (2017) summarizes that 'long-term debt flows are less volatile and that foreign banks with larger presence, more domestic funding, and closer relationships provide more finance and share risks better'. We also speak to literature analyzing the real effects of financial shocks and highlighting the relevance of syndicated lending for firm performance. See Giannetti and Laeven (2012); Correa, Sapriza and Zlate (2016); De Haas and Van Horen (2013); Hale, Tümer and Minoiu (2016); Jiménez, Mian, Peydró and Saurina (2014a); Popov and Van Horen (2015); Morais, Peydró and Ruiz (2019); Doerr, Raissi and Weber (2018).

[7]For an exception, see De Haas and Van Lelyveld (2006).

ica. As bank lending is a major source of firm financing, it is important to understand how banks react to host country shocks. So far, the discussion has mainly highlighted the costs and benefits of cross-border banking and how foreign banks spread home market shocks to connected markets (Claessens, 2017).

Our results contribute to the discussion on retrenchment in financial integration since the global financial crisis (Milesi-Ferretti and Tille, 2011). Since the financial crisis, there has been a significant decline in cross-border banking and financial integration.[8] In addition, we show that banks' geographic diversification declined. The verdict on whether this is enhances or weakens financial stability is still out. While some studies find that foreign banks adversely affect economic conditions in host markets, our results show that integrated banks with a diversified portfolio smooth local financial shocks. Presence in several markets reduces banks' exposure to local shocks and gives them better access to new funds, which they can allocate towards countries in distress. This not only stabilizes lending in affected countries, but also mitigates contagion. In light of our results the recent decline in global banking is worrisome, as weaker integration into the global financial system, and hence less geographic diversification, has detrimental effects on stability in host markets.

The remainder of the paper proceeds as follows. Section 2 discusses data and empirical strategy. Section 3 presents our main results and evidence on the mechanism. In Section 4 we check the robustness of our findings to alternative explanations. Section 5 concludes.

[8] See also Cerutti and Claessens (2016); Bremus and Fratzscher (2015); Claessens and Van Horen (2015); Bussière, Schmidt and Valla (2016); Emter, Schmitz and Tirpák (2018); European Central Bank (2017).

2 Data & Empirical Strategy

This section describes data and construction of main variables. We then discuss the empirical strategy to identify changes in loan supply by banks during borrower country banking crises, as well as their real effects on firms.

2.1 Geographic Diversification

We categorize banks according to the cross-country geographic diversification of their international syndicated loan portfolio. Building on recent literature, we argue that diversification allows banks to access new funding, which they allocate towards borrower countries in crisis (Gilje, Loutskina and Strahan, 2016; Cortés and Strahan, 2017; Levine, Lin and Xie, 2016). The mechanism is especially important during episodes of financial turmoil (Bord, Ivashina and Taliaferro, 2018). We will discuss the mechanism in more detail below. For each bank we construct a Herfindahl-Hirschman Index (HHI), based on the share of outstanding loans to each borrower country in each year. The index reflects the geographic dispersion of banks' loan portfolios across multiple countries. Based on the HHI, we then define *diversification (DIV)* for bank b in year t as

$$DIV_{b,t} = 1 - \sum_{j=1}^{J^b} s_{b,j,t}^2 \quad \in [0, \frac{J^b - 1}{J^b}], \tag{1}$$

where $s_{b,j,t}$ measures the share of a bank b's outstanding loans to borrowers in country j relative to its total outstanding loans in year t, i.e. $s_{b,j,t} = \frac{loan_{b,j,t}}{loan_{b,t}}$. Each bank is active in J^b distinct countries, i.e. where it has at least one borrower. We invert the scale of the HHI for ease of interpretation. A value of zero ($DIV = 0$) implies no diversification (all credit goes to borrowers from one country, what we will call *concentrated portfolio*), while higher values reflect increasing diversification of banks' loan portfolios across countries.

We reason that banks with higher diversification have better access to funds during local financial shocks. A potential source of endogeneity is that a bank's decision to diversify is correlated with unobservable bank characteristics. We will discuss identification in Section 2.4.

2.2 Data

For our main analysis and to construct banks' diversification, we use data on worldwide syndicated lending. We additionally use country-specific data and further information on borrowing firms' balance sheets. Bank-firm level data with detailed bank-firm relations comes from Thomson Reuters Dealscan and covers the universe of syndicated loans. Compustat (Global and US) provides firms' balance sheet information. Macroeconomic variables come from the World Bank's World Development Indicators. Finally, we use bank balance sheet data from Bankscope.

Laeven and Valencia's (2013) Systemic Banking Crises Database provides country-year level information on episodes of financial distress.[9] From 1995 to 2012, it reports 189 banking crisis (BC) observations. The two conditions that define a banking crisis are *i*) significant signs of financial distress in the banking system (such as bank runs, losses in the banking system, and/or bank liquidations); and *ii*) significant banking policy intervention measures in response to the losses in the banking system. In our sample, there is a concentration of financial turmoil around the time of the Asian crisis and from 2008 onward, during the Great Financial Crisis.

To construct main variables, we use Dealscan data on syndicated loans. Syndicated lending constitutes a significant share of total lending. Around one-third of total inter-

[9]While there exist different databases on financial crises, Laeven and Valencia is the most comprehensive for banking crises occurring after 1970 (Chaudron and De Haan, 2014).

national lending is done through the syndicated loan market (Gadanecz and von Kleist, 2002) and it is an important source of financing in both developed and emerging economies (Cerutti, Hale and Minoiu, 2015). Syndicated loans are issued jointly by a group of banks to a single borrower. The lending syndicate includes at least one lead bank (also called lead arranger) and usually further participant banks. Lead banks negotiate terms and conditions of deals, perform due diligence, and organize participants. Therefore, lead arrangers stand in direct contact with the borrower and retain larger loan shares for signaling purposes (Sufi, 2007). Participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers.

Dealscan provides extensive information on syndicated loans at origination, including loan amount, maturity, and interest, as well as identity of lenders and borrowers. All data are aggregated at banks' and firms' parent level. We restrict our analysis to loans by banks to non-financial firms and consider lending only by commercial, savings, cooperative and investment banks.[10] We keep both lead arrangers and participants in our sample, and do so for two reasons. First, we are interested in banks' loan portfolio allocation across countries and not specific contractual frictions. As the focal point of our analysis is total credit supply, including both lead arrangers and participants provides a comprehensive picture of the syndicated loan market. Second, excluding participants leads to sample-selection bias. Lead arrangers are large banks operating on a global scale. We aim to compare banks along the dimension of their international diversification. Hence, excluding smaller participant banks with a rather concentrated portfolio will change the control group. Instead of comparing diversified with concentrated banks,

[10]In Dealscan, we use lender types Commercial Banks, Finance Companies, Investment Banks, Mortgage Banks, Thrift/S&L, and Trust Companies. Investment banks constitute 3 % of our sample and excluding them does not change results. Borrower types included are Corporations, Insurance Companies, Law Firms, Leasing Companies and Other. In robustness checks we exclude borrowers in finance, insurance, and real estate industries.

focusing on lead arrangers only will lead to a selected group of globally active banks in our sample. We would compare banks' diversification within a group of diversified and internationally integrated banks. To avoid this pitfall, we include leaders and participants in our analysis.[11]

Bank-firm level We decompose syndicated loan deals into loan portions provided by each lender to obtain granular credit level data. Whenever Dealscan provides information on lending shares of each bank, we use this information to split loan volume accordingly (available for 28 % of the deals).[12] In cases where lending shares are missing we split loan volume on a pro-rata basis among all banks in a syndicate. Transactions with deal status 'canceled', 'suspended', or 'rumor' are removed and all loan nominations transformed into million U.S. Dollars (USD) using the spot exchange rate at origination, provided by Dealscan. If after this allocation procedure the loan portion is smaller than 10,000 USD, we drop the observation to remove erroneously small loans (0.6 % of observations). Overall, we split a total of 293,163 deals into 1,724,073 loan portions.

We next use the loan portions to construct each bank's outstanding loan volume as a stock variable to proxy the loan's entry on the loan book (Jiménez, Ongena, Peydró and Saurina, 2014b; Morais, Peydró and Ruiz, 2019). Each outstanding loan remains active until it matures.[13] We disregard all firm-bank links with zero exposure, that is, we drop

[11] In the Online Appendix, we show that our results hold when we include lead arrangers only.

[12] See Giannetti and Laeven (2012); De Haas and Van Horen (2013). In the sub-case of partial information on loan shares, we first use the available information to allocate loan shares. Then, we split the remaining amount equally among banks with missing information. If the sum of the allocation rule is larger than 110 % we consider this an erroneous entry and treat it as if lending share information was not available in the first place. In robustness checks, we impute loan shares according to i) the role of the lender (leader or participants) and ii) the syndicate size using respective sample means from non-missing loan shares (see Online Appendix).

[13] As Dealscan captures information at loan origination only, this construction assumes that loans are not repaid before maturity and that loan shares are not sold by banks on secondary markets as in Morais, Peydró and Ruiz (2019). To test the relevance of loan share sales by participating banks, we employ robustness checks on lead arrangers only, as they are found to retain a larger loan share for signaling purposes (Sufi, 2007). As results hold, this indicates that reselling loan shares on secondary markets is

all inactive loans one period before the origination of the loan and one period after the loan matures. Therefore, our estimation draws only on variation form non-zero lending outcomes. We aggregate all outstanding loan portions between a bank-firm combination to obtain bank b's outstanding loan volume to firm f in year t, which we define as a loan observation.[14]

To measure geographic diversification, we construct each banks' distribution of cross-border loans by destination country of the borrowers. Essentially, geographic diversification captures the distribution of a banks' loans across borrower countries. To construct this metric, we proceed in three steps. First, we sum bank b's active loans to all borrowers in country j at time t, for example all loans by Deutsche Bank to firms in France. Second, we divide bank b's lending to all borrowers in country j over bank b's total lending. Thereby, we obtain bank b's lending share to country j at time t ($s_{b,j,t}$). For example, Citigroup's lending share to the US is 52 % out of its total syndicated lending in 2007. Third, we construct *geographic diversification* as a Herfindahl index using lending shares by country as defined in Equation (1).[15]

We merge lending banks active in Dealscan with balance sheet data from Bankscope. To link Dealscan with Bankscope, we match the ultimate parent of the parent institution in Dealscan with the bank holding company in Bankscope by hand using name, address, newspaper reports and bank websites as information.[16] We are able to successfully merge 229 institutions. Once we restrict the sample to banks with consistent information on

not driving results (see Online Appendix).

[14] Note that we treat relationship and transaction borrowers the same. While literature has shown that the distinction matters during crisis times (Bolton, Freixas, Gambacorta and Mistrulli, 2016), the issue is more important to rather opaque segments, such small businesses lending or local mortgage lending. The syndicated loan market is comprised of large borrowers, where relationships are less important and information is public (for example rating).

[15] Note that geographic diversification is constructed independently of a bank's nationality as it depends only on the destination countries. In robustness checks, we use an alternative measure based on parent bank nationality by bank headquarter. See Section 4 for a discussion and details on this distinction.

[16] We would like to thank Camelia Minoiu for providing us with a crosswalk file.

total assets, share of wholesale deposits, tier 1 capital ratio, leverage ratio, and return on equity, we end up with a sample of 200 banks and 474,784 bank-firm observations; these cover around 30 % of the total loan level sample.

Firm level To examine effects of credit supply on firm behavior, we merge our data set with firm balance sheet information. We aggregate the firm-bank-year data to the firm-year level and then match borrowers in Dealscan with firms in Compustat (Global & US). For merging we use the file provided by Chava and Roberts (2008). Combining Dealscan with Compustat reduces observations, since information for some firms, especially smaller ones, are missing in Compustat. Overall, we are able to successfully match around 32 % of our firm-year observations.[17] We use information on firms' syndicated loan volume, investment, employment, total assets, sales and fixed assets, where we compute growth rates as log differences.

To capture firms' relationships with geographically diversified banks, we construct the firm level metric *exposure*. Intuitively, exposure measures whether firms borrow a lot or little from diversified banks. Specifically, we weight firm f's outstanding loan volume by each bank with the bank's geographic diversification value ($DIV_{b,t}$) in year t. Then, we divide weighted loan volume by firm f's total outstanding loan volume in year t across all banks:

$$exposure_{f,t} = \frac{\sum_{b=1}^{B} DIV_{b,t} \cdot loan_{f,b,t}}{\sum_{b=1}^{B} loan_{f,b,t}} \quad \in [0, max(DIV_{b,t})], \tag{2}$$

where B is the total number of banks with outstanding loans to firm f in year t. Similar to *diversification* on the bank-firm level, $exposure = 0$ implies that a firm borrows exclusively from concentrated banks ($DIV = 0 \; \forall \; B$). Higher values of exposure indicate stronger relationships with diversified banks. An overview over all variables and their

[17] Note we can extend the Dealscan-Compustat link to all facilities (or syndicated loans) post-2008 issued by borrowing firms already linked in the pre-2008 Chava-Roberts file, as these firms have already been matched in previous syndicated loans.

units of measurement is provided in Table B.1.

2.3 Descriptive Statistics

Figures 1 shows the distribution of *diversification* on the bank-firm level (Panel 1a) and *exposure* on the firm level (Panel 1b). About 8 % of all loans are extended by banks with no geographic diversification. The remaining banks have at least some diversification, with a bunching around 0.9. Panel 1b shows that more than 97 % of firms borrow from at least one bank with non-zero geographic diversification. The median (mean) firm has 4 (8) bank connections in a given year. This suggests that firms accessing the syndicated loan market are potentially able to substitute across lenders during crises. The median (mean) number of outstanding loans by banks per year is 2 (33).[18]

[Figure 1 about here]

Our sample covers the years 1995 to 2012 and includes information on 35,510 firms and 6,962 banks forming a total of 1,724,073 firm-bank-year observations, and 194,726 firm-year observations (9,393 firms and 60,953 observations for the matched Compustat sample). There are a total of 2,046 banks with some diversification and 4,916 banks with zero geographic diversification. The median (mean) value of *diversification* for banks with non-zero diversification is 0.41 (0.40). The group of diversified banks extends around 93 % of all loans, which reflects that they are large lenders. Table 1 highlights the geographical distribution of loans, firms, and banks by region. The majority of loans are extended to borrowers located in Europe, East Asia and Pacific, and North America. Moreover, countries in Europe and Asia have the highest number of geographically diversified banks.[19]

[18] In the Online Appendix, we show that excluding the smallest and largest banks (in terms of number of loans) does not materially affect results.

