Specialization in Bank Lending: Evidence from Exporting Firms *

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Abstract

This paper develops an empirical approach for identifying bank specialization in export markets. Combining loan and shipment data for all exporters in Peru, we find that all banks have abnormally large and persistent loan portfolio exposures to at least one export destination market. Specifications that saturate all bank-time and firm-time variation show that firms that expand exports to a country are more likely to borrow from banks that specialize in that country. This link between exports and bank specialization holds both for existing and new lending relationships. Using differential exposure to the 2008 financial crisis, we further find that shocks to the credit supply of banks has a larger effect on exports to the bank's markets of specialization, implying that specialized bank debt is difficult to replace. These results suggest that banks have *market-specific* areas of expertise that are distinct from *firm-specific* knowledge gathered through relationship lending.

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1 Introduction

Are banks differentially equipped to evaluate projects in different markets or sectors of economic activity? The answer to this question is fundamental for evaluating the economic consequences of bank failures, runs, liquidity shortages, and other events that reduce a bank's credit supply. If banks have special expertise in funding specific markets or economic activities, their funding will be difficult to replace and credit shortages by a single bank may have first-order effects on the real output of the market or activity in which the bank specializes. Answering this question is also essential for the appropriate assessment and regulation of bank competition. Traditional measures of bank competition based on the geographical density of bank branches will be misleading if lending advantages allow neighboring banks to act as monopolists in their respective areas of expertise.

In this paper, we construct a novel measure of bank specialization based on a bank's lending portfolio, and we develop a new methodology to test whether banks have an advantage in funding firms that operate in their market of specialization. We apply this methodology in the context of lending to exporters in Peru, where banks may specialize in funding exports to different destination markets (countries). We use a non-parametric approach to define bank specialization in any given country. We first characterize the distribution of the share of funding that each bank allocates to exporters to a destination country. We document that this distribution is heavily right-skewed: each country has a subset of banks with abnormally large loan portfolio exposure to its exports. The outliers are also persistent: 94% of the banks remain heavily exposed to the same country for over half of the observed sample period between 1994 and 2010. We use these facts to define a bank as specialized in a country if it is an outlier in the right tail of the exposure distribution of that country.

To illustrate the specialization definition, consider banks' exposures to exports to China and Switzerland presented in the table below. Exports to China account for 18.2% of total Peruvian exports in 2010 but represent a much larger fraction (30.1%) of Santander's associated exports. Exports to Switzerland account for 9.3% of total exports but account for 34.3% of CitiBank's associated exports. In this example, Santander and Citibank are defined as specialists in China and Switzerland, respectively. Measuring specialization as portfolio share outliers implies that each of the specialized banks has a relatively low exposure to the other's country of specialization: Santander has a below-average exposure to Switzerland exports (0%) and Citibank has a below-average exposure to China (11.7%).

Bank Exposure to Country of Export Destination. An Example

	Country of Export Destination	
	China	Switzerland
Weight in Total Exports	0.182	0.093
Weight in bank's exporter portfolio		
Santander	0.301	0.000
CitiBank	0.117	0.343

The observed patterns of specialization are consistent with the existence of bank advantages in lending across markets. With regard to financing exporters, a bank has an advantage if it can provide credit at a lower cost, more credit for the same borrower characteristics, or more value-added services attached to the issuance of credit (letter of credit, network of contacts in the destination country, etc.) than other lenders. However, in most empirical settings, including ours, the econometrician cannot observe either firm credit demand or the value-added services provided by banks.

We propose a revealed preference approach to identify advantages in lending that circumvents this problem. If banks are substitutable sources of funding, the variation in a firm's export activity with one country should be uncorrelated with the identity of the bank providing the funding. In the absence of special bank expertise, a firm that expands exports to China is equally likely, in expectation, to increase its borrowing from the bank that specializes in China (Santander) as from the bank that specializes in Switzerland (Citibank). Our empirical approach is based on testing the alternative hypothesis: that firms disproportionately fund export expansions to a country with credit from a bank specialized in that country.

The empirical strategy takes advantage of the highly disaggregated nature of our credit and export data. The empirical model represents exporting firms as a collection of projects (destination countries) in which banks may specialize. We observe a measure of the output of each project (exports to a country) for each firm, a measure of specialization in that project (defined above) for each bank, and a measure of credit for each bank-firm pair. The first step in our estimation strategy is to isolate the variation in credit that is specific to the firm-bank relationship. We use firm-time dummies to account for firm demand shocks that are common to all banks, and bank-time dummies to account for bank credit supply shocks that are common across all firms. The residual in this saturated model is the firm-bank variation in credit, which is our object of interest: it captures the equilibrium lending that results from the firm's credit demand that is bank-specific and the bank's credit supply that is firm-specific. The second step in our estimation strategy is to test whether lagged measures of bank specialization predict how the firm-bank credit component changes with the firm's exports to the country of specialization.

Our baseline results show that when firms expand exports to a country, they increase borrowing by 52% more from banks that are specialized in the destination country than from non-specialized banks, once all firm-specific and bank-specific shocks are accounted for. We also explore the lending advantage of specialized banks on the extensive margin. We test whether the probability that a firm starts borrowing from a bank increases after the firm starts exporting to the country of specialization. We find that during the year after a firm starts exporting to a country, the firm is 6.4 times more likely to establish a new relationship with a bank that specializes in the new export destination than with a non-specialized one.

We explore whether potential determinants of banks' geographical specialization — e.g., country of ownership of the bank, geographical and cultural distance from the bank's headquarters to the export market, geographical distribution of the bank's subsidiary network— can account for the observed pattern of lending. We find that, even though specialization is correlated with country of ownership, banks' advantage in lending to an export destination cannot be summarized as a home-country advantage. Our measure of specialization explains the pattern of lending, even after controlling for the physical presence of global banks in the destination market.

Existing theories that emphasize the role of financial intermediaries in producing information have long recognized that bank debt is difficult to replace with uninformed capital.[1] Our results stress that different banks may have distinct advantages in different markets or economic activities, and, thus, funding *across* financial intermediaries is less-than-perfectly substitutable because of market-specific expertise. The documented market-specific advantages are distinct from the *firm-specific* advantage conferred by proprietary information gathered through the lending process —i.e., relationship lending.[2] This is particularly clear from the extensive margin results, in which banks have no prior firm-specific knowledge.