[19] We split geographic diversification along the annual median and denote banks with an above median value as diversified.

North American banks are less diversified as they lend mostly to borrowers located in the U.S. or Canada. Finally, the highest incidence of banking crises occurs in Europe, Asia, and, to a lesser extent, in Latin America.

[Table 1 about here]

Tables 2 and 3 provide summary statistics of main variables. We split the respective samples by diversification or exposure along the yearly median. For the syndicated loan market, Table 2, Panel (a), shows that loans by geographically diversified banks are larger, have lower interest rates, and are issued at longer maturity than loans by banks with geographically more concentrated portfolios. The large difference in loan volume suggests that geographically diversified banks are on average larger than their less diversified counterparts. Panel (b) shows that diversified banks are significantly larger, have a higher share of wholesale deposits, and a lower leverage ratio (for the sample of banks we succesfully match to Bankscope). The difference in bank characteristics highlights the need to control for observable and unobservable bank characteristics. In Table 3, Panel (a), the average firm with an above median exposure to diversified banks obtains loans with larger volume, lower interest rates and longer maturity compared to firms with fewer relationships with diversified banks. Panel (b) restricts the sample to firms with balance sheet information from Compustat. Borrowers with high exposure to diversified banks tend to grow slower and are larger than their peers borrowing from banks with a geographically concentrated portfolio. Long-term debt as share of total assets is similar across both groups indicating that they are on average comparable in terms of their need for external finance. Similar to the bank level, the difference in firm characteristics highlights the need to control for firm characteristics to isolate the effects of loan supply.

[Tables 2 and 3 about here]

2.4 Empirical Strategy and Identification

To analyze lending behavior by geographically diversified banks and their effect on firms, we use two aggregation levels. To isolate loan supply from loan demand, we begin on the bank-firm-year level (*bank-firm level*). Then, we aggregate the data to the firm-year level (*firm level*) to examine substitution across loans, as well as real effects on firms.

Bank-firm level Our baseline specification tests how geographic diversification (DIV) affects loan volume for each firm-bank pair. To see whether diversification has a positive effect on loan supply during financial turmoil in the borrower country, we interact diversification with a banking crisis dummy (BC):

$$log(loan)_{f,b,t} = \beta_1 \; BC_{c,t} + \beta_2 \; DIV_{b,t-1} + \beta_3 \; BC_{c,t} \times DIV_{b,t-1} + \phi_{f,b} + \tau_t + \psi_{b,t} + \varepsilon_{f,b,t}. \quad (3)$$

The dependent variable $log(loan)$ denotes the log of outstanding loan volume of firm f from bank b in year t. Banking crisis dummy $BC_{c,t}$ is at the country level and takes value one during a crisis in firm country c in year t. $DIV_{b,t-1}$ is the geographic diversification index on the bank-year level. We lag DIV by one period to avoid contemporaneous effects of the banking crisis on banks' diversification.[20] $\phi_{f,b}$ are firm*bank fixed effects, τ_t are either firm*year or country*industry*year fixed effects; $\psi_{b,t}$ denote bank*year fixed effects. We cluster standard errors on the firm-country*year level (i.e. treatment level of the banking crisis) to account for correlation within the same borrower country across firms.[21] Regression (3) is similar in spirit to a difference-in-difference regression. The coefficient of interest β_3 reflects the change in loan supply by diversified banks minus the

[20] We assume that a firm's bank relationship can be proxied by its previous year credit dependence. This builds on the finding of Ongena and Smith (2001) and Chodorow-Reich (2014) that banking relationships are sticky over time.

[21] See Abadie, Athey, Imbens and Wooldridge (2017), who suggest clustering on the unit of treatment if treatment is at the aggregate level. In our case, the individual level is at the bank-firm level, heterogeneity at the bank level (diversification), and the treatment at the firm country-year level (banking crisis).

change in loan supply by concentrated banks. If diversified banks have better access to funds during crises, their loan supply is higher compared to less diversified banks. This is, we expect $\beta_3 > 0$.

The key identification challenge is to absorb changes in loan demand to isolate loan supply. Firms borrowing from diversified banks are on average bigger, so loan demand is likely to be correlated with banks' geographic diversification. Due to the granularity of our data, we can overcome this issue. First, firm*bank fixed effects exploit the variation within the same firm-bank combination over time and control for unobservable and time-invariant bank and firm heterogeneity (such as industry, location or average size), as well as for unobservable time-invariant characteristics at the bank-firm level, such as relationship or distance. Second, firm*time fixed effects allow shocks to affect each firm at each point in time heterogeneously. Thereby we control for unobservable time-varying firm fundamentals (such as profitability, risk, and other balance sheet characteristics) to identify credit supply.[22] Essentially, we are comparing the same firm borrowing from different banks in a given year, while using only the within variation of each bank-firm combination for estimation (Jiménez, Mian, Peydró and Saurina, 2014a). After absorbing any changes in loan demand our estimates reflect loan supply effects.[23]

Since diversification (DIV) is a choice variable, it raises concerns about endogeneity in Equation (3). We do not have a bank level instrument to directly solve the problem. Instead, we make indirect attempts to address the issue. First, we include bank*year fixed

[22]For each firm-year pair, firm*time fixed effects require observations from at least two banks. On the syndicated loan market, around 97 % of all loans satisfy this condition. The sample selection effect due to this demanding specification is therefore negligible.

[23]Note that with granted loans, firm*year fixed effects may not fully address demand (Paravisini, Rappoport and Schnabl, 2014), since they control for general changes in firm level characteristics, but not differential demand by firms across banks. With this caveat in mind, generally the Khwaja-Mian approach is a reasonable approximation to firms' loan demand. To mitigate the problem of bank-firm selection, we repeat our analysis on the restricted sample of firms that borrow from both diversified and concentrated banks in each year (Khwaja and Mian, 2008). Coefficients for the reduced sample have the similar sign, size and significance as for the full sample (unreported).

effects to control for unobservable time-varying bank characteristics, for example bank size, risk taking, or capital ratios. With bank*year fixed effects, we hold all time-varying unobservable bank characteristics constant and compare lending by the *same* bank to the *same* firm (due to firm*time fixed effects) at different levels of diversification. Second, we directly control for observable determinants of diversification at the bank-year level ($X_{b,t}$), interacted with *banking crisis* ($BC_{c,t}$). If the controls explain both banks' level of diversification and their lending during crises, then controlling for their interaction allows us to isolate the direct effect of diversification on lending. For example, diversified banks could be larger. If larger banks maintain relatively higher loan supply during local crises, the coefficient on diversification would be biased. We match a sub-sample of banks in Dealscan with bank balance sheet data in Bankscope. Bank characteristics we deem important predictors of diversification are bank size (log assets), Tier 1 capital ratio, the share of wholesale deposits over total deposits, leverage ratio, and return on equity. To test how important these balance sheet items are in explaining bank diversification, we estimate regressions with diversification as dependent variable and bank covariates as explanatory variables.

[Table 4 about here]

Table 4 shows that bank size and share of wholesale deposits are statistically and economically significant explanatory variables of diversification. We use two dependent variables, diversification as continuous variable (defined in Equation (1)) and as a dummy with value one for banks with diversification above the yearly median. Columns (1) and (2) compare levels of diversification across banks. *log(assets)* and *share wholesale deposits* have positive coefficients, significant at the 1 % level, indicating that diversified banks differ in terms of size and funding structure from concentrated banks. Since our baseline regression (Equation (3)) includes bank*firm fixed effects, they are exploiting *within-*

bank variation. Hence, columns (3) and (4) replicate columns (1)-(2), but add bank fixed effects. Only size remains a significant predictor for diversification.[24] As we will show below, both methods − including bank*year fixed effects and bank characteristics interacted with the crisis dummy − leave main estimates similar in terms of sign and significance, with only modest changes in magnitude. These findings alleviate concerns about omitted variable bias, despite the lack of a proper instrument for diversification.

Firm level On the bank-firm level we observe whether credit at the firm-bank level changes differentially during crises, depending on the type of lender. However, the analysis neglects potential substitution effects and remains silent about the real effects of loan supply on firms. If firms can easily substitute syndicated loans from banks that reduce loan supply with loans by banks that increase loan supply, the substitution offsets the credit contraction of individual banks. In this case, firm exposure to geographically diversified banks becomes irrelevant for firms' syndicated loan growth. Beyond the syndicated loan market, firms may also be able to substitute a fall in syndicated lending through other debt instruments, for example non-syndicated credit or corporate bonds. Such a substitution would imply that we do not find any effect of bank diversification on firms' total debt or investment, *even if* we find an effect on firms' syndicated loan growth. Loan supply only has real effects on firm performance if firms can at most partially substitute the fall in credit.

[24]Note the strong increase in R^2 when adding bank fixed effects, suggesting that most of the variation diversification within banks is explained by a bank fixed effects, i.e. a bank characteristics that is constant over time. In the Online Appendix, we run within-bank regressions of bank diversification at the end of our sample on bank diversification at the beginning of the sample. This yields a highly significant coefficient of 0.64 and R^2 of 0.38, confirming that diversification is stable over time. This alleviates concerns about banks choosing to diversify over time and then being more or less likely to lend to crisis countries.

To test for substitution and real effects, we run the following firm level regression:

$$\Delta y_{f,t} = \gamma_1 \ BC_{c,t} + \gamma_2 \ exposure_{f,t-1} + \gamma_3 \ BC_{c,t} \times exposure_{f,t-1} + \phi_f + \tau_{c,i,t} + u_{f,t}, \quad (4)$$

In the baseline specification, the dependent variable $\Delta y_{f,t}$ is the log difference of outstanding syndicated loan volume of firm f to *all* its lenders in year t. In further regressions, we use the log difference of total long-term debt to test for substitution into non-syndicated debt instruments. To analyze real effects, we also use investment and employment growth in log differences. Banking crisis dummy ($BC_{c,t}$) varies at the country level and equals one during banking crisis years in the firm country c. $exposure_{f,t-1}$ is the share of firms f's outstanding credit from diversified banks as defined in Equation (2), lagged by one period. ϕ_f denote firm fixed effects, and $\tau_{c,i,t}$ denote time-varying country*industry*year fixed effects, where c and i denote firm f's country and industry. For our Compustat sample we additionally control for time-varying firm demand by including return on assets, leverage, and log of assets. We cluster standard errors at the firm level in all estimations.

Our main coefficient of interest, γ_3, is on the interaction term ($BC \times exposure$). γ_3 is the firm level counterpart of β_3, which is the estimated interaction coefficient ($BC \times DIV$) from bank-firm level Equation (3). It shows the change in loan growth for high exposure firms minus the change in loan growth for low exposure firms. If firms can perfectly substitute a fall in lending by one bank with other forms of financing, then $\gamma_3 = 0$ in the respective regression. In turn, a non-zero estimate of γ_3 suggests imperfect substitution. We expect $\gamma_3 > 0$, as higher exposure to diversified banks should lead to higher loan growth during crises.

To identify loan supply, we employ country*industry*time fixed effects to absorb time-varying demand changes for each industry in each country. The identifying assumption is that all firms within one industry of one country change their loan demand equally. How reasonable is it to assume no heterogeneity in firm demand within industries? If there is differential loan demand within industries, our coefficient is biased and does not reflect supply effects. We test the validity of this identifying assumption on the bank-firm level, where we compare estimates using country*industry*time fixed effects with estimates employing the more rigorous firm*time fixed effects.[25] As we will show, coefficients are close, but somewhat larger under country*industry*time fixed effects, so we interpret our firm level estimates as upper bounds of the true effect.

3 Results

In Section 3.1 we first establish on the bank-firm level that diversified banks smooth local financial shocks, relative to non-diversified banks. Time-varying borrower fixed effects control for changes in firm demand to isolate supply effects. To examine real effects, we then aggregate to the firm level and show that firms with higher exposure to diversified banks have stronger loan, investment, and employment growth during banking crises. Section 3.2 sheds light on the underlying mechanism and shows that geographically diversified banks can raise new funding during crises.

Before moving to the regression analysis, Figure 2 shows the stabilizing effect of diversified banks in a non-parametric way. Panel 2a plots log loan volume in the four years prior, during, and after a banking crisis. We split loans into loans by diversified (blue solid line) and non-diversified (dashed black line) banks according to the yearly median of *diversification*. Loan volume follows a similar trend for diversified and non-diversified banks in the years preceding a crisis. However, it diverges sharply during the crisis. Both types of banks see a sharp and persistent contraction in loan volume, but the decline is almost twice as strong for non-diversified banks. The divergence in

[25]Our baseline sample requires each country-industry-year pair to have at least two firms. When we use firm*time fixed effects, we lose around 2 % of observations, as some firms only have one lender connection.

loan volume is because of banks' geographic diversification and we will estimate it as the difference in the change in loan supply by diversified banks and the change in loan supply by concentrated banks (coefficient β_3 in regression (3)). We now confirm that the pattern shown in Figure 2 holds in regression analysis.