To explore this issue further, we evaluate whether the lending advantages suffer the trade-off between relationship lending advantages and bank size theorized in Stein (2002) and documented in Berger et al. (2005). We find no evidence of such a trade-off: neither the bank specialization measure nor the bank lending advantage vary systematically with bank size in the cross-section or in the time series. More conclusively, we analyze banks' patterns of lending around acquisitions and find that the set of countries in which the *target* bank specializes before the merger predicts the lending advantage of the combined bank after the acquisition. The results imply that banks retain their capabilities in their markets of specialization even as they grow larger and that they inherit the specialization set of the target bank after an acquisition. The evidence indicates that the source of the bank advantage uncovered here is scalable and not hindered by organizational con-

[1] See, for example, Leland and Pyle, 1977; Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985; Sharpe, 1990; Diamond, 1991; Rajan, 1992; Rajan and Winton, 1995; and Holmstrom and Tirole, 1997.

[2] See Bernanke, 1983; James, 1987; Hoshi et al., 1990; Petersen and Rajan, 1994; Petersen and Rajan, 1995; Berger and Udell, 1995; Degryse and Ongena, 2005; Chava and Purnanandam, 2011; Bolton et al., 2013; for surveys, see Boot, 2000 and Ongena and Smith, 2000.

straints.

Existing work has documented that a well functioning banking sector is a potential source of comparative advantage for industries intensive in the usage of external finance (Rajan and Zingales, 1998) and affects export patterns (Manova, 2013). Our results add to that conclusion by identifying a separate mechanism in which banks affect the pattern of exports across products and destinations. Banks' expertise in different export activities directly contributes to the economy's pattern of comparative advantage.

A corollary of our findings is that it is extremely difficult to empirically identify the supply of bank credit in the presence of shocks that affect the sector of economic activity in which banks specialize. The now-standard econometric approach for identifying the lending supply channel accounts for credit demand variation with firm-time fixed effects.[3] This strategy relies on the assumption that changes in firms' credit demand are, in expectation, equally spread across all banks lending to the firm. In the presence of bank specialization, this assumption holds only under restrictive conditions— e.g., for shocks to bank credit supply that are either uncorrelated with sectoral demand or that proportionally affect all the potential sectors of economic activity in which banks may specialize.[4] We illustrate how this identification assumption can be tested using within-firm specifications that account for the banks' pattern of export specialization. Using the empirical setting in Paravisini et al. (2015), we show that demand shocks can explain a larger amount of the within-firm variation in credit than bank funding shocks, which implies that confounding the two effects can lead to severely biased results.

We exploit the same empirical setting to evaluate whether a bank's credit supply shock has a disproportionate effect on exports to the country of bank specialization. We find that it does: the same decline in bank credit supply reduces exports by 33% more to countries in which the bank specializes than those in which it does not. This implies that firms

[3] See, for example, Khwaja and Mian, 2008; Paravisini, 2008; Schnabl, 2012; Jimenez et al., 2014; Chodorow-Reich, 2014.

[4] Identification is complicated further by the relatively large exposure that the balance sheet of specialized banks have to the market or the sector that faces the shock. This means that a pure demand shock to a sector may disproportionately affect the supply of credit by banks specializing in that sector.

cannot easily replace specialized sources of funding and that the bank lending advantages are economically significant.

Our results have two additional implications for understanding the industrial organization of bank credit markets. First, bank specialization provides a new rationale for why firms have multiple banking relationships and why banks form syndicates. Leading theories for multi-bank relationships hinge on arguments of ex post-renegotiation (Bolton and Scharfstein, 1996), information rents by relationship lenders (Rajan, 1992), and diversification of firms' exposure to bank failures (Detragiache et al., 2000), while existing explanations for loan syndicates include risk diversification and regulatory arbitrage (Pennacchi, 1988). Multiple bank relationships and syndicates may arise naturally in a world in which banks are differentially equipped to evaluate different projects by the same firm: multi-project firms demand credit from specialized banks for each project, and banks' combined expertise allows a more accurate risk assessment of complex, multi-project firms. Second, our results highlight the limits of bank diversification. Traditional banking theory argues that full diversification across sectors and projects is optimal (e.g., Diamond, 1984; Boyd and Prescott, 1986). Comparative advantages in bank lending can limit the extent to which it is optimal for banks to diversify their loan portfolios.

The rest of the paper proceeds as follows. Section 2 describes the data. In Section 3 we present a theoretical framework that guides our exercise; we define our measure of bank specialization; and we present the methodology to empirically assess whether this measure is an indicator of an advantage in lending. The results are presented in Section 4. Section 5 illustrates the importance of accounting for bank specialization when measuring credit supply shocks and their consequences. Finally, Section 6 concludes.

2 Data

We use two datasets: monthly loan-level data for each bank in Peru and customs data for Peruvian exports over the period 1994-2010. Both datasets cover the universe of firms operating in Peru.

We collect the customs data from the website of the Peruvian tax agency (Superintendence of Tax Administration, or SUNAT). Collecting the export data involves using a web crawler to download each individual export document. To validate the consistency of the data collection process, we compare the sum of the monthly total exports from our data, with the total monthly exports reported by the tax authority. On average, exports from the collected data add up to 99.98% of the exports reported by SUNAT.

The Peruvian bank regulator (Superintendencia de Banca, Seguros, and APF, or SBS) provides the loan-level data. These data consists of a monthly panel of the outstanding debt of every firm with each bank operating in Peru. We also collect the time-series of bank financial statements from the SBS website. We check the validity of the loan-level data by aggregating total lending, and we find that total loan volume corresponds to total lending volume reported on bank balance sheets. We match the loan data to export data using a unique firm identifier assigned by SUNAT for tax collection purposes.

Table 1 shows summary statistics describing the data. The unit of observation in our empirical analysis in Section 3.3 is at the bank-firm-country-year level. Each observation combines the annual average bank-firm outstanding debt with the firm's annual exports to each destination country, expressed in US dollars (FOB). The total number of observations in the full dataset, described in Panel 1, is 378,766. The average annual firm-bank outstanding debt is US$ 2,044,488, and the average firm-destination annual export flow is US$ 2,148,237 (conditional on bank debt being greater than zero). However, as it is usual for this type of data, exports and debt are right-skewed. The median debt and export flow are only US$ 259,764 and US$ 87,218, respectively.

Panel 2 in Table 1 describes the 14,267 exporting firms in our data. On average, the median firm borrows from two banks and exports to only one destination. In this dimension, the data are also right-skewed; the average number of banking relationships per firm is 2.42 and the number export countries is 2.65. We restrict the sample to include the export destination to the 22 main markets, which represent 97% of Peruvian exports across the entire period of analysis.[5]

3 Framework and Methodology

This section presents a model in which banks are imperfectly substitutable sources of funding and are heterogeneous in their lending capabilities for specific economic activities, which we pair in the data with advantages in funding exports to specific destinations. This framework guides our definition of bank specialization and the empirical methodology used to assess whether bank specialization in a country is an indicator of an advantage in lending to exporters to that destination—that is, whether our measure of specialization, based on the stock of existing loans, predicts the flow of new loans.

3.1 Theoretical Framework of Specialized Bank Lending

This section presents a simple partial equilibrium model that guides our empirical methodology and rationalizes the results in the paper. Firms are characterized by a collection of activities that require funding, and banks differ in their pattern of activity-specific lending advantages. Without explicitly defining either the market structure for the firms' output or the sources of banks' lending advantages, our goal is to present a reduced-form framework in which different sources of funding are not freely substitutable.

Each firm $i = 1, ..., I$ uses bank credit to finance a variety of activities $j \in J_i$ according to the following production function:

$$q_i^j \left(\{L_{ib}^j\}_{b=1}^B \right) = \left[\sum_{b=1}^{B} (\gamma_b^j)^{\frac{1}{\rho}} \left(L_{ib}^j \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{1}$$

where $b = 1, ..., B$ are the different banks in the banking industry; $\rho > 0$ is the elasticity of substitution between credit from different banks; and γ_b^j is the comparative advantage of

[5] The countries are Belgium, Bolivia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Denmark, Ecuador, France, Germany, Italy, Japan, Korea, Netherlands, Panama, Spain, Switzerland, United Kingdom, United States, and Venezuela.

bank b in credit specific to activity j.[6]

The optimal borrowing of firm i from each bank b to fund each activity j responds to the following cost-minimization problem:

$$\min_{\{L_{ib}^j\}_{j,b}} \sum_{b=1}^{B} r_{ib}\, L_{ib} \qquad s.t. \quad q_i^j\left(\{L_{ib}^j\}_{b=1}^B\right) = \overline{q}_i^j \quad \forall j \in J_i,$$

where $L_{ib} = \sum_{j \in J_i} L_{ib}^j$ is total credit with bank b, and $q_i^j\left(\{L_{ib}^j\}_{b=1}^B\right)$ is defined in equation 1. Then, the optimal funding of firm i from bank b allocated to activity j is:

$$L_{ib}^j = \left(\frac{1}{r_{ib}}\right)^{\rho} \lambda_i^j\, q_i^j\, \gamma_b^j,$$

$(\lambda_i^j)^{1/\rho}$ is the multiplier on the output constraint, which is the marginal cost of producing q_i^j. We use the transformation of marginal cost λ_i^j to translate quantities q_i^j into monetary values, and we denote $X_i^j \equiv \lambda_i^j q_i^j$.[7] Then, the overall debt of firm i with bank b can be expressed as:

$$L_{ib} = \left(\frac{1}{r_{ib}}\right)^{\rho} \sum_{j \in J_i} X_i^j\, \gamma_b^j, \tag{2}$$

Each bank b is characterized by the price of lending, r_{ib}, which can be firm-specific, and a vector of activity-specific capabilities $\gamma_b = \left[\gamma_b^1, ..., \gamma_b^J\right]$. This parameter can be interpreted as an activity-specific monitoring advantage, an activity-specific discount on interest rate, r_{ib}, or as a service associated with the activity. For example, in the case of exporting to a given country, it could be the bank's presence in the destination market.

Note that if all sources of credit are perfect substitutes (i.e., $\rho = \infty$), the funding of activity j in (1) is given by the overall funding of firm i allocated to activity j, without

[6]This CES specification generates the same credit demand function as the aggregate of a large number of firms, each discretely choosing the bank and then borrowing a given amount from the selected one, to fund activity j (see Anderson et al., 1987).

[7]If, similar to the empirical exercise in the body of the paper, firms produce homogeneous goods in a competitive market and $j = 1, ..., J$ correspond to different destination markets, then the marginal costs are equalized across firms and destinations, and they are equal to the international price. In that case, X_i^j corresponds to the value of exports by firm i to destination j.

differentiating the lending institution, $q_i^j = \sum_{b=1}^{B} L_{ib}^j$. If this were the case, firms would borrow only from the bank that offers funding at the lowest price, r_{ib}. On the other hand, if sources of credit are not perfect substitutes (i.e., $0 < \rho < \infty$) and banks are heterogeneous, then firms have multiple banking relationships. The price of credit charged by each bank influences its size, measured in overall lending (i.e., $\frac{\partial \ln \sum_i L_{ib}}{\partial \ln r_{ib}} = -\rho < 0$), but in equilibrium, there is room for multiple banks of different sizes.

This framework guides our empirical methodology. We derive from it the measure of the bank's portfolio share associated with a given economic activity, and we use that measure in subsection 3.2. Our framework implies that, if banks are imperfectly substitutable sources of funding, then each bank has a larger portfolio share associated with the activity in which they have a lending advantage. Moreover, we derive from this framework the rationale for our revealed preference identification strategy presented in Section 3.3. If a firm increases its outcome in activity j, and banks are imperfectly substitutable sources of funding, it will increase its share of credit with the bank that has a lending advantage in that activity.

More formally, consider two banks b, b' that have the same productivity parameters for all activities, with the exception of sectors j and j' for which $\gamma_b^j = \gamma_{b'}^{j'} > \gamma_b^{j'} = \gamma_{b'}^j$. The following results follow from equation 2.

Result 1. *The share of lending associated with activity j is higher for bank b than for bank b'. That is, let S_b^j be defined as:*

$$S_b^j \equiv \frac{\sum_{i=1}^{I} L_{ib} X_i^j}{\sum_{k=1}^{J} \sum_{i=1}^{I} L_{ib} X_i^k}.$$

Then, $S_b^j > S_{b'}^j$.[8]

Result 2. *The elasticity of lending to the outcome of activity j is higher for the bank with a comparative advantage in activity j. That is, $\frac{\partial \ln L_{ib}}{\partial \ln q_i^j} \geq 0$ and increases with γ_b^j.*

[8]The derivation of this result is in the Appendix.

3.2 Specialization Measure

In this section, we use the definition of bank portfolio share associated with an economic activity in Result 1 to obtain a measure of specialization that is scaled by bank size. Each economic activity in the framework presented in subsection 3.1 represents a geographical market—an export destination country—in the data.

Let $i = 1, ..., I$ be the universe of exporting Peruvian firms and $c = 1, ..., C$ be the destination country of exports. We define S_{bt^c} to be bank-b borrowers' exports (weighted by their debt in bank-b) to country c, as a share of bank-b borrowers' total exports. That is:

$$S_{bt}^{c} \equiv \frac{\sum_{i=1}^{I} L_{bit} X_{it}^{c}}{\sum_{c=1}^{C} \sum_{i=1}^{I} L_{bit} X_{it}^{c}}, \tag{3}$$

where X_{it}^{c} are exports by firm i to destination country c in year t, and L_{bit} is the outstanding debt of exporting firm i with bank b in year t.