3.1 Main Results

Bank-firm level Table 6 reports results for regression Equation (3) and shows that diversified banks maintain higher loan growth during banking crises, relative to non-diversified banks. The dependent variable is log loan volume. Column (1) looks at variation within each firm-bank connection by using fixed effects on the firm*bank level. Diversified banks extend loans with higher volume in general, as indicated by the positive coefficient on *diversification*. The coefficient of interest (β_3) on the interaction term ($DIV \times BC$) is highly significant and positive. During banking crises, increasing diversification by one standard deviation increases loan volume by ($0.31 \times 0.135 =$) 4.2 %. To ensure that the positive effect is due to supply effects, column (2) adds firm*time fixed effects to absorb any time-varying changes in firm demand.[26] Borrowing from a diversified bank is now not statistically different to borrowing from a non-diversified bank during non-crisis times. The positive effect of diversified banks during banking crises remains significant: increasing diversification by one standard deviation during a banking crisis increases firms' loan volume by 1.2 %. Borrowing from a fully diversified bank ($DIV = 1$) increases the positive effect to 3.9 %, compared to borrowing from banks with an entirely concentrated portfolio ($DIV = 0$). Comparing columns (1) and (2), we see that absorbing demand effects reduces the coefficient on the interaction term by around two-thirds. The change in size suggests that diversified banks lend to borrowers

[26]The coefficient on banking crisis is now absorbed by firm*year fixed effects.

of higher resilience and better quality during crises. However, after controlling for loan demand, there remains a positive and significant loan supply effect associated with higher geographic diversification.

[Table 6 about here]

Figure 2, Panel 2b, plots log loan volume after removing loan demand effects through firm*time fixed effects.[27] Comparing it to Panel 2a, we see that demand effects explain a large part of the overall decline in loan volume. Strikingly, after removing demand effects, diversified banks maintain their loan supply during the crisis and increase it in the following years. Non-diversified banks reduce loan volume persistently.As in Panel 2a, loan supply follows a similar trend for both bank types prior to the crisis. By absorbing any changes in firms' loan demand, Panel 2b illustrates the stabilizing effect of geographic diversification on loan supply, after controlling for unobservable firm characteristics.

When we move to the firm level, we can no longer control for credit demand through firm*time fixed effects. Instead, we use country*industry*year fixed effects, so we assume that firms within the same country-industry-year pair change demand similarly. To verify this assumption, column (3) runs the bank-firm level regression with country*industry*year fixed effects. Comparing coefficients with column (2) indicates how appropriate we capture demand effects. The coefficient of interest has the same sign and significance, but is larger in column (3). Controlling for time-varying industry demand leads to an overestimation of the effect by about one third. The increase in the coefficient on $DIV \times BC$ suggests that even within four-digit industries, there is variation in loan demand. We therefore interpret our firm level results as an upper bound of the true effect.[28]

[27]We plot the residual of a regression of log(loan volume) on firm*time fixed effects that absorb any unobservable change in firms' loan demand. After absorbing demand effects the residual reflects banks' credit supply.

[28]Observation vary due to fixed effects. The firm level requires ≥ 2 firms in each country*industry*year cell, so we set this minimum requirement when defining our baseline bank-firm level sample.

Firm*year fixed effects control for loan demand. However, it could still be that diversified banks fundamentally differ from concentrated banks. Table 2 Panel (b) shows that diversified banks are larger and rely more on wholesale funding. To account for observable and unobservable differences across banks that could be related to diversification, columns (4)-(6) include bank*year fixed effects and bank balance sheet items. Including bank*year fixed effects in addition to bank*firm and firm*year fixed effects controls for unobservable time-varying bank characteristics, for example bank size, risk taking, capital, or bank nationality. Column (4) thus compares lending by the *same* bank to the *same* firm during a crisis at different levels of diversification − we hold all unobservable bank characteristics constant. Compared to column (2), the coefficient of interest almost doubles in magnitude.[29] A fully diversified bank now supplies 7.2 % more credit than a concentrated one, suggesting that the positive effect of diversification is not explained by unobservable bank characteristics.

While the positive and significant coefficient on $DIV \times BC$ suggests that bank diversification has a positive effect on loan supply conditional on basic bank covariates, it could still be that bank characteristics have a *marginal* effect during crises. We thus include bank balance sheet items, interacted with the banking crisis dummy, in column (6). Since the matched Dealscan-Bankscope sample leads to a fall in the number of observations, column (5) first shows that within the sample of banks for which we obtain balance sheet information, diversification has a positive effect on loan supply (after controlling for bank*firm, firm*year, and bank*year fixed effects). Relative to the baseline specification in column (4), the coefficient of interest increases in size. However, the standard deviation of DIV is now 0.24, compared to 0.31 for the full sample, yielding comparable magnitudes. Once we include bank balance sheet items interacted with BC in column (6), the coefficient on $DIV \times BC$ remains positive and significant, but declines

[29]The coefficient on diversification is now absorbed by fixed effects

in magnitude compared to column (5). While large banks and banks with a higher share of wholesale deposits also exhibit higher loan supply during local crises, diversification still matters. All in all results in Table 6 show that diversified banks sustain higher loan supply during crisis times, relative to banks with a concentrated loan portfolio; and that the effect is robust to bank size, bank funding structure, as well as unobservable bank characteristics.

Firm level Loan level regressions identify changes in individual firm-bank connections. If firms can substitute between bank types during banking crises, changes in individual loans need not affect firms. Suppose a firm borrowing from a non-diversified bank sees a contraction in loan supply. Forming a new borrowing relationship with a diversified bank mitigates the negative credit supply shock. To examine whether credit supply shocks have real effects, we aggregate to the firm-year level. Tables 7 and 8 show results for estimating regression Equation (4). Firms with higher exposure to diversified banks fare better during banking crises, relative to firms with low exposure.

[Tables 7 and 8 about here]

In Table 7, column (1) controls for unobservable time-invariant firm characteristics through firm fixed effects. The dependent variable is loan growth $\Delta loan_{f,b,t}$. In line with expectations, the coefficient on *exposure* is negative, because diversified banks lend predominately to larger firms in developed economies, which have lower average growth rates. The negative coefficient on banking crisis implies that borrowers' credit growth declines by 14.2 % during banking crises when they have no connections to diversified banks (exposure= 0). Higher exposure to diversified banks attenuates the negative effect. The coefficient on the interaction term of exposure and banking crisis ($exposure \times BC$) is positive and statistically significant at the 1 % level. Increasing exposure from the 25^{th} to 75^{th} percentile increases loan growth during a crisis by ($0.39 \times 0.055 =$) 2.1 %. To remove time-varying demand shocks, column (2) absorbs shocks on the country*year level, column (3) on the more granular country*industry*year level.[30] In both specifications, coefficients are of similar sign, magnitude, and significance. In our preferred specification in column (3), moving a firm from the 25^{th} to 75^{th} percentile in terms of exposure to diversified banks leads to 1.5 % higher loan growth. Average loan growth equals 3.6 %, so the positive effect of borrowing from diversified banks is sizeable. The effect on the firm level is similar in size to effects on the bank-firm level. This suggests that frictions hamper firms from switching across bank types during recessions, a common finding in the literature (Ongena and Smith, 2001; Chodorow-Reich, 2014).

In Table 8 we restrict our sample to firms for which we have balance sheet information. To analyze real effects, we use long-term debt, employment, and investment as dependent variables (all in log differences). For each dependent variable, we run a parsimonious specification with firm fixed effects, as well as one enriched with time-varying firm controls and time-varying fixed effects at the country*year level.[31] We consistently find that firms borrowing from diversified banks have significantly higher growth rates during crises. In the more stringent specification, moving borrowers from the 25^{th} to 75^{th} percentile in terms of exposure to diversified banks leads to higher long-term debt (4.1 %, column (2)), employment (1.1 %, column (4)), and investment growth (4.6 %, column (6)) during crises. Similar to loan growth in Table 7, growth rates are lower for high-exposure borrowers in normal times and fall during banking crises. This reflects that diversified banks lend to larger firms that have lower average growth rates (see Table 3). Controlling for common time-varying shocks on the country level as well as time-varying firm controls in general reduces the magnitude and significance of the effect.

[30] As *banking crisis* does not vary on the industry level, the coefficient is absorbed by fixed effects.

[31] Unfortunately, the low number of observations per industry leads to a large loss of observations when we use country*industry*year fixed effects.

Our loan and firm level findings show that firms can at most imperfectly substitute declines in syndicated lending by other forms of funding. Credit supply by diversified banks leads to real effects for firms. Results from Table 7 suggest that firms cannot switch from concentrated to diversified banks in the syndicated loan market. Otherwise, exposure in previous periods would not affect loan growth. The positive effects of exposure in Table 8 on long-term debt, as well as investment and employment, additionally indicate that firms cannot substitute from syndicated into non-syndicated lending. In sum, Tables 6−8 establish that changes on the syndicated loan market have real economic effects, which cannot be undone through other forms of credit. Borrowing from diversified banks significantly increases firms' loan growth during times of local financial distress. In the following sections, we provide evidence that diversified banks are financially less constrained during local shocks, which is why they can raise new funding and stabilize lending.

3.2 Mechanism

We argue that banks' geographic diversification across countries gives them better access to new funding, for example to wholesale deposits, during local shocks in one of their borrower countries. The mechanism is based on recent literature that causally shows that geographically diversified banks have lower risk, because geographic expansion reduces exposure to idiosyncratic local shocks (Goetz, Laeven and Levine, 2016). Better diversification and lower risk thus provide better access to funding, especially during times of crises (Levine, Lin and Xie, 2016; Bord, Ivashina and Taliaferro, 2018).[32] Based on these findings, in this section we provide evidence that banks that are geographically diversified

[32] Related papers show that banks use their internal capital market to distribute resources among affiliates to smooth local shocks. See for example Morgan, Rime and Strahan (2004); Goldberg (2009); Cetorelli and Goldberg (2012); Buch and Goldberg (2015); Coleman, Correa, Feler and Goldrosen (2017); Cortés and Strahan (2017).

across countries are financially less constrained during local shocks in borrower countries. We first show direct evidence for the subset of banks that borrow on the syndicated loan market, and for banks for which we have balance sheet data. We then report indirect evidence for the full sample of banks that lend in our syndicated loan market sample.

To shed light on banks' liability side, we analyze bank *borrowing* on the syndicated loan market. First, for all financial institutions (SIC codes 6000-6199, 35,876 loans) that borrow on the syndicated loan market, we construct the yearly log-change in banks' syndicated borrowing in a given year.[33] This provides us with a sample of 351 banks and 2,964 bank-year observations across 53 countries. Second, we use our matched Dealscan-Bankscope sample of around 200 banks and use the change in absolute (or share over total) wholesale deposits as dependent variable (867 bank-year observations, 23 countries). To see whether host country shocks lead to an increase in deposits for diversified banks, we then regress banks' interbank borrowing or wholesale deposit growth on their diversification (DIV), interacted with a dummy equals one if a bank has extended syndicated loans to crisis countries (*loans in crisis*). We control for bank size, Tier 1 capital ratio, and return on equity in Bankscope regressions. If diversified banks can tap new funds during times of distress, we expect a positive effect of diversification on interbank borrowing and wholesale deposits.[34]

[Table 9 about here]

Table 9 shows that diversified banks increase interbank borrowing and their deposits in response to a host country shock. For the Dealscan sample, column (1) shows that for the average bank, interbank (syndicated) borrowing falls when it has a higher share

[33] We compute bank b's syndicated (interbank) borrowing from lenders $l \in L$ in year t as $interbank_{b,t} = \sum_{l=1}^{L} loan_{b,l,t}$.

[34] Matching banks active in the Dealscan interbank market to Bankscope results in too few observations for analysis, which is why we analyze both samples separately.

of loans in distress. This could reflect that depositors question liquidity or solvency of the bank when parts of its loans are in distress. Looking at interaction terms, we find that diversified banks increase their bank-borrowing during crises in borrower countries. Increasing diversification by one standard deviation leads to an increase in deposits of around 5.9 %. Thus, diversified banks raise new funds in the interbank market when faced with a shock in borrowing countries. The same is true when we replace the dependent variable with a dummy that takes on value one if a bank sees an increase in total bank-borrowing in a given year (column (2)). To control for unobservable bank characteristics and unobservable shocks to banks' home countries, each regression in columns (1)-(4) includes bank and bank country*year fixed effects (standard errors are clustered on the bank level). Since Dealscan does not provide balance sheet data, we strengthen identification in columns (3)-(4) by adding fixed effects at the bank size*year level (where bank size is defined as quintiles of total bank loan volume in a given year), to better control for unobservable differences across banks of different size. Results narrow slightly in magnitude, but coefficients of interest remain significant at the 5 % level.

For the Bankscope sub-sample, columns (5) and (7) use the change in total bank wholesale deposits as dependent variable, columns (6) and (8) the change in the share of wholesale deposits (over total deposits). All specifications use bank and bank country*year fixed effects, columns (7)-(8) add bank controls. Across specifications, diversification has a positive effect on banks' wholesale funding during crises. In column (5), a one-standard deviation increase in diversification raises wholesale deposit growth by around 4 %. The strong positive effect of diversification on deposit growth supports the hypothesis that diversified banks can raise new funds during times of distress.[35] All in

[35] Note that changes in interbank borrowing reflect demand and supply. We argue that both diversified and non-diversified banks would like to borrow to sustain lending (i.e. have positive demand), but only diversified banks are supplied new funds. Hence, the positive coefficients are likely an over-estimation of the true supply effect.

all, Table 9 provide evidence that diversified banks can raise new funds in the interbank market to maintain lending during local shocks.

Table 9 uses data for a subset of banks to provide direct support for the mechanism. We now use data on the universe of banks extending loans (to non-financial borrowers) in the syndicated loan market to further investigate the importance of geographic diversification for access to funding. If banks are 'financially constrained', they cannot raise new funds when facing a negative shock. Instead, they must trade off where to allocate existing liquidity within their bank network. Any reallocation of funds towards crisis countries will then lead to negative spillover effects to borrower markets that are connected to the bank. This is not the case if unconstrained banks can raise new funds − as suggested by results in Table 9. By analyzing changes in loan supply in connected countries, we can provide indirect evidence on banks' access to new funds for all banks in our sample.