The share of bank lending associated with exports to any given destination is heavily influenced by the importance of that destination market in overall Peruvian exports. For example, since a large fraction of total Peruvian exports is to the U.S., most banks will show a high share of exports by their borrowers to the U.S. We want the specialization measure to capture banks' departures from the overall specialization pattern of Peruvian exports: A bank is specialized if its portfolio is skewed (relative to other banks) towards loans associated with a given country. We adopt a non-parametric approach to systematically identify the outlier banks in the distribution of $\{S_{bt}^{c}\}$ for each country-year.

To illustrate the approach, we depict the distribution of $\{S_{bt}^{c}\}$ across banks for each country in 2010 with a box-and-whisker plot in Figure 1. To facilitate the interpretation, we plot $\{S_{bt}^{c} - \overline{S}_{t}^{c}\}$ instead of $\{S_{bt}^{c}\}$, so that all the country distributions are centered at zero. The ends of each box denote the 25$^{\text{th}}$ to 75$^{\text{th}}$ percentiles of the distribution, and the size of the box is the interquartile range (IQR). The "whiskers" delimit the range between the upper and lower extreme values of the distribution, defined as the highest datum still within 1.5 IQR of the 75$^{\text{th}}$ percentile and the lowest datum still within 1.5 IQR of the 25$^{\text{th}}$

percentile, respectively. Then, for a given country and year, we consider a bank to be an outlier of the distribution if its observation lies outside the "whiskers."[9] The outliers are identified with dots in the plot for each country. We define a bank as specialized in a country if it is an outlier on the right tail of the $\{S^c_{bt}\}$ distribution. More formally:

Definition 1 (Specialization)**.** *We consider a bank-country-year observation, S_{bct}, to be an outlier, which we signal with the dummy $O(S^c_{bt}) = 1$, if S^c_{bt} is above the upper extreme value, defined by the 75th percentile plus 1.5 interquartile ranges of the distribution of $\{S^c_{bt}\}$ across banks for a given country-year. We refer to an outlier bank as* ***specialized*** *in the corresponding country during the corresponding year.*

Our measure of specialization captures bank exposure that is driven by both the number of firms and firm size. Consider, for example, two polar cases: a bank's portfolio exposure to a country may be abnormally large because it lends to a large number of small exporters relative to other banks, or because it provides a large fraction of the credit to a large exporter relative to other banks. Both polar cases would arise in a framework in which firms are modeled as a collection of economic activities, and banks have a lending advantage in a subset of these activities (as in the framework in subsection 3.1). It remains to be shown whether this measure of specialization, based on the existing portfolio of loans, can also predict the pattern of new credit. This is the subject of the next subsection.

3.3 Identifying Advantage in Lending

In the context of the financing of exporters, a bank has an advantage if it can provide credit at a lower cost, more credit for the same borrower characteristics, or more value-added services attached to the issuance of credit (letters of credit, presence in the country

[9] This method for identifying outliers makes no assumption about the data distribution model. See Hodge and Austin (2004) for a survey of outlier detection methods. In a normally distributed sample, this definition would correspond to observations above (below) the mean plus (minus) 2.7 times the standard deviation of the distribution.

of destination, etc.) than other lenders.[10] The empirical problem rests in the fact that the econometrician does not observe firms' project-specific demand for credit or the value-added services provided by banks.

We adopt a revealed preference approach to evaluate advantages. Under the null hypothesis that banks do not have advantages in lending—e.g., that credit from one bank is as good as credit from any other—variation in a firm's export activity with one country should be uncorrelated with the identity of the bank providing the funding (ceteris paribus). For example, a firm that expands its exports to China is equally likely, in expectation, to increase its borrowing from the bank that specializes in exporters to China as from the bank that specializes in Switzerland.

Our empirical strategy tests the alternative hypothesis: variations in firm exports to a country are correlated with credit from banks that specialize in that country, as shown in Section 3.1 (Result 2). We build on the recent literature that uses micro-data to account for firm credit demand shocks that are common across all banks with firm-time dummies, and for bank credit supply shocks that are common across all firms with bank-time dummies (see, for example, Jimenez et al., 2014). In a nutshell, we show that once *all* time-varying firm-specific and bank-specific shocks are accounted for, firms borrow more from banks that specialize in the country they export to.

Consider the following general characterization of the lending by bank b to firm i at time t:

$$L_{bit} = L\left(L^S_{bt}, L^D_{it}, \mathcal{L}_{bit}\right). \tag{4}$$

Bank-firm outstanding credit is an equilibrium outcome at time t, determined by the overall supply of credit by the bank, L^S_{bt}, which varies with bank-level variables such as overall liquidity, balance-sheet position, etc.; the firm's overall demand for credit L^D_{it}, which varies with firm-level productivity, demand for its products, investment opportunities, etc.; and, finally, a firm-bank specific component, $\mathcal{L}_{bit}$, which corresponds to our

[10] Niepmann and Schmidt-Eisenlohr (2014) document that U.S. banks are specialized in export countries when issuing letters of credits.

element of interest: the component of bank-b's lending that depends on its relative advantage in markets supplied by the firm i.

The goal of our empirical strategy is to test whether the bank-firm pair component of lending varies with firm-i's export activity in markets in which bank-b specializes. In other words, we test whether the covariance between $\mathcal{L}_{bit}$ and X^c_{it} (firm i's exports to destination market c) increases in $\mathcal{S}^c_{bt}$ (a measure of bank b's specialization in destination market c).

In the baseline specification, we use specialization up to the year of the loan: for every year t, it corresponds to the fraction of years up to year $t-1$ in which bank b is an outlier in the loan distribution associated with country c:

$$\mathcal{S}^c_{bt-1} = \frac{1}{(t-1)-t_0} \sum_{\tau=t_0}^{t-1} O(S^c_{b\tau}), \tag{5}$$

where t_0 is the first year that the bank appears in our dataset, and $O(S^c_{bt})$ is our measure of specialization in Definition 1.