For illustration, suppose there is a negative financial shock in Germany. Will a bank that is active in Germany and France move funds from France to Germany and reduce lending in France to prop up German affiliates? Or can it raise new funds, which allows it to stabilize lending in Germany while maintaining loan supply in France? The answer to the question has important implications, as the former implies spillover effects to unaffected markets, while the latter does not. To measure spillover effects we aggregate the data to the bank-borrower country-year level and define the dummy variable $connected_{b,k,t}$. In particular, $connected_{b,k,t}$ equals one for all non-crisis countries k ($\neq j$) in year t, to which bank b is actively lending in t, if at least one other borrower country j of bank b experiences a banking crisis in t. The coefficient on *connected* shows how bank b, in response to a crisis in j, changes its lending to all *connected countries* k that do not experience a crisis themselves, which is in the spirit of Giroud and Mueller (2015, 2017).[36] We run regressions of the following form:

$$\Delta loan_{b,j,t} = \phi_{b,j} + \tau_t + \rho_1\ BC_{j,t} + \rho_2\ connected_{b,k,t} + \rho_3\ DIV_{b,t-1} \\ + \rho_4\ DIV_{b,t-1} \times BC_{j,t} + \rho_5\ DIV_{b,t-1} \times connected_{b,k,t} + u_{b,j,t}, \tag{5}$$

where the dependent variable is loan growth by bank b to all borrowers in j at t in log differences. DIV is our diversification metric on the bank level. We use bank-borrower country ($\phi_{b,j}$) and time (τ_t) fixed effects to analyze changes within a bank-borrower country connection and absorb common trends. We expect banking crises to affect loan growth negatively, so $\rho_1 < 0$. If there are spillover effects, connected markets see a fall in loan growth and $\rho_2 < 0$.[37] From our previous results, we expect that diversified banks stabilize loan growth in host country j, so $\rho_4 > 0$. If diversified banks are financially unconstrained, they mitigate spillover effects and the coefficient on the interaction term ($DIV \times connected$) is positive ($\rho_5 > 0$). In other words, if $\rho_5 > 0$ we conclude that diversified banks have better access to new financing during host market shocks. We cluster at the borrower country*year (treatment) level to account for serial and cross-sectional dependence across borrowers.

Table 10 shows that globally diversified banks have higher loan growth in crisis countries, and shield connected countries from spillovers. Column (1) reports a negative and significant coefficient on *banking crisis (BC)* which implies that banks reduce lending by 12.3 % in affected countries. The negative coefficient on *connected* shows that banks reduce lending by 7 % in unaffected countries when another borrowing country experiences a banking crisis. Note that the spillover effect is about two-thirds the size of the coefficient on banking crisis. The positive and highly significant coefficients on $DIV \times BC$ and $DIV \times connected$ show that diversified banks stabilize loan supply in their host country,

[36]For example, for a bank that lends to Germany, France, and Italy, where only Germany experiences a crisis in 2005, *connected* takes value one for France and Italy in 2005, and zero otherwise.

[37]Since our data are a bank-country-year panel, note that for connected countries k, coefficients ρ_2 and ρ_5 reflect the effect on changes in loans by bank b to country k, so $\Delta loan_{b,k,t}$.

and reduce contagion effects. Moving a bank from the 25^{th} to the 75^{th} percentile reduces spillover effects from -7 % to almost zero. Fully diversified banks are thus able to offset the crisis-induced decline in loan supply both in affected and connected countries. When we control for unobservable characteristics at the borrower country level by including borrower country*year fixed effects in column (2), coefficients decline somewhat in magnitude, but remain qualitatively close to column (1). Effects remain highly significant.[38]

[Table 10 about here]

Our argument rests on the assumption that a diversified loan portfolio insures against local crises, so that diversified banks are financially less constrained. To provide further evidence on the mechanism, columns (3)-(6) show that diversification is no longer stabilizing when a significant share of banks' total loan portfolio is in distress. For each bank, we first compute its yearly share of loans extended to borrowers in countries with a banking crisis. We then define *low distress* as bank-year observations for which the share is below the yearly median (i.e. only a low share of banks' total loan portfolio is in distress), and *high distress* those for which it is above (i.e. a significant share of banks' asset side is subject to a shock). Results show that diversified banks stabilize lending in crisis and connected countries during periods of low distress $-$ when they are expected to be financially unconstrained (column (3)). During high distress in column (4), there is no stabilizing effect, in line with the hypothesis that financial constraints bind also for diversified banks during 'global shocks'.[39] As an alternative, we split the sample by the yearly median according to the share of banks' borrower countries in crisis (out of total bank borrower countries). *few (many) crises* denotes bank-year observations for which

[38]Note that BC is now absorbed by fixed effects. We cannot include bank*year fixed effects, because $DIV \times connected$ varies on the bank-year level and would then be absorbed.

[39]Note that in column (4), we restrict the sample to banks with at least some loans under distress. Hence, banking crisis always has value one and connected value zero, so the coefficients on *diversification, BC*, and *connected* are no longer separately identified.

a small (large) fraction of borrower countries experiences a crisis.[40] Results in columns (5)-(6) are similar to those in columns (3)-(4). Diversification is stabilizing during 'local crises', but no longer provides benefits during crises that affect a significant share of banks' borrower countries.

Table 10 suggest that there is a difference between *within* and *across* country diversification. We analyze systemic banking crises, i.e. crises that affect a whole country. Since diversification *within* one country provides insurance against idiosyncratic local shocks within one country, it does not provide insurance against a country-wide (systemic) shock. Instead, diversification *across* countries provides insurance even during local systemic crises, as long as only a modest share of banks' host markets is hit by shocks. However, the larger the fraction of borrower markets in distress, the lower the benefits of diversification across countries. We interpret our results in Tables 9 and 10 as evidence that being geographically diversified allows banks to tap into new funds during crises, which reduces the need to withdraw capital from other markets. The ability to raise new funds stabilizes banks' loan growth in the crisis country, but also shields connected markets from negative spillovers.

4 Extensions & Robustness

We argue that banks' geographic diversification is the reason that they stabilize loan supply. In this section we highlight the importance of banks' nationality and address potential alternative explanations to diversification. To ensure identification of supply effects, we run variants of loan level regression Equation (3). In all regressions, firm*bank and firm*time fixed effects absorb credit demand.

[40] The correlation between our *distress* and *crisis* dummies is 0.73.

Foreign banks and local affiliates Diversified banks lend a significant share of their loans to foreign markets. A large literature finds that foreign and domestic banks differ during crisis episodes, which raises the concern that our classification by portfolio allocation reflects banks' nationality (Claessens, 2017). Table 11 shows that a categorization of banks by diversification is different from a categorization by nationality. We include a foreign bank dummy that takes on value one if a banks' home country is not equal to its host country.[41] Column (1) shows that foreign banks reduce lending by 1.5 % during host banking crises. Once we include our diversification metric in column (2), a non-diversified foreign bank reduces loan supply by 4.4 %. Diversified banks, on the other hand, are still stabilizing. Compared to baseline results in Table 6, the coefficient on $DIV \times BC$ increases in size to 8.5 % once we control for banks' nationality. This suggests that domestic banks with a diversified portfolio are the most stabilizing source of funding. We confirm this finding in column (3), where we interact the foreign dummy with diversification. For ease of interpretation we redefine *diversification* as a dummy with value one if diversification is above the yearly median. The interaction effect between diversification and foreign bank during banking crises is highly significant and negative. The coefficient on interaction terms $DIV \times BC$ ($foreign\ bank \times BC$) remains positive (negative) and significant at the 1 % (10 %) level. In terms of economic significance, effects differ extensively across bank types. During banking crises, non-diversified foreign banks reduce lending by 1.9 %. Domestic diversified banks increase their relative loan supply by 8.2 %. The intermediate group of diversified foreign banks increases loan supply by 2.4 %. Results in columns (1)-(3) confirm the following pecking order: diversified domestic banks ($DIV = 1$, foreign bank $= 0$) are the most stable source of funding, while foreign banks with little diversification (DIV $= 0$, foreign bank $= 1$) are the most fickle. Foreign diversified banks lie in the middle. The ordering ties with findings on the

[41] As nationality is constant within firm-bank connections, the coefficient on foreign bank is absorbed by fixed effects.

flight home effect (Giannetti and Laeven, 2012) and behavior of gross capital flows during crises (Broner, Didier, Erce and Schmukler, 2013): Literature has shown that banks and domestic agents often protect their home markets during times of distress.

To further shed light on the role of distance and nationality, columns (4)-(6) repeat the same regressions, but replace the *foreign bank* dummy with the dummy *local affiliate*. *local affiliate* takes on value one if a bank operates an affiliate or subsidiary in the borrower country, and value zero otherwise.[42] Literature has shown that local presence and distance to borrowers matter for lending decisions, especially during crisis times (Degryse and Ongena, 2005; De Haas and Van Lelyveld, 2014; Bolton, Freixas, Gambacorta and Mistrulli, 2016). When we include *local affiliate*, we find that banks with local affiliates behave similar to domestic banks: Column (4) shows that banks with local affiliates stabilize lending during host market shocks. Including our diversification measure in a horse race in column (5), we find that diversification still matters for loan supply above and beyond having a local affiliate. Finally, column (6) presents a similar picture as column (3). Diversified banks are stabilizing, but the more so, if they also have a local affiliate in the crisis country (positive coefficient of *local affiliate* $\times$ *BC* and on triple interaction effect).

[Table 11 about here]

Portfolio risk Banks differ in terms of borrower risk (Neuhann and Saidi, 2018; Levine, Lin and Xie, 2016). If diversified banks extend loans to less risky borrowers, they are less exposed to the negative effects of a crisis. To address this issue, for each bank we compute portfolio risk by taking the standard deviation of sales growth for each firm in non-crisis years. We consider non-crisis years only, as the stabilizing role of diversified banks during

[42] We use data on subsidiaries from Dealscan.

crises could lead to a downward bias in measured volatility. Table 5 shows that firms with low exposure to diversified banks are riskier in terms of volatility of investment, employment, asset, and sales growth. Firms are assigned into top and bottom tercile according to their exposure for each year.[43] In Table 12, column (1), we control for banks' portfolio risk, interacted with the banking crisis dummy, in column (2) we interacted portfolio risk with diversification and the crisis dummy. Diversified banks still have significantly higher loan supply. Once we include portfolio risk (interacted with banking crisis) in column (1), we see that higher portfolio risk reduces loan supply during a banking crisis.[44] However, the main coefficient of interest on $DIV \times BC$ increases. Including a triple interaction effect in column (2) keeps the main coefficient stable. We also see that higher portfolio risk reduces loan supply for non-diversified banks. The insignificant triple interaction term close to zero indicates that portfolio risk has no differential effect through diversification. Since we absorb borrower characteristics through firm*year fixed effects, this is to be expected. We interpret this as evidence that portfolio risk is not responsible for the stabilizing effect we find, but that banks' diversification still leads to significantly higher loan supply during crises.

[Tables 5 and 12 about here]

Alternative concentration measures The fact that banks extend international loans could itself reflect a different business model, regardless of diversification, and be responsible for our main findings. To take into account the international allocation of banks' loan portfolio, analogous to our diversification metric in Equation (1) we define banks' international portfolio as the ratio of international loans to total loans.[45] Column (3)

[43] We restrict the analysis to observations for which we have balance sheet data, which reduces the number of loan level observations by around 60 %.

[44] Portfolio risk is constant for banks and thus absorbed by fixed effects.

[45] International portfolio is defined as $INT_{b,t} = \frac{intl.\ syndicated\ loan\ volume_{b,t}}{total\ syndicated\ loan\ volume_{b,t}} \in [0,1]$. $Intl.\ syndicated\ loan\ volume_{b,t}$ is the sum of all loans by bank b in year t to firms located in a different

in Table 12 shows that diversification, not internationality, leads to positive loan supply effects. Banks with a fully international portfolio reduce loan supply by 1.6 % during crises, but the coefficient is insignificant. The positive stabilizing role of diversified banks remains. Columns (4)-(6) control for additional bank specialization metrics. Column (4) introduces banks' *country share*, i.e. the share of loans by bank b to country c in a given year t, out of bank b's total loans in year t. Similarly, column (5) adds banks' *industry share*, i.e. the share of loans by bank b to industry i in a given year t. These columns address the fact that banks might have superior knowledge in certain geographies or industries (De Jonghe, Dewachter, Mulier, Ongena and Schepens, 2019). We find that bank diversification still significantly increases loan supply during crises. Column (6) investigates whether *firm* diversification matters. For each borrower, we construct a (1- Herfindahl index) of its loans (analogous to bank diversification in equation (1)). Firms that borrow from multiple banks to a similar extent receive a higher value. We define dummy *firm DIV* that takes on value one if a firm is in the top tercile of borrower diversification in a given year. If diversified firms borrow from diversified firms, our diversification metric reflects that borrowers can switch among lenders. When we interact DIV with *firm* DIV and the banking crisis dummy, we find this not to be the case: The coefficient on the triple interaction term is insignificant and close to zero, while the coefficient on $DIV \times BC$ remains positive and highly significant.[46]

Finally, columns (7)-(8) show a horse race of diversification (DIV) vs. alternative metrics (excluding triple interaction terms for ease of interpretation). Column (8) uses bank*firm and firm*year fixed effects, column (9) adds bank*year fixed effects. The

country than the bank's parent entity. $Total\ syndicated\ loan\ volume_{b,t}$ is total lending in year t to all firms, domestic and foreign. We call banks with a low value of INT 'national', those with a high value 'international'.

[46] Note that our regressions include bank*firm fixed effects and firm*year fixed effects. We thus compare changes in lending within the same firm-bank combination and account for unobservable borrower characteristics that vary over time (including firm diversification). Hence, the insignificant coefficient likely reflects the fact that we are controlling for firms' funding structure.

interaction term $DIV \times BC$ maintains its positive and significant coefficient across specifications. Controlling for other potential bank specialization measures increases the size of the coefficient on $DIV \times BC$. We conclude that diversification, not banks' portfolio risk, lending to foreign borrowers, industry, or country specialization explain the positive effects on loan supply during host country banking crises.