Our empirical estimation accounts for the bank-specific credit supply shocks L^S_{bt} (common in expectation across all firms) by saturating the empirical model with a full set of bank-time dummies, α''_{bt}. We account for the firm-specific credit demand shocks L^D_{it} (common in expectation across all banks) by saturating the model with a full set of firm-time dummies, α'_{it}. Then, for each country-bank-firm-year, our baseline specification is:

$$\ln L_{bit} \quad = \quad \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \; \ln X^c_{it} + \beta_2 \; \mathcal{S}^c_{bt-1} + \beta_3 \; \mathcal{S}^c_{bt-1} \times \ln X^c_{it} + \epsilon^c_{ibt}. \tag{6}$$

Outstanding debt is a firm-bank-year value, L_{bit}—i.e., we do not observe the credit that a bank provides for each exporting activity, but only the total credit that the bank provides. However, for each firm-bank-year, there are 22 relationships like the one in (6)—one for each country c in our analysis sample. To estimate the parameters of (6), we stack the observations for all countries and adjust the standard errors for clustering at the bank and firm level to account for the fact that L_{bit} is constant across countries for a given bank-firm-time triplet. The c superindices on exports X^c_{it}, the bank specialization measure $\mathcal{S}^c_{bt}$, the fixed-effects α^c_b and the error term ϵ^c_{ibt} indicate that they vary by country in the stacked estimation. The set of time-invariant bank-country fixed effects, α^c_b, accounts for all unobserved heterogeneity in the bank-country lending relationship, such as the distance between bank headquarters (for international banks) and the destination country. We estimate this specification demeaned to eliminate the time-invariant fixed effects.

Parallel to specification 6, we also test whether the the probability that a firm starts borrowing from a bank increases after the firm starts exporting to the country of specialization. We estimate the following linear probability model:

$$\begin{aligned}(L_{bit} > 0 | L_{bit-1} = 0) \quad = \quad & \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1\,(X^c_{it-1} > 0 | X^c_{it-2} = 0) + \beta_2\,\mathcal{S}^c_{bt-1} \\ & + \beta_3\,\mathcal{S}^c_{bt-1} \times (X^c_{it-1} > 0 | X^c_{it-2} = 0) + \epsilon^c_{ibt}, \qquad (7)\end{aligned}$$

where $(L_{bit} > 0 | L_{bit-1} = 0)$ is a dummy equal to 1 if firm i borrows from bank b in year t, but not in year $t-1$; and, correspondingly, $(X^c_{it-1} > 0 | X^c_{it-2} = 0)$ is a dummy equal to 1 if firm i exports to country c in year $t-1$, but not in year $t-2$.

Our coefficient of interest in specifications 6 and 7 is β_3. A coefficient $\beta_3 > 0$ indicates that, for a given firm, the correlation between its exports and outstanding debt is higher for banks specialized in the destination country (equation 6), or that the probability of starting to borrow from a bank increases when the firm starts exporting to the bank's country of specialization (equation 7). This is the case if, for example, a firm needing credit to fund its export activities to China is more likely to obtain it from banks that specialize in China than from other banks. In contrast, if all sources of credit are perfect substitutes (e.g., banks do not have comparative advantages), or if our measure of specialization is pure noise and uncorrelated with comparative advantage, then $\beta_3 = 0$.

It is important to highlight that our approach tests a joint hypothesis: that banks have advantages in lending and that firms require credit to sustain export activities. If the second part of the hypothesis is false, a change in the amount of exports does not translate into an increase in the demand for credit, which would mean that our tests would not reject the null hypothesis. In previous work using Peruvian data from the 2008 Great Recession, we test the second hypothesis independently and find that, indeed, firm's exporting activity is bank-finance dependent (Paravisini et al., 2015).[11]

4 Results

In this section, we characterize the patterns of bank specialization according to the definitions in subsection 3.2. We then show, following the empirical strategy in subsection 3.3, that bank specialization at a given moment in time predicts the subsequent pattern of credit.

4.1 Patterns of Bank Specialization

We compute the shares of lending associated with each export market using the outstanding debt of Peruvian firms in the 33 banks operating in Peru between 1994 and 2010, as well as the firm shipment-level export data to the 22 largest destination markets.[12]

The values of S_{bt}^{c} defined in (3) provide information on the heterogeneity in lending shares by country across banks. In Table 2, we present descriptive statistics of S_{bt}^{c} by country, demeaned by the average share across all banks in the corresponding country, $\overline{S}_{t}^{c}$. The median of $S_{bt}^{c} - \overline{S}_{t}^{c}$ is negative for every country, indicating that the within-country distribution of $\{S_{bt}^{c}\}$ is right-skewed. This is confirmed in column 5, where we report a large and positive skewness for every country. This skewness implies that for every destination country in the sample, there is at least one bank heavily specialized in financing exports to that destination. Figure 1, which shows the box-plot of distribution of $S_{bt}^{c} - \overline{S}_{t}^{c}$ for each

[11] Amiti and Weinstein (2011), Feenstra et al. (2014), and Manova (2013), among others, also find that bank credit affects the intensive margin of exports (i.e., variations in the amount of exports of exporting firms).

[12] The bank panel is unbalanced because of entry, exit and M&A activity (we discuss M&A activity in more detail in subsection 4.3).

country, confirms this finding.

Table 3, column 1, reports the number of countries in which each bank specializes at least once in the sample period, according to Definition 1. Banks specialize in several countries during the 17-year period, with one bank (code 73) reaching a maximum of 15 countries out of a total of 22. These numbers decline considerably once we count the countries in which each bank specializes for at least 25%, 50%, or 75% of the time that the bank appears in the sample (columns 2 to 4). Even using a stringent definition of specialization—in which the bank must be an outlier in the country for at least 75% of the observed sample period in order to be considered specialized—25 out of 33 banks in the sample specialize in at least one country.

In summary, banks specialize in the export markets of related firms, and each bank is associated with a subset of countries for which it exhibits long-lasting specialization.

4.2 Baseline Results

In this subsection, we use the methodology described in subsection 3.3 to evaluate whether specialized banks have an advantage in lending for specific export activities. We present the OLS estimates of specification 6, demeaned, in Table 4, column 1.

We start by examining the results on the intensive margin. The coefficient on (log) exports is positive and significant, with elasticity an of 0.026. This coefficient captures the correlation between the firm-bank specific component of debt and the firm's average exports to the countries in which bank b does not specialize.[13] The positive coefficient implies that, when firms expand exports to a country, they borrow more, on average, from all banks, regardless of whether the destination country is outside the bank's markets of expertise.

Our coefficient of interest on the interaction between log exports and the specialization measure is 0.014 and significant at the 5% level. This shows that when a firm expands its

[13] Note that there is independent bank-firm variation in exports —variation that is not captured by the firm-time dummies— because not all banks specialize in the same countries.

total exports to a specific country, it also borrows more from banks that specialize in that market than from non-specialized banks. The coefficient implies that the elasticity of credit to exports is 52% higher for a bank that has specialized in the country for the full sample period up to t ($\mathcal{S}^c_{bt-1}$=1), relative to a non-specialized bank ($\mathcal{S}^c_{bt-1}$=0).

We verify the robustness of this result to using a *leave-one-out* measure of specialization that does not include the past behavior of firm i. That is, we compute a new specialization measure with the same procedure as above, but excluding firm i, $\mathcal{S}^c_{-ibt-1}$, in specification 6.[14] The coefficient on the interaction between exports and $\mathcal{S}^c_{-ibt-1}$, reported on Table 4, column 2, is positive and statistically significant at the 10% level, and its magnitude is statistically indistinguishable from the one reported in column 1. This result rules out the possibility that the findings are driven by a single large firm that tilts the bank's portfolio and future lending in the same direction.

We now consider the extensive margin. Table 4, column 3, presents the OLS estimates of the entry margin specification in (7). The sample for this estimation is the combination of all possible bank-firm relationships—meaning all the bank-firm pairs that do not have a positive outstanding balance in any given year (thus the large sample size and the low probability of a new relationship). The coefficient estimates indicate that the probability of starting a banking relationship with a non-specialized bank ($\mathcal{S}^c_{bt-1}$=0) after exporting to a new destination is 0.06%, and it increases 6.4 times (to 0.38%) for a bank that has specialized in that destination for the full sample period up to t ($\mathcal{S}^c_{bt-1}$=1). These magnitudes are economically significant when compared to the unconditional probability that an exporter starts a new relationship with a bank at any point in time (0.74%). The comparison implies that the year after a firm starts exporting to a country, it is about 8% more likely to start a relationship with a non-specialized bank (0.06/0.74) and 51% more likely to start a relationship with a specialized one (0.38/0.74).

These results show that banks are more likely to fund export activities to countries in

[14] $\mathcal{S}^c_{-ibt-1} \equiv \frac{1}{(t-1)-t_0}\sum_{\tau=t_0}^{t-1} O(S^c_{-ib\tau})$ as in (5), but the share of lending is computed excluding firm i: $S_{-ibc\tau} \equiv \frac{\sum_{h\neq i} L_{hb}X^c_h}{\sum_{c=1}^{C}\sum_{h\neq i} L_{hb}X^c_h}$.

which the bank specializes. This indicates a bank-specific advantage in lending, such that firms fund exports to country c with a marginal dollar obtained from a bank specializing in country c. The coefficient captures an equilibrium correlation that may be originated by demand shocks, supply shocks, or both. Under the demand interpretation, exporting to country c becomes more profitable, and firms seek additional credit from the specialized banks. For the supply interpretation, banks that expand credit supply allocate the marginal dollar to the sector in which they specialize.

The intensive-margin result is hard to reconcile with a collusion interpretation—i.e., banks tacit agreement to focus on certain markets. It is difficult to enforce a collusive agreement not to enter each others' markets once the firm is already borrowing from competing banks.

Also, the extensive margin results cannot be explained by relationship lending —a lending advantage conferred by firm-specific information gained through prior interaction. First-time exporters establish new relationships with banks that specialize in the destination market, which points to market-specific, as opposed to firm-specific, advantages in bank lending.

4.3 Specialization and Bank Size

In this subsection, we characterize the pattern of specialization in the cross-section of bank size and, over time, as banks increase their overall amount of lending. The exercise is motivated by the theoretical framework in Stein (2002), which suggests that there is a trade-off between bank size and the firm-specific advantage generated through relationship lending. This lending advantage is understood as firm-specific information, difficult to communicate across hierarchical layers of the organization (*soft* information). In contrast, if the source of the lending advantage is scalable —as is assumed in the model presented in subsection 3.1— not only will the advantage persist for large banks, but the banks with larger advantages will be larger. Thus, the relationship between comparative advantage and bank size in our context can tell us something about the source of comparative advantage.

Table 5, columns 1 and 2, show the correlation between our measure of specialization, defined in 5, and bank size, measured by total (real) lending in Peru. Since foreign-owned banks are much larger than implied by their lending in Peru, we also include the dummy $Foreign_{bt}$ to capture this global size difference. Larger and foreign-owned banks are not more likely, in the cross-section, to specialize in export markets (column 1). For a given bank over time (column 2), the number of countries in which banks specialize does not grow with size, but banks do increase their set of specialization after being acquired by a foreign bank.

We are interested in whether the patterns obtained from estimating the baseline regressions in Table 4 are similar in the cross-section of bank size and foreign ownership status. We estimate specification 6 augmented with interactions of the right-hand-side variables with $Foreign_{bt}$ and $SmallBank_b$, a dummy equal to 1 if b is not one of the ten largest institutions measured in total loans over the full sample period.[15] The results are reported in Table 5, columns 3 and 4. The coefficient on exports interacted with specialization is similar to that in the baseline specification in Table 4. This implies that the ten largest banks in Peru have a significant comparative advantage in lending to the countries in which they specialize. The coefficient on the interaction with $SmallBank_b$ is negative but statistically insignificant (column 3). Although the point estimate is noisily estimated, its magnitude suggests that smaller banks may have a smaller lending advantage or none at all. Similarly, the lending advantages of foreign and domestic banks are not significantly different from each other (column 4).

To analyze whether the lending patterns described in the baseline regressions in Table 4 are preserved for the same bank after expanding in size, we evaluate the relationship between lending and exports around mergers and acquisitions. We modify the data and specification 6 to perform event studies around the years in which bank mergers take place. Eight-year interval subsamples around the time of the merger—four years before

[15]Since not all banks appear in all years, we rank the banks according to their average inflation-adjusted amount of total loans outstanding during the years they appear in the sample to create this variable.

and four years after the event—are drawn from the original data and stacked to perform a single estimation. We use as measure of bank specialization the variable defined in definition 1, $\mathcal{S}_b^c = O(S_{bt}^c)$, computed the year before the merger. In one specification (column 3), we combine the merging entities into a single one before the merger, and we use the maximum of the outlier indicators of the two banks as a measure of their combined specialization (e.g., if, before the merger, bank 1 specialized in country A and bank 2 specialized in country B, then the combined entity is considered to specialize in A and B before the merger). To analyze the transmission of expertise within the merged bank, we also test whether the specialization set of the *target* bank (i.e., the smallest of the two institutions participating in the merger) predicts the lending pattern of the merged bank after the acquisition (column 4).