Online Appendix The Online Appendix presents extensions and further robustness checks of our baseline findings. We show that our diversification metric correlates with macro variables of financial integration; effects are stronger for financially constrained firms; and that, following a crisis, there is a shift in firms' portfolios towards lending by diversified banks. We also show that our results are robust to excluding FIRE industries, as well as smallest and largest banks; including lead arrangers only; excluding loans with on lender, credit lines and term loans; and when we split loan shares based on imputation instead of pro-rata.

5 Conclusion

We develop a metric to categorize banks according to the geographic diversification of their international loan portfolio. For a large sample of international syndicated loans, we find that diversified banks are a resilient source of financing for firms that experience a countrywide financial crisis. Borrowing from diversified banks increases loan, investment, and employment growth significantly. Detailed bank-firm level data ensure proper identification of supply effects, as we absorb changes in unobservable borrower characteristics through time-varying fixed effects on the firm level. Our results show that diversification allows banks to raise new funds during times of distress. This not only stabilizes loan supply in affected countries, but also reduces spillover effects to connected markets.

When we contrast our measure with the standard classification by nationality, we find that domestic, diversified banks are the most resilient source of financing, while foreign banks provide no insurance. The negative effect of foreign banks is increasing in the concentration of their portfolio. We also exclude candidate explanations other than diversification. Geographic diversification remains a significant factor contributing to higher stability in lending even after we control for banks' international orientation, industry specialization, and portfolio risk.

This paper contributes to the debate on the costs and benefits of financial integration. Figure 3 shows that bank diversification declined during the global financial crisis and remained depressed thereafter. Our results suggest that the recent retrenchment in financial integration following the Great Financial Crisis is worrisome (Milesi-Ferretti and Tille, 2011; Cerutti and Claessens, 2016; Claessens and Van Horen, 2015). While cross-border lending constitutes a potential source of contagion, we show that internationally active and geographically diversified banks have better access to funds during banking crises in their borrower countries and increase resilience to local shocks.

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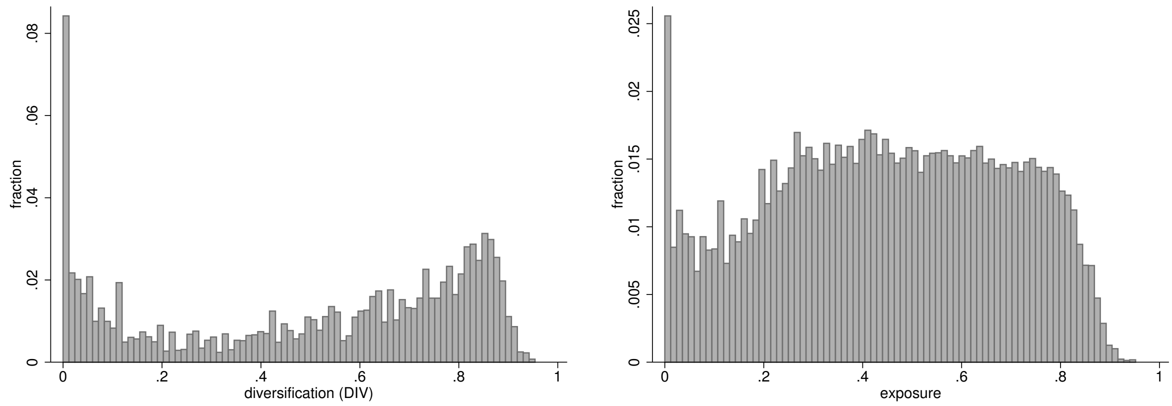
A Tables and Figures

Figure 1: **Bank diversification and firm exposure**

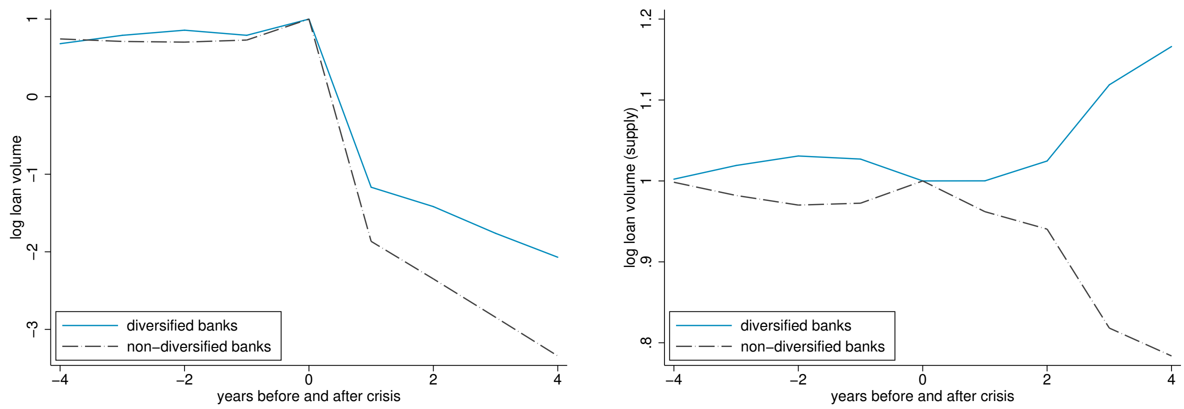
(a) Diversification − bank-firm level (b) Exposure − firm level



Note: Figure 1a shows the loan level distribution of banks' diversification, Figure 1b the firm level distribution of firms' exposure. The mass of observations shifts from the right tail towards the middle, indicating that most firms borrow from both diversified and concentrated banks in each year. For detailed variable definitions see Table B.1 and text.

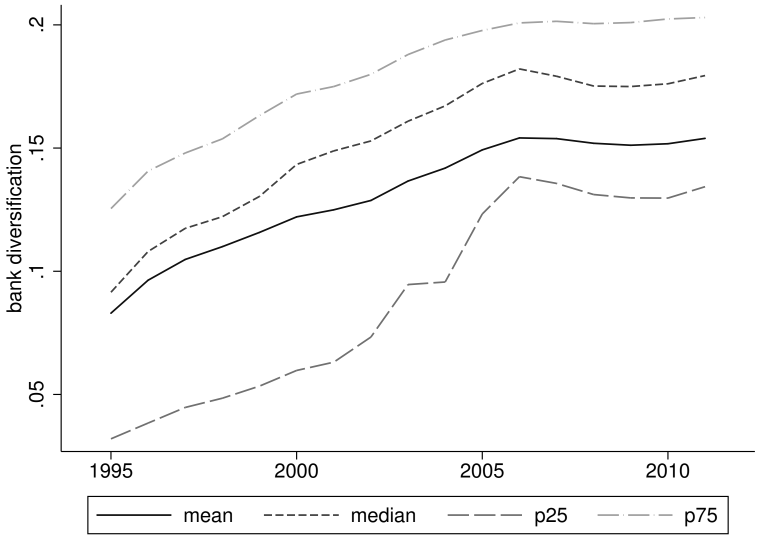
Figure 2: **Loan volume during a crisis**

(a) Total loan volume (b) Loan supply



Note: Both panels show the evolution of log(loan volume) in the four years prior, during, and the four years after a banking crisis. A value of 0 on the x-axis denotes the year of the banking crisis. We split the sample by the yearly median for banks with high and low values of diversification. Loan volume is normalized to 1 in year 0. Panel 2a shows the unconditional average across all banks. Both diversified and concentrated banks see a decline in outstanding loan volume during the crisis and the following years, but concentrated banks see a stronger fall. Panel 2b plots the residual of a regression of log(loan volume) on firm*time fixed effects that absorb unobservable change in loan demand. After absorbing demand effects, both lines reflect changes in loan supply. Diversified banks do not reduce loan supply during the crisis and increase it in the following years, while concentrated banks reduce loan volume during and after the crisis. For detailed variable definitions see Table B.1 and text.

Figure 3: **Banks' diversification over time**



Note: This figure shows the change in bank diversification over time. Diversification is computed according to Equation (1). It plots mean, median, 25^{th}, and 75^{th} percentile from 1995 to 2012. Diversification increased steadily until around 2006, but then decreased during the recent global financial crisis and remains depressed ever since. Less-diversified banks see a stronger retrenchment. For detailed variable definitions see Table B.1 and text.

Table 1: **Summary statistics – by region**

	loans	firms	banks	DIV	BC
East Asia and Pacific	386973	8767	1642	266	28
Europe and Central Asia	379177	6033	1118	269	128
Latin America and Caribbean	39622	626	126	21	24
Middle East and North Africa	30164	334	176	54	0
North America	860634	19176	3711	74	6
South Asia	20379	458	116	8	0
Sub-Saharan Africa	7124	116	73	14	3
Total	1724073	35510	6962	706	189

Note: This table shows the geographic distribution of our sample. *loans* denotes the number of firm-bank-year observations, *firms* and *banks* the number of individual firms and banks. *DIV* stands for diversification and denotes the number of banks with non-zero geographic diversification. Finally, *BC* stands for banking crisis and denotes the number of country-year observations with banking crises. For detailed variable definitions see Table B.1 and text.

Table 2: **Summary statistics – bank-firm and bank level**

Panel (a): Bank-firm level (Dealscan)

	diversified		**concentrated**		**mean diff.**
	mean	sd	mean	sd	t
Δ loan volume	0.02	(0.36)	0.01	(0.34)	-17.00
loan volume (m)	101.67	(296.04)	75.53	(266.63)	-60.94
loan spread (bp)	137.08	(107.52)	191.17	(131.07)	263.55
maturity (months)	76.12	(49.16)	71.39	(42.22)	-67.76
Observations	854370		869703		1724073

Panel (b): Bank level (Bankscope)

	diversified		**concentrated**		**mean diff.**
	mean	sd	mean	sd	t
diversification (DIV)	0.74	(0.18)	0.20	(0.22)	-64.94
log(assets)	12.14	(1.96)	11.09	(1.88)	-12.24
tier 1 capital ratio	10.27	(5.24)	10.50	(3.55)	-0.33
share wholesale deposits	0.29	(0.23)	0.26	(0.29)	-3.13
leverage ratio	5.06	(2.76)	6.81	(2.93)	10.11
return on equity	7.60	(18.83)	8.92	(18.52)	1.41
Observations	863		873		1736

Note: Panel (a) shows descriptive statistics on the bank-firm-year (loan) level, Panel (b) on the bank-year level for the smaller sample of matched Bankscope banks. The sample is split by the yearly median according to banks' diversification. The sample is split by the yearly median according to banks' diversification. Highly diversified observations are denoted *diversified*, those with low diversification as *concentrated*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table B.1 and text.

Table 3: **Summary statistics − firm level**

Panel (a): Dealscan

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
Δ loan volume	0.04	(0.39)	0.03	(0.39)	-2.34
loan volume (m)	763.80	(1982.62)	323.47	(723.77)	-65.52
loan spread (bp)	169.81	(130.74)	235.06	(137.16)	92.05
maturity (months)	83.62	(64.15)	64.91	(42.38)	-76.95
Observations	99948		99986		199934

Panel (b): Compustat

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
Δ employment	0.03	(0.17)	0.03	(0.20)	2.96
Δ investment	0.03	(0.59)	0.04	(0.64)	2.66
Δ sales	0.07	(0.32)	0.09	(0.22)	6.66
investment ratio	0.22	(1.39)	0.23	(0.26)	1.71
return on assets	0.06	(0.08)	0.06	(0.11)	-4.76
employment (th)	17.04	(37.40)	6.48	(15.09)	-45.22
log total assets	8.51	(2.30)	6.48	(2.06)	-115.61
market to book ratio	1.58	(1.01)	1.61	(1.11)	2.06
long-term debt ratio	0.25	(0.20)	0.24	(0.22)	-7.53
Observations	29613		33168		62781

Note: Panel (a) shows descriptive statistics on the firm-year (firm) level for the full sample of Dealscan firms. Panel (b) shows descriptive statistics on the firm-year (firm) level for the smaller sample of matched Compustat firms. The samples are split by the yearly median according to firms' exposure. High exposure firms are denoted *high exposure*, those with low exposure as *low exposure*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table B.1 and text.

Table 4: **Determinants of bank diversification**

VARIABLES	(1) DIV (cont)	(2) DIV (median)	(3) DIV (cont)	(4) DIV (median)
log(assets)	0.044***	0.051***	0.071***	0.005
	(0.011)	(0.019)	(0.023)	(0.042)
tier 1 capital ratio	0.001	-0.003	-0.001	-0.001
	(0.003)	(0.006)	(0.001)	(0.002)
share wholesale deposits	0.364***	0.407***	-0.058	-0.255*
	(0.091)	(0.139)	(0.049)	(0.141)
leverage ratio	-0.015	-0.025	0.010*	-0.015
	(0.010)	(0.016)	(0.005)	(0.012)
return on equity	0.001**	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	1,045	1,045	1,038	1,038
R-squared	0.206	0.117	0.934	0.803
Bank FE	-	-	Yes	Yes
Cluster	Bank	Bank	Bank	Bank

Note: This table shows determinants of bank diversification, as defined in equation (1). Dependent variable is *diversification* or a dummy with value one if diversification is above the yearly median, and zero if below. Bank balance sheet data are from Bankscope. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: **Risk − firm level**

	high exposure		**low exposure**		**mean diff.**
	mean	sd	mean	sd	t
investment growth sd	0.54	(0.32)	0.62	(0.37)	10.63
employment growth sd	0.14	(0.10)	0.16	(0.12)	7.20
assets growth sd	0.18	(0.14)	0.20	(0.16)	6.87
sales growth sd	0.18	(0.12)	0.19	(0.14)	2.94
Observations	3689		3893		7582

Note: This table shows descriptive statistics on the firm-year (firm) level for the smaller sample of matched Compustat firms. *Risk* is defined as firms' standard deviation of investment/employment/asset7sales growth in non-crisis times. The sample is split by the yearly median according to firms' exposure. High exposure firms are denoted *high exposure*, those with low exposure as *low exposure*. *mean* denotes the mean, *sd* the standard deviation, and *mean diff.* the t-value for the difference in means across both groups. For detailed variable definitions see Table B.1 and text.