We first replicate our baseline estimation in (6) without the merger interaction terms to corroborate that the point estimates are robust to the change in sample and specification (Table 6, columns 1 and 2). The coefficients on the term $\mathcal{S}_b^c \times \ln(X_{it}^c)$ are positive and significant, similar in magnitude to those in our baseline result in Table 4. The relationship between exports and lending is somewhat smaller (0.011 vs. 0.026 in the baseline regression), which implies that, in this subsample, the elasticity between exports and bank credit of specialized banks is about twice as large as that of non-specialized banks (it was 52% in the baseline regression).

In columns 3 and 4, these regressions are augmented with the interaction of $Merger_{bt}$, a dummy equal to 1 during the four years after the event for the merging entity. We also augment the bank-time, firm-time, and bank-country sets of dummies with an event dummy interaction (e.g., there is a separate bank-time dummy for every merger event). The coefficient on the triple interaction with the Merger indicator, $\mathcal{S}_b^c \times \ln(X_{it}^c) \times Merger_{bt}$, measures whether the link between the specialization and lending is affected by the merger. The point estimate in column 3 is positive and statistically significant at the 10% level. More decisively, column 4 shows that lending by the merged institution is characterized by the specialization patterns of the *target* bank before the merger. That is, the merged entity inherits (and even deepens) the specialization of the *target* bank.

These results imply that banks retain their capabilities in their markets of specialization even as they grow or merge into larger institutions. Thus, the source of the lending advantage analyzed here is distinct from that derived from firm-specific information (as emphasized in Stein, 2002), and it is not hindered by organizational constraints.

4.4 International and Local Geographical Advantages of Banks

In this subsection, we explore whether bank specialization patterns are related to the geographical presence of banks. That is, country of ownership or location of international subsidiaries in the case of global banks, and the location of domestic branches for all banks in the Peruvian banking system.

Market expertise may be global, derived from the natural advantages provided by the superior information that multinational banks may have in their home countries, neighboring countries, and countries where they have established subsidiaries or branches. We first evaluate the correlation between our measure of bank specialization in a country and the variables that capture the geographical advantages conferred by the ownership country and subsidiary network. Table 7, column 1, shows the cross-sectional correlation between the bank-country specialization index and: 1) $CountryOwnership_b^c$, a dummy equal to 1 if bank b's headquarters are located in country c; 2) $CountrySubsidiary_b^c$, a dummy equal to 1 if bank b has a subsidiary in country c in 2004;[16] 3) $CommonLanguage_b^c$, a dummy equal to 1 if the language in bank b's headquarters coincides with that in country c; and 4) $DistanceToHeadquarters_b^c$ between the country of ownership and the export destination c.[17] For this cross-sectional analysis, we use the measure of specialization in

[16]We construct the subsidiary network using Bankscope data. We start by identifying the ultimate owner of the Peruvian bank (e.g., Citibank U.S. for Citibank Peru). We then use the Bankscope subsidiary data to identify all countries in which the ultimate owner has a subsidiary as of 2005 (e.g., all countries with Citibank subsidiaries).

[17]We obtain these bilateral measures from Mayer and Zignago (2011).

Definition 1, $O(S^c_{b\tau})$, averaged during the entire life of the bank.[18] We find that, indeed, there is a connection between the bank's country of ownership and the set of specialization. Banks are more likely to specialize in the country of their headquarters or in countries with the same language.

We then explore whether the bank's country of ownership is a sufficient statistic of the market-specific lending advantages found in our baseline regressions in Table 4. If lending advantages were driven exclusively by the location and network of the headquarters, including the above variables in our baseline revealed preference regression would make the specialization measure redundant. We explore this possibility by expanding the baseline regression in (6) with the four indicators above, interacted with exports (i.e., $CountryOwnership^c_b \times \ln(X^c_{it})$, $CountrySubsidiary^c_b \times \ln(X^c_{it})$, $CommonLanguage^c_b \times \ln(X^c_{it})$, $DistanceToHeadquarters^c_b \times \ln(X^c_{it})$). Results are presented in Table 7, columns 2 and 3. None of these interaction terms is statistically significant, and their inclusion in the regression does not change the magnitude or the significance of the interaction of exports and specialization.

We conclude that, even though our specialization measure is correlated with the bank's country of ownership, banks' advantage in lending for an export destination cannot be summarized as a home-country advantage.

Another potential source of destination-specific lending advantage is the geographical proximity between exporters and banks in Peru. If firms that export to a specific country are geographically clustered, then banks that have a larger presence in that area may end up specializing in funding exports to this country. We explore this relationship empirically in our setting. There are 1,853 districts in Peru and each denotes a relatively small geographical area. Exporter location, obtained from the tax authority web page (SUNAT), is concentrated in 305 districts, and the top ten districts account for 52.3% of the exporters.

[18] That is, $\mathcal{S}^c_b$, as defined in equation 5, up to t_F, the last year the bank appears in our dataset:

$$\mathcal{S}^c_b = \frac{1}{t_F - t_0} \sum_{\tau=t_0}^{t_F} O(S^c_{b\tau}).$$

Bank branch location data is from the bank supervision agency in Peru and is only available after 2001, so we restrict the sample to the 2001 to 2010 period for this analysis. Bank branch location is also geographically concentrated: the 1,455 bank branches in Peru in 2010 were located in only 144 districts. Hence, both bank branches and exporters cluster in certain areas of the country.

We test whether the destination-specific lending advantage can be explained by local clustering. To do so, we augment the baseline regression 6 with two measures of proximity between firm i and bank b (and their interaction with firm exports, $\ln(X^c_{it})$): 1) a dummy if bank b has a branch in year t in the district in Peru where firm i is located, and 2) the number of branches that bank b has in year t in the district in Peru where firm i is located. Table 8, column 1, replicates the baseline regression estimates on the 2001 to 2010 and obtains very similar estimates to those in Table 4. Column 2, shows the estimated coefficients on the specification augmented with the local distance variables and their interaction with firm exports. We find that the coefficient on the interaction between the bank specialization measure and exports does not change after the inclusion of the local geography variables. This implies that local distance to a branch does not explain the bank advantages related to specialization.

4.5 Product or Destination Advantage?

There are potentially many confounding effects behind banks' advantage in lending towards export destinations. In our sample, for example, export markets differ greatly in the mix of Peruvian products demanded. Coffee, which in 2010 totaled approximately 2.5% of Peruvian exports, accounted for 18% of the exports towards Germany. Possibly, banks' advantage in lending to firms exporting to Germany may not only involve expertise related to this destination but also on monitoring the activities of coffee producers.