Table 6: **Diversified banks have higher loan supply during local crises**

VARIABLES	(1) log(loan vol)	(2) log(loan vol)	(3) log(loan vol)	(4) log(loan vol)	(5) log(loan vol)	(6) log(loan vol)
banking crisis (BC)	0.040					
	(0.029)					
diversification (DIV)	0.309***	0.005	0.013			
	(0.060)	(0.018)	(0.017)			
DIV × BC	0.135***	0.039***	0.063***	0.072**	0.127***	0.103**
	(0.026)	(0.013)	(0.013)	(0.037)	(0.049)	(0.048)
log(assets) × BC						0.016**
						(0.006)
WS deposits × BC						0.057*
						(0.033)
Tier 1 capital ratio × BC						0.000
						(0.000)
leverage ratio × BC						0.006*
						(0.003)
return on equity × BC						-0.000
						(0.000)
Observations	1,724,073	1,691,064	1,724,073	1,621,124	474,784	474,784
R-squared	0.954	0.976	0.965	0.978	0.978	0.978
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	-	Yes	-	Yes	Yes	Yes
Country*Industry*Year FE	-	-	Yes	-	-	-
Bank*Year FE	-	-	-	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm country-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: **Firms borrowing from diversified banks have higher loan growth in crises**

VARIABLES	(1) Δ loan volume	(2) Δ loan volume	(3) Δ loan volume
banking crisis	-0.142***		
	(0.006)		
exposure	-0.475***	-0.185***	-0.182***
	(0.019)	(0.021)	(0.022)
exposure × BC	0.055***	0.050***	0.039**
	(0.014)	(0.017)	(0.019)
Observations	196,337	196,337	196,038
R-squared	0.138	0.172	0.317
Firm FE	Yes	Yes	Yes
Country*Year FE	-	Yes	-
Country*Industry*Year FE	-	-	Yes
Cluster	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is log difference of firms' total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Table 8: **Firms borrowing from diversified banks: real effects**

VARIABLES	(1) Δ long-term debt	(2) Δ long-term debt	(3) Δ employment	(4) Δ employment	(5) Δ investment	(6) Δ investment
banking crisis	-0.084***		-0.064***		-0.131***	
	(0.023)		(0.006)		(0.017)	
exposure	-0.269***	-0.261***	-0.155***	-0.074***	-0.242***	-0.163***
	(0.037)	(0.049)	(0.013)	(0.014)	(0.032)	(0.038)
exposure × BC	0.131***	0.105*	0.071***	0.029**	0.123***	0.119***
	(0.043)	(0.057)	(0.012)	(0.014)	(0.034)	(0.042)
Observations	53,574	49,340	51,445	47,496	54,638	51,845
R-squared	0.172	0.233	0.279	0.349	0.137	0.231
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	-	Yes	-	Yes	-	Yes
Controls	-	Yes	-	Yes	-	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variables are log difference of firms' long-term debt, employment, and investment; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. *log total assets*, *return on assets*, and *leverage* are firm level controls. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Table 9: **Diversified banks can raise new funding during crises**

VARIABLES	(1) DS Δ loan vol	(2) DS P(increase)	(3) DS Δ loan vol	(4) DS P(increase)	(5) BS Δ WS dep	(6) BS Δ WS dep (share)	(7) BS Δ WS dep	(8) BS Δ WS dep (share)
loans in crisis (dummy)	-0.145**	-0.151	-0.103	-0.134	-0.268**	-0.141	-0.274***	-0.149
	(0.065)	(0.109)	(0.074)	(0.109)	(0.115)	(0.172)	(0.102)	(0.163)
Diversification (DIV)	-0.298	-0.140	-0.373*	-0.219	-0.478***	-0.361	-0.402***	-0.279
	(0.219)	(0.251)	(0.225)	(0.258)	(0.157)	(0.236)	(0.140)	(0.223)
DIV × loans in crisis (dummy)	0.337***	0.420**	0.271**	0.408**	0.402***	0.202	0.425***	0.232*
	(0.121)	(0.181)	(0.132)	(0.185)	(0.088)	(0.132)	(0.079)	(0.126)
Observations	2,694	2,694	2,694	2,694	704	704	704	704
R-squared	0.567	0.628	0.589	0.638	0.459	0.378	0.573	0.447
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size*Year FE	-	-	Yes	Yes	-	-	-	-
Bank Controls	-	-	-	-	-	-	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-year level for Dealscan (DS) and Bankscope (BS) data. The dependent variables are log differences in bank-to-bank syndicated loans in columns (1) and (3) and a dummy with value one if banks see an increase in loan volume in columns (2) and (4); and the change in wholesale deposits (absolute or as share of total deposits) in columns (5)-(8). *loans in crisis* is a dummy if banks have a positive share of loans extended to countries with a banking crisis, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. Regressions in columns (5)-(8) include *log(assets)*, *tier 1 capital ratio*, and *return on equity* as bank controls. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

Table 10: **Diversified banks mitigate spillover effects**

VARIABLES	(1) Δ loan vol.	(2) Δ loan vol.	(3) low distress Δ loan vol.	(4) high distress Δ loan vol.	(5) few crises Δ loan vol.	(6) many crises Δ loan vol.
banking crisis (BC)	-0.123***					
	(0.025)					
connected	-0.070***	-0.039***	0.012		0.006	
	(0.016)	(0.013)	(0.011)		(0.014)	
diversification (DIV)	-0.093***	-0.091***	-0.054***		-0.034**	
	(0.020)	(0.017)	(0.014)		(0.014)	
DIV × BC	0.113***	0.039	0.035*	-0.077**	0.055*	-0.072**
	(0.038)	(0.030)	(0.020)	(0.038)	(0.030)	(0.030)
DIV × connected	0.073***	0.053***	0.040**	-0.047	0.034*	-0.065*
	(0.023)	(0.019)	(0.017)	(0.042)	(0.020)	(0.034)
Observations	180,115	180,115	108,545	70,603	108,935	70,180
R-squared	0.120	0.200	0.201	0.310	0.210	0.293
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	-	-	-	-
Borrower Country*Year FE	-	Yes	Yes	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm country-year (bank) level. The dependent variable is log difference of total outstanding loan volume by bank b to all borrowers in country j; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. *connected* is a dummy with value one when $BC = 1$ for all countries connected to bank b that are not country j and have no contemporaneous banking crisis. *low distress* denotes bank-year observations for which banks' share of loans (out of total bank loans) extended to borrowers in crisis countries is below the yearly median, *high distress* those for which it is above. *few (many) crises* denotes bank-year observations for for which banks' share of borrower countries in crisis (out of total bank borrower countries) is below (above) the yearly median. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

Table 11: **Foreign banks and local affiliates**

VARIABLES	(1) foreign log(loan vol)	(2) foreign log(loan vol)	(3) foreign log(loan vol)	(4) affiliate log(loan vol)	(5) affiliate log(loan vol)	(6) affiliate log(loan vol)
diversification (DIV)		-0.001	0.006		-0.007	-0.016
		(0.017)	(0.017)		(0.017)	(0.019)
DIV × BC		0.085***	0.079***		0.045***	0.050**
		(0.015)	(0.011)		(0.014)	(0.022)
foreign bank × BC	-0.015*	-0.044***	-0.017*			
	(0.008)	(0.011)	(0.010)			
DIV × foreign bank			0.006			
			(0.007)			
DIV × foreign bank × BC			-0.046***			
			(0.010)			
local affiliate × BC				0.054***	0.055***	0.043***
				(0.007)	(0.007)	(0.017)
DIV × local affiliate						0.044*
						(0.027)
DIV × local affiliate × BC						0.023
						(0.020)
Observations	1,677,958	1,677,958	1,677,958	1,677,958	1,677,958	1,677,958
R-squared	0.977	0.977	0.977	0.977	0.977	0.966
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. *foreign bank* is a dummy with value one if bank country and firm country differ. *local affiliate* is a dummy with value one if a bank has an affiliate in the borrower country. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm country-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 12: **Crisis loans and portfolio risk**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			GBP	country share	industry share	firm DIV	horse race	horse race
VARIABLES	log(loan vol)	log(loan vol)	log(loan vol)	log(loan vol)	log(loan vol)	log(loan vol)	log(loan vol)	log(loan vol)
diversification (DIV)	-0.025	-0.025	-0.024	0.075***	0.030	-0.016	-0.010	
	(0.019)	(0.019)	(0.022)	(0.018)	(0.019)	(0.020)	(0.020)	
DIV × BC	0.047***	0.047***	0.059***	0.104***	0.025**	0.034***	0.129***	0.147***
	(0.013)	(0.013)	(0.017)	(0.019)	(0.012)	(0.012)	(0.028)	(0.030)
portfolio risk (sales) × BC	-0.021***	-0.021***					-0.019***	0.007
	(0.003)	(0.006)					(0.003)	(0.006)
DIV × portfolio risk (sales) × BC		-0.002						
		(0.011)						
int. portfolio (INT)			0.059***				0.080***	
			(0.018)				(0.014)	
INT × BC			-0.016				-0.004	-0.058**
			(0.017)				(0.019)	(0.023)
country share				0.286***			0.241***	0.560***
				(0.028)			(0.029)	(0.027)
BC × country share				0.061***			0.094***	0.030
				(0.020)			(0.022)	(0.024)
industry share					0.436***		0.448***	1.824***
					(0.023)		(0.030)	(0.050)
BC × industry share					-0.116***		-0.171***	-0.072
					(0.020)		(0.028)	(0.065)
DIV × firm DIV						0.050***	0.060***	0.018
						(0.014)	(0.013)	(0.015)
DIV × BC × firm DIV						0.003		
						(0.012)		
Observations	1,596,872	1,596,872	1,691,064	1,691,064	1,691,064	1,691,064	1,596,872	1,540,841
R-squared	0.974	0.974	0.976	0.976	0.976	0.976	0.974	0.977
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	-	-	-	-	-	-	-	Yes
Cluster	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. *portfolio risk (sales)* is banks' portfolio risk, measured as the average standard deviation of borrowers' sales growth in non-crisis times. *int. portfolio (INT)* is banks' portfolio share that is extended to foreign borrowers. *country share* denotes the share of loans by bank b to country c, *industry share* the share of loans by bank b to industry i. *firm DIV* denotes firm diversification across lenders. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm country-year level. *** p<0.01, ** p<0.05, * p<0.1

B Variable Definitions

Table B.1: **Variable definitions**

variable	description/item	unit/comment
loan volume	outstanding syndicated loans	million
loan spread	interest spread over LIBOR	basis points
maturity	loan maturity	months
banking crisis (BC)	banking crisis in borrower country	dummy
connected	connected countries with no contemporaneous banking crisis	dummy
diversification (DIV)	diversification index	[0,1-1/J], bank level
exposure	firm exposure to diversified banks	[0,1-1/J], firm level
(bank) assets	data11350 (BS)	million
(bank) Tier 1 capital ratio	data2130 (BS)	%
(bank) whole sale deposit share	data2185/data11580 (BS)	%
(bank) leverage ratio	data2140/data11350 (BS)	%
(bank) return on equity (ROE)	data4025 (BS)	%
(firm) investment ratio	capx/ppent$_{t-1}$ (CS)	%
(firm) long-term debt ratio	dltt/at (CS)	%
(firm) employment	emp (CS)	thousand
(firm) sales	sale (CS)	million
(firm) assets	at (CS)	million
(firm) return on assets (ROA)	(opid - depam)/at (CS)	%
(firm) sales growth	ln(sale$_t$) - ln(sale$_{t-1}$) (CS)	%
(firm) payout ratio	(dvt + prstkc)/oibdp (CS)	%
(firm) fixed assets	ppe (CS)	million
(firm) capital-labor ratio	ppe/emp (CS)	%
foreign bank (FB)	borrower country $\neq$ lender country	dummy, bank level
international portfolio (INT)	int. loan volume to total loan volume	[0,1], bank level
great financial crisis (GFC)	years 2008-2010	dummy
regional BC	regional banking crisis for Asia, Latin America, Europe, and US	dummy
home BC	banking crisis in lender country	dummy, bank level
share of loans in crisis	share of syndicated loans extended to crisis countries in year t	%
portfolio risk (sales)	standard deviation of borrower sales growth in non-crisis times	

Note: CS stands for Compustat, BS for Bankscope.

C Online Appendix

Macro evidence We use syndicated loan market data to construct our bank diversification metric. Syndicated lending represents a sizable share of firm debt and cross-border loans (Gadanecz and von Kleist, 2002). We now show that our metric (aggregated to the country level) correlates with aggregate country level variables. Figure C.1, Panel a) shows a strong positive relationship between borrowing countries' total syndicated lending (as share of GDP) against total credit (as share of GDP). Countries with a high level of overall credit also have a high level of syndicated loan volume.[47] Panels b)−d) show the relationship between our diversification metric and aggregate measures of banking integration. Diversification is positively correlated with the share of foreign bank assets (as share of total bank assets), claims by foreign banks, as well as foreign liabilities (both as share of GDP).[48] Hence, countries with a high share of firms borrowing from diversified banks are also better financially integrated. They have higher foreign bank presence in their domestic market, as well as larger claims on foreign countries. Taken together, this implies that syndicated lending in our data is positively correlated with total credit, and our diversification metric captures financial integration.

Diversification and international portfolio Figure C.3 plots both metrics against each other, where international portfolio (INT) is on the x-axis, and banks' geographic diversification (DIV) on the y-axis (the blue line represents the quadratic fit). The humped shaped relationship that fans out for higher values of INT reflects the conceptual differences underlying each metric: banks that only lend domestically are in the bottom left corner (local on both metrics). Banks that lend exclusively to one foreign country are in the bottom right corner. They are globally integrated by our second definition (INT), but concentrated by our first (DIV), as they lend internationally but are not diversified.[49] The dispersion in diversification for a given level of 'internationality' indicates that banks lending internationally differ widely in the geographic allocation of their portfolio − being international does not automatically imply diversification. That being said, the correlation between both metrics is high (0.81).

Financial constraints, maturity, and interest rates We split firms into financially constrained and unconstrained. As constrained firms rely more on external credit to finance employment and investment, higher exposure to diversified banks should have stronger effects. For each year we group firms into bottom and top tercile according to

[47] A regression of total credit on syndicated credit with country fixed effects yields a coefficient of 0.29 with t-value 11.47.

[48] Data are provided by the Bank for International Settlements, the World Bank World Development Indicators, as well as Global Financial Development Database. See Table B.1 for details.

[49] The lower bound of the arch reflects the minimum level of diversification for each bank, given that it lends to more than one country. The upper bound, in turn, shows banks that lend to more than one country, but have a diversified (read: not geographically concentrated) portfolio.

their payout ratio (*payout*) and size (*size*). We classify firms as financially constrained if they are in the bottom tercile, and unconstrained if they are in the top tercile (Almeida and Campello, 2007; Chaney, Sraer and Thesmar, 2012). In Table C.1, columns (1)-(4) use employment growth as dependent variable, columns (5)-(8) investment growth. All regressions include baseline controls, as well as firm and country*year fixed effects. For both dependent variables, the positive effect of exposure to diversified banks during crises is significantly stronger for constrained (*cons.*) than unconstrained (*uncons.*) firms. Note that our Compustat sample covers large and listed firms. The stronger effects for financially constrained firms reassure us that effects would extend to a sample covering small firms as well. In general, small firms are found to be more bank dependent and also more credit constrained and therefore loan supply decisions matter more.
Beside changes in loan amount, banks can alter maturity or the interest rate of loans. To test whether banks use these margins to restrict or expand loan supply, we rerun firm level regression Equation (4), but replace the dependent variable by *maturity* (in months), and *interest spread* over LIBOR (in basis points). Table C.2 shows that borrowing from diversified banks leads to a higher spread and longer maturity during crises. While the effect on maturity is quantitatively negligible and insignificant, a one standard deviation increase in exposure increases the spread by around 7 basis points. We interpret this as evidence that diversified banks are willing to extend loans during crises, but compensate higher risk through higher interest rates. Columns (3)-(5) further examine the robustness of our results. The dependent variable is loan growth. Column (3) excludes the global crisis and restricts the sample to years 1995−2008. Column (4) introduces a global financial crisis (GFC) dummy with value one during banking crises in years 2008, 2009, and 2010. In both columns, our main effect remains positive and significant. The recent financial crisis does not drive our results. Column (5) introduces a regional crisis dummy.[50] The negative coefficient on $exposure \times regional\ BC$ suggests that during crises affecting several countries at once, the positive effect of diversification is weakened. Yet, our baseline effect remains stable. Finally, column (6) excludes firms with $exposure = 0$, and column (7) replaces continuous exposure with a dummy with value one if exposure is above its yearly median.

Substitution effects While we showed above that diversified banks sustain higher loan supply and credit growth to firms during crises, we now investigate how the differing behavior of diversified and concentrated banks changes the structure of the economy. First, we look at substitution effects on the firm level. While firms cannot perfectly offset changes in loan supply by switching across banks, Table C.3 shows that there is nonetheless an increase in reliance on diversified lenders. We run a regression of firms' exposure (i.e. the share of loans coming from diversified banks) on the banking crisis dummy. Columns (1)-(4) use firm and region*year fixed effects, and look at within

[50]The *regional BC* dummy takes on value one for Asian countries during the Asian crisis (1997-1999), South American countries during the Latin crisis (1995-1996), as well as the Great Financial Crisis in Europe and the US.

firm changes, while controlling for common regional shocks. There is a significant and positive effect of banking crisis on firms' exposure. The average firm sees an increase in its exposure to diversified lenders by 0.7 % during the year of the crisis. Effects are highly persistent even three years after the crisis. Besides a shift in exposure within firms, there could also be a shift across firms towards firms that borrow more from diversified banks. Columns (5)-(8) use country*industry instead of firm fixed effects and compare how exposure changes across firms within a given country-industry pair. Results show that during a banking crisis there is a shift towards borrowers from diversified banks. The share of loans from diversified banks increases by 0.3 % in the year of the crisis. It is still 1.1 % higher three years after the crisis. The stronger effect on the industry level suggests that on top of a shift towards diversified lenders *within* firms, there is also a shift within industries *across* firms towards borrowers with higher exposure.

The increase in firms' reliance on diversified banks should be mirrored in banks' loan portfolios. We run the following regression on the bank (b) − borrower country (j) − year (t) level:

$$share_{b,j,t} = \gamma_1 BC_{j,t} + \gamma_2 diversification_{b,t} + \gamma_3 DIV_{b,t} \times BC_{j,t} + X_{j,t} + \epsilon_{b,j,t}.$$

$share_{b,j,t}$ denotes bank b's share of total loans in country j in year t and X is a set of controls for the borrower country. Based on our above findings, we expect that a banking crisis leads to a decline in $share$ ($\gamma_1 < 0$), but the decline should be smaller or absent for diversified banks ($\gamma_3 > 0$), as they are a more stable source of funding. The coefficient γ_2 on DIV is expected to be negative, as diversified banks will have a lower average loan share than concentrated banks. In each regression, we use bank*borrower country fixed effects and analyze variation in loan shares within a specific bank-borrower country connection. We also employ time-varying fixed effects on the bank country level to absorb changes in each banks' home country. If, for example, there is a contemporaneous negative shock in a banks' home country that we do not account for, the stabilizing effect of diversification is likely to be muted.

Table C.4, column (1), shows that a banking crisis in host country j reduces banks' share of loans extended to j by 0.7 %. The effect is significant at the 1 % level and economically meaningful. The median loan share is 2.2 %, so a banking crisis reduces banks' loan share by around 31 % relative to the median. Once we interact our crisis dummy with our diversification metric in column (2), we see that *i*) in non-crisis times, diversified banks have a lower loan share in host countries than concentrated banks; and *ii*) their share falls by less during banking crises. Columns (2)-(5) lead the dependent variable by subsequent periods. In each specification we find that diversified banks reduce their loan share by less. For example, in column (2), fully diversified banks reduce their loan share by 0 %, compared to 1.3 % for banks with no diversification. Combining our evidence in Tables C.3 and C.4, we find that banking crises in host countries increase borrowers' reliance on lending by diversified banks.

Cross-sectional analysis Table C.5 re-runs our baseline bank-firm level analysis in the cross-section, instead of a panel. We collapse our data to bank-firm level and define the dependent variable as the (log) change in loan volume from year $t-1$ to year T, where t denotes the start year of a banking crisis and T the end year. In other words, we look at the change in lending by bank b to firm f over the pre- to post-crisis period. Columns (1)-(4) use diversification as defined in equation (1) and look at the intensive (columns 1 and 2) and extensive margin (column 3 and 4). The extensive margins adds a value of zero to loans that start (end) in the year before (last year of) the crisis, i.e. we allow for formation and termination of bank-firm relationships. Columns (5)-(8) repeat the exercise, but use a diversification dummy with value one if a bank is in the yearly top tercile of diversification, and zero if it is in the bottom tercile. Across specifications, diversification has a positive effect on loan supply, and is significant (except for column (3)). Across specifications, we control for unobservable bank characteristics through bank fixed effects, and then contrast specifications with borrower country*industry vs. firm fixed effects (analogous to the main specification on the bank*firm*year level). We find that diversification has a positive effect even after controlling for firms' loan demand through fixed effects.

Clustering Table C.6 shows that our results are robust to clustering on different levels. Column (1)-(4) cluster on the country*year, country, country and bank, as well as firm*year and bank*year level. Across specifications, the effect of diversification on loan supply during crises remains significant at the 5 % top 1 % level.

Further robustness Table C.7 provides additional robustness checks. Our results are robust to

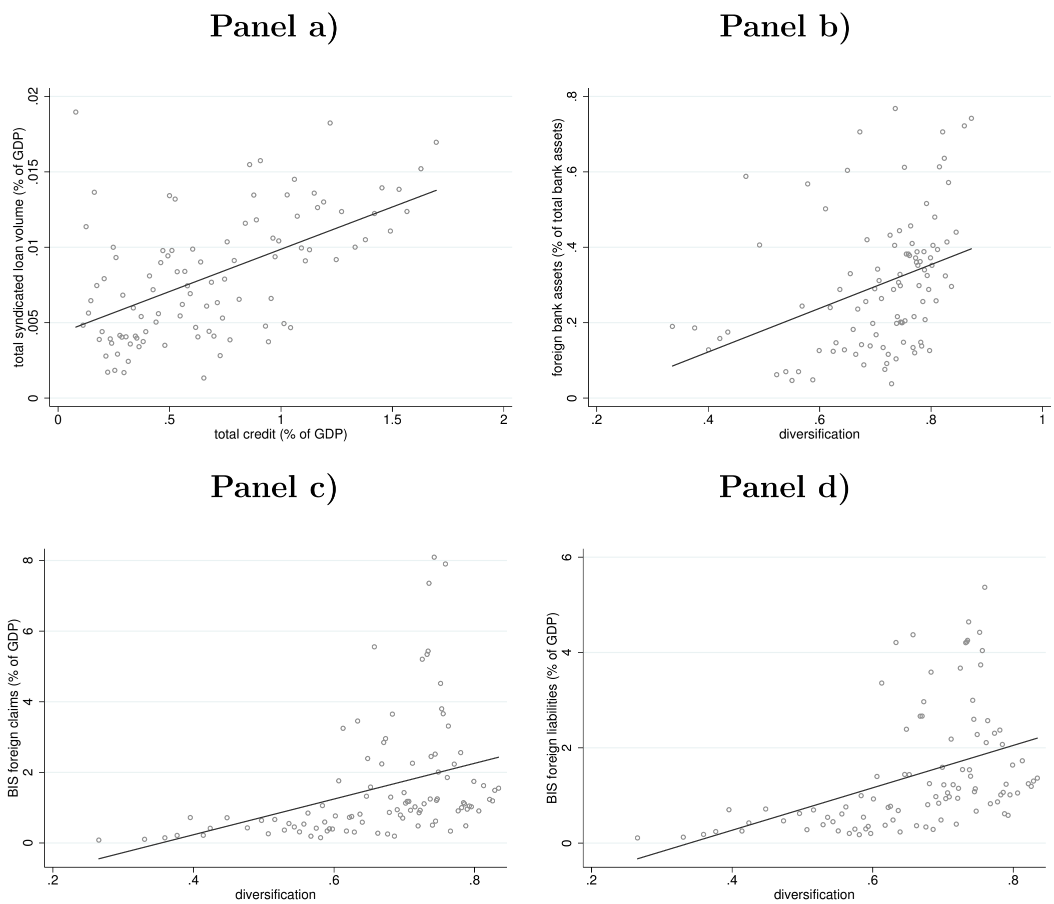
- Panel (a), column (1): excluding borrowers in finance, insurance and real estate industries (FIRE)
- Panel (a), column (2): excluding borrowers in insurance industries
- Panel (a), column (3): excluding banks with only one loan per year
- Panel (a), column (4): excluding banks in the top 10 % of total loans per year
- Panel (a), column (5): excluding banks with $diversification$ $(DIV) = 0$
- Panel (a), column (6): replacing continuous *diversification* with a dummy for above and below median
- Panel (b), column (1): focusing on lead arrangers only
- Panel (b), column (2): excluding loans (facilities) with only one lender (no syndicate de facto).
- Panel (b), column (3): excluding credit lines
- Panel (b), column (4): excluding term loans

- Panel (b), column (5): imputing participants loans shares based on existing information on 'lender role' using respective sample means from non-missing loan shares
- Panel (b), column (6): imputing participants loans shares by 'lender role' and 'syndicate size' using respective sample means from non-missing loan shares

Bank-country-year level Table C.8 reports regressions on the bank-borrower country-year level. Column (1) shows that during banking crises, and in line with bank-firm-year level findings, countrywide loan growth drops significantly. For borrowers from banks with $DIV = 0$, loan supply declines by 10.4 %. Also on the aggregate level, diversified banks are stabilizing, relative to banks with a concentrated portfolio. Similar to findings on the loan and firm level, the coefficient on diversification, interacted with banking crisis, is significant and positive. For banks with zero diversification, loan growth falls by 10.4 % during banking crises. Increasing diversification from the 25^{th} to the 75^{th} percentile attenuates the effect by $(0.63 \times 0.107 =)$ 6.7 %. Note that the highly significant coefficient on $DIV \times BC$ is equal in magnitude to the negative coefficient on banking crisis. This implies that banks with a fully diversified portfolio are able to completely offset the negative effect of a banking crisis on countrywide loan growth. Similar to the bank-firm level, columns (2) and (3) show that results survive when we control for unobservable country and bank characteristics. Including borrower country*year fixed effects in column (2) absorbs common shocks to all firms within one country. Column (3) adds bank*year fixed effects to ensure that unobservable bank characteristics are not explaining the positive effect of diversification.

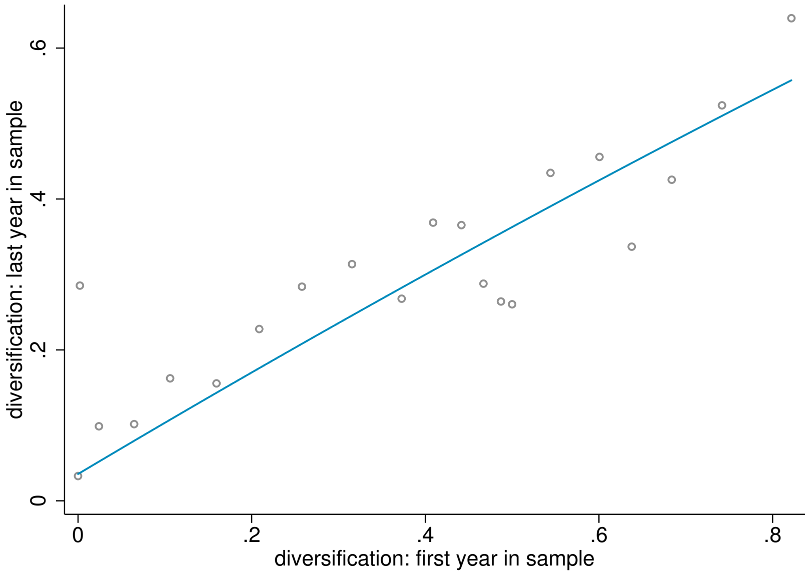
C.1 Tables and Figures

Figure C.1: **Macro evidence**



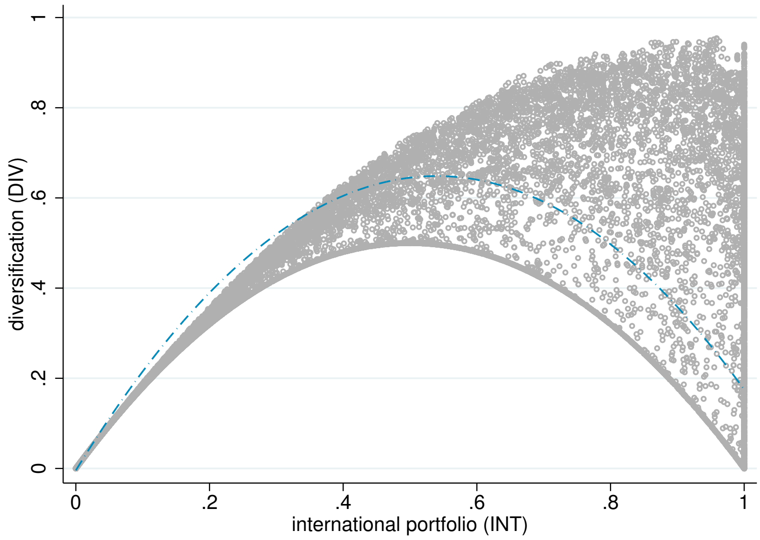
Note: This figure shows the relationship between our sample data and aggregate data on total credit, as well as our diversification metric and aggregate measures of financial integration. All scatter plots depict scatter points as well as a linear fit, where the underlying data are aggregated to the country-year level. For detailed variable definitions see Table B.1 and text.

Figure C.2: **Diversification: Stability over time**



Note: This figure provides a binscatter plot of bank diversification in banks' first (x-axis) and last (y-axis) year in the sample. Sample period is from 1995 to 2008, pre-ceeding the great retrenchment period during and after the GFC. A regression of last on first year diversification yields $\beta = 0.64, t = 59, 43, R^2 = 0.38, N = 5, 799$. For the sub-sample of banks with diversification > 0 in their first year, $\beta = 0.55, t = 15.65, R^2 = 0.18, N = 1, 109$.

Figure C.3: **Diversification and international portfolio**



Note: This figure shows the relationship between banks' geographic diversification (DIV) and the international allocation of their loan portfolio (INT) on the bank-firm level. The blue dashed line is a quadratic fit. Higher values denote more geographic diversification, and a higher share of loans extended to foreign borrowers, respectively. For detailed variable definitions see Table B.1 and text.

Table C.1: **Firm level – financial constraints**

VARIABLES	(1) uncons. payout Δ employment	(2) cons. payout Δ employment	(3) uncons. size Δ employment	(4) cons. size Δ employment	(5) uncons. payout Δ investment	(6) cons. payout Δ investment	(7) uncons. size Δ investment	(8) cons. size Δ investment
exposure	-0.055*	-0.103***	-0.033	-0.033	0.024	-0.265***	-0.075	-0.106
	(0.029)	(0.032)	(0.024)	(0.024)	(0.080)	(0.083)	(0.067)	(0.079)
exposure × BC	-0.003	0.094***	0.063	0.041*	-0.058	0.277**	-0.077	0.201**
	(0.024)	(0.033)	(0.041)	(0.025)	(0.072)	(0.109)	(0.134)	(0.084)
Observations	11,347	12,207	15,598	15,433	12,017	12,808	16,742	16,660
R-squared	0.336	0.472	0.333	0.413	0.272	0.317	0.249	0.260
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variables are log difference of firms' employment and investment; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. All regressions include *log total assets*, *return on assets*, and *leverage* as firm level controls. *uncons.* and *cons.* denote constrained and unconstrained firms, split into bottom and top tercile of payout ratio or size for each year. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: **Firm level − maturity and sample selection**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			1995-2008	GFC	regional crisis	exp > 0	DIV dummy
VARIABLES	loan spread	maturity	Δ loan volume	Δ loan volume	Δ loan volume	Δ loan volume	Δ loan volume
exposure	-35.486***	6.392***	-0.249***	-0.186***	-0.182***	-0.155***	
	(6.932)	(1.763)	(0.027)	(0.022)	(0.022)	(0.023)	
exposure × BC	30.816***	2.636	0.070***	0.057***	0.054**	0.062***	
	(6.288)	(1.899)	(0.023)	(0.022)	(0.022)	(0.020)	
exposure × GFC				0.066**			
				(0.025)			
exposure × GFC × BC				-0.100***			
				(0.031)			
exposure × regional BC					-0.029*		
					(0.018)		
exposure (median)							-0.030***
							(0.006)
exposure (median) × BC							0.037***
							(0.008)
Observations	139,505	199,799	133,542	196,038	196,038	191,445	196,038
R-squared	0.905	0.951	0.338	0.317	0.317	0.321	0.317
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country*Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is firms' average *loan spread* over LIBOR (in basis points) and *maturity* (in months) in columns (1) and (2), and log difference of firms' total outstanding loan volume in columns (3)-(5); *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *exposure* is firms' exposure to diversified banks. *Great Financial Crisis (GFC)* is a dummy with value one during banking crises from 2008-2010. *regional crisis* is a dummy with value one during regional banking crises in Asia, Latin America, and Europe. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Table C.3: **Substitution towards diversified lenders**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	firm	firm	firm	firm	industry	industry	industry	industry
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
VARIABLES	exposure	exposure	exposure	exposure	exposure	exposure	exposure	exposure
banking crisis	0.007***	0.006**	0.010***	0.007**	0.003	0.005	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	192,495	155,610	123,045	98,076	192,495	159,703	127,892	101,469
R-squared	0.924	0.926	0.928	0.928	0.505	0.497	0.489	0.485
Firm FE	Yes	Yes	Yes	Yes	-	-	-	-
Country*Industry FE	-	-	-	-	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows regressions on the firm-year (firm) level. The dependent variable is firms' exposure to diversified banks (the share of total loans extended by diversified banks), where we lead the dependent variable by up to 3 periods. *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013). Columns (1)-(4) use firm fixed effects and look at within firm variation, columns (5)-(8) use country-industry fixed effects and look at changes across firms within industries. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Table C.4: **Diversified banks increase their loan share**

VARIABLES	(1) t share	(2) t share	(3) t+1 share	(4) t+2 share	(5) t+3 share
banking crisis (BC)	-0.007***	-0.013***	-0.012***	-0.010***	-0.010***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
diversification (DIV)		-0.310***	-0.198***	-0.125***	-0.067***
		(0.013)	(0.011)	(0.010)	(0.010)
DIV $\times$ BC		0.013***	0.008*	0.005	0.003
		(0.005)	(0.005)	(0.004)	(0.005)
Observations	199,427	173,368	149,664	127,568	109,366
R-squared	0.959	0.967	0.968	0.970	0.971
Bank*Borrower Country FE	Yes	Yes	Yes	Yes	Yes
Bank Country*Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm country-year (bank) level. The dependent variable is banks' share of total outstanding loan volume extended to all borrowers in country j, up to a lead of three years; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1

Table C.5: **Bank-firm level – cross-section**

VARIABLES	(1) continuous Δ loan (int.)	(2) continuous Δ loan (int.)	(3) continuous Δ loan (ext.)	(4) continuous Δ loan (ext.)	(5) dummy Δ loan (int.)	(6) dummy Δ loan (int.)	(7) dummy Δ loan (ext.)	(8) dummy Δ loan (ext.)
diversification (DIV)	0.179***	0.090*	0.115	0.382***				
	(0.050)	(0.051)	(0.292)	(0.137)				
diversification (DIV, terciles)					0.058***	0.052**	0.230***	0.256***
					(0.020)	(0.024)	(0.044)	(0.044)
Observations	27,079	26,741	64,346	64,185	18,107	17,505	44,658	43,544
R-squared	0.251	0.500	0.358	0.655	0.271	0.555	0.371	0.664
Country*Industry FE	Yes	-	Yes	-	Yes	-	Yes	-
Firm FE	-	Yes	-	Yes	-	Yes	-	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Note: This table shows regression results on the bank-firm level. Dependent variable is the pre/post crisis change in loans from the last year before the start of the banking crisis to the last year of the banking crisis. *int.* refers to the intensive margin, where we do not include new or terminated bank-firm lending relationships. *ext.* refers to the extensive margin and adds "zeros" for bank-firm connections that did not exist before the crisis or were terminated over the crisis. It includes pre-crisis bank diversification as continuous variable, as well as a dummy with value one (zero) for banks in the top (bottom) tercile of diversification. All standard errors are clustered on the bank level. *** p<0.01, ** p<0.05, * p<0.1

Table C.6: **Bank-firm level − cluster**

VARIABLES	(1) log(loan vol)	(2) log(loan vol)	(3) log(loan vol)	(4) log(loan vol)
diversification (DIV)	0.005	0.005	0.005	0.005
	(0.018)	(0.051)	(0.055)	(0.016)
DIV × BC	0.039***	0.039**	0.039**	0.039***
	(0.013)	(0.016)	(0.018)	(0.014)
Observations	1,691,064	1,691,064	1,691,064	1,691,064
R-squared	0.976	0.976	0.976	0.976
Firm*Bank FE	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes
Cluster	Country*Year	Country	Country & Bank	Firm*Year & Bank*Year

Note: This table shows regressions on the bank-firm-year (loan) level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table B.1 and text. Standard errors are clustered on different level, as indicated by the last table row. *** p<0.01, ** p<0.05, * p<0.1

Table C.7: **Bank-firm level – further robustness checks**

Panel (a)

VARIABLES	(1) no FIRE log(loan vol)	(2) no insurance log(loan vol)	(3) banks > 1 loan log(loan vol)	(4) no large banks log(loan vol)	(5) DIV > 0 log(loan vol)	(6) high/low DIV log(loan vol)
diversification (DIV)	0.005	0.009	0.001	0.030**	-0.002	
	(0.017)	(0.017)	(0.018)	(0.015)	(0.022)	
DIV × BC	0.043***	0.040***	0.036***	0.055***	0.025**	
	(0.015)	(0.013)	(0.013)	(0.015)	(0.011)	
DIV (median)						-0.000
						(0.004)
DIV (median) × BC						0.040***
						(0.009)
Observations	1,493,505	1,655,935	1,670,470	1,505,505	1,551,928	1,691,064
R-squared	0.977	0.976	0.976	0.977	0.974	0.976
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year

Panel (b)

VARIABLES	(1) lead arr. log(loan vol)	(2) no one lender log(loan vol)	(3) no credit lines log(loan vol)	(4) no term loans log(loan vol)	(5) alt shares 1 log(loan vol)	(6) alt shares 2 log(loan vol)
diversification (DIV)	-0.004	0.015	-0.031	0.038***	-0.026***	0.014
	(0.026)	(0.016)	(0.026)	(0.012)	(0.008)	(0.017)
DIV × BC	0.022*	0.043***	0.036***	0.050***	0.047***	0.045***
	(0.013)	(0.014)	(0.009)	(0.016)	(0.011)	(0.014)
Observations	471,046	1,571,942	1,173,320	1,151,499	1,492,557	1,678,008
R-squared	0.975	0.977	0.970	0.981	0.971	0.976
Firm*Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year	Ctry*Year

Note: This tables shows regressions on the bank-firm-year level. The dependent variable is log of total outstanding loan volume; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the firm country-year level. In Panel (a), *FIRE* and *no insurance* denote the exclusion of all borrowers in finance, insurance and real estate industries (FIRE) and 'insurance companies' from the respective sample. In column titled *bank* > 1 *loan*, we drop all banks with one loan per year on the syndicated loan market; *no large banks* drops all banks above the 90^{th} percentile of their total outstanding lending. In the column titled $DIV > 0$, we include only banks with non-zero values of *geographic diversification*. *DIV (median)* is a dummy variable taking value one for banks with values of geographic diversification above the annual median, and of value zero for banks below. In Panel (b), column *lead arr.* includes only banks with syndicate role lead arrangers in the sample. *no one lender* denotes the exclusion of all syndicates consisting of only one lender. *no credit lines* drops all loans (i.e. facilities) that are credit lines, defined in Dealscan as 'Revolvers' or '364-Day Facility'. *no term loans* drops all loans (i.e. facilities) that are of type 'Term Loan'. Column titled *alt shares 1* provides imputations of missing loan shares in Dealscan by 'lender role' using respective sample means from non-missing loan shares. Column *alt shares 2* provides imputations of missing loan shares in Dealscan by 'lender role' and 'syndicate size' using respective sample means from non-missing loan shares. *** p<0.01, ** p<0.05, * p<0.1

Table C.8: **Bank-country-year regressions**

VARIABLES	(1) Δ loan vol.	(2) Δ loan vol.	(3) Δ loan vol.
banking crisis (BC)	-0.104***		
	(0.005)		
diversification (DIV)	-0.074***	-0.074***	
	(0.011)	(0.011)	
DIV × BC	0.107***	0.025***	0.043**
	(0.008)	(0.009)	(0.021)
Observations	180,115	180,115	128,555
R-squared	0.120	0.200	0.570
Bank FE	Yes	Yes	-
Year FE	Yes	-	-
Borrower Country*Year FE	-	Yes	Yes
Bank*Year FE	-	-	Yes
Cluster	Country*Year	Country*Year	Country*Year

Note: This table shows regressions on the bank-firm country-year (bank) level. The dependent variable is log difference of total outstanding loan volume by bank b to all borrowers in country j; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in Laeven and Valencia (2013); *diversification (DIV)* is banks' geographic diversification. For detailed variable definitions see Table B.1 and text. All standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1