We test for industry-specific lending advantage in Table 9. We show in Column 1 that, indeed, there exists an industry-specific advantage when we measure bank specialization according to the products exported by related firms, $\mathcal{S}^p_{bt}$ (products defined according to

2-digit categories of the Harmonized System). When a firm expands its total exports on a specific product, it borrows more from banks specialized in that product, relative to non-specialized banks. The coefficient implies that the elasticity of credit to exports doubles for a bank that has been specialized in the product for the full sample period up to t ($\mathcal{S}^{p}_{bt-1}$=1) relative to a non-specialized bank ($\mathcal{S}^{p}_{bt-1}$=0).

In column 2 we further disaggregate firms' annual exports into product-destination flows (i.e., X^{pc}_{it}). We can therefore analyze whether the baseline measure of bank specialization based on country of destination ($\mathcal{S}^{c}_{bt-1}$) or the one based on export products ($\mathcal{S}^{p}_{bt-1}$) is a better predictor of the pattern of credit. When both interactions are included, the baseline results are maintained: The elasticity of credit to exports, at the product-destination level, is 67% larger for a bank that has been specialized in the country of destination during the whole sample relative to a non-specialized bank. The interaction with product-specialization, on the other hand, turns insignificant when the two measures of specialization are included. We conclude that in our sample, although both measures of specialization are economically relevant, bank specialization on export destination is a better predictor of bank lending patterns.

5 Specialization and Credit Supply

In this final section, we use the empirical tools developed in the paper to revisit two issues raised in the introduction. First, we show how the presence of market specialization in bank lending imposes additional challenges for the identification of bank credit supply shocks with the standard within-firm estimators used in the lending channel literature (see Khwaja and Mian, 2008; Paravisini, 2008; Schnabl, 2012; Jimenez et al., 2014; Chodorow-Reich, 2014). And second, we show that when banks have lending advantages and their debt is difficult to substitute, declines in the supply of credit by a bank can have a disproportionate effect on real economic activity in the bank's market or sector of specialization. To explore these two issues, we take advantage of the overlap in the data and analysis period with Paravisini et al. (2015) (hereafter, PRSW), and we reassess the key empirical findings in that paper under the lens of a specialized banking sector.

5.1 Within-Firm Identification of Credit Supply Shocks

International portfolio capital inflows to Peru decreased sharply in 2008, and, as a result, funding to banks with a high share of international liabilities dropped substantially. PRSW identify the effect of this funding shock on bank credit supply using the now-standard strategy of absorbing demand for credit with firm-time fixed effects. The approach compares how credit to the same firm, by banks with high and low shares of foreign liabilities, changed around the event. Firm-time dummies absorb credit demand variation only if a change in firm credit demand is, in expectation, equally spread across all banks lending to the firm. As our results so far demonstrate, this assumption may not hold in the presence of bank specialization. The goal of this subsection is twofold. First, we illustrate with an example how the identification assumptions may still hold when the shock driving variations in credit supply is uncorrelated with shocks affecting the bank's market of expertise. We use the PRSW setting to provide a simple test to corroborate this assumption. And, second, we use the example to compare the relative magnitude of the demand-driven and supply-driven credit variation in a firm-time fixed effects specification. This allows us to assess the potential magnitude of the bias that may result when variation in demand is confounded with variation in supply.

We estimate the within-firm estimator, adopting, for simplicity, a dichotomic classification of banks into *exposed* and *not-exposed* to the capital outflows. Exposed banks are those with more than 10% of their assets funded with foreign liabilities in 2006 (identified by the dummy $Exposed_b$).[19] This leads to the empirical model:

$$\ln(L_{ibt}) = \alpha_{ib} + \alpha_{it} + \beta \cdot Exposed_b \times Post_t + \nu_{ibt}, \tag{8}$$

[19] The threshold is the average exposure taken across the 13 commercial banks in 2006. The entire sample of 41 banks also includes 28 S&Ls at year-end 2006 with minimal exposure.

where L_{ibt} is the average outstanding debt of firm i with bank b during the intervals $t = \{Pre, Post\}$, and Pre and $Post$ periods correspond to the 12 months before and after July 2008, the approximate date of the portfolio flow reversal. $Post_t$ is a dummy equal to one when $t = Post$. The regression includes firm-bank fixed effects, α_{ib}, which control for all (time-invariant) unobserved heterogeneity in the demand and supply of credit. It also includes a full set of firm-time dummies, α_{it}, that control for the firm-specific evolution in overall credit demand during the study period. The coefficient β measures how lending by exposed and not-exposed banks changed before and after the capital flow reversals, and it is interpreted as the effect of the capital flow reversals on the supply of credit. The estimated coefficient is presented in Table 10, column 1 (this is an exact replication of the within-firm estimates in PRSW). The point estimate suggests that the supply of credit by exposed banks dropped by 16.8%, relative to not-exposed banks, after the capital flow reversals.

We augment specification 8 with the variable $(C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0)) \times Post_t$. The dummy $(C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0))$ is equal to one if the set of countries supplied by firm i, $C(X_i^c > 0)$, has at least one country that belongs to the set of specialization of bank b, $C(\mathcal{S}_b^c > 0)$—i.e., countries for which $\mathcal{S}_b^c$ defined in (5) is positive in the Pre period. The coefficient on this additional term measures the change in the equilibrium amount of credit to firms that export to the country in which bank b specializes, relative to the change in credit to firms that do not. The estimated coefficients of the augmented specification are shown in Table 10, column 2. The estimated coefficient on the additional term, -0.222, most likely has a demand interpretation: the global demand for Peruvian exports declined during 2008, and firms reduced their demand for credit from banks specializing in their exporting activities. The magnitude of the coefficient indicates that the demand for export-related credit dropped by 22.2% during the sample period. Thus, the variable $(C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0))$ recovers bank-specific credit demand shocks that *are not* accounted for by the firm-time dummies in specification 8.

Adding $(C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0))$ to specification 8 does not have a statistically significant impact on the magnitude of the coefficient on $Exposed_b$. This implies that, in the context of the PRSW application, the foreign funding shock affecting Peruvian banks was virtually uncorrelated with confounding effects related to the banks' export market of expertise. This is a necessary condition for disentangling credit supply from credit demand.

The signs and magnitudes of the estimated supply and demand effects are informative of the potential bias that may result if the two sources of variation simultaneously affect the bank and its market of expertise. Both estimates have the same sign, indicating that, in this setting, confounding demand and supply would lead to an overestimation of the credit supply shock. The magnitude of the potential bias is large. Interpreting the entire within-firm variation in credit as supply-driven would lead to overestimating the size of the supply shock by a factor of 2.4 —i.e, $(0.222 + 0.157)/0.157$.

5.2 Effect of a Bank Funding Shocks on Exports

PRSW use the credit supply shock described in the previous subsection to show that a decline in bank credit supply leads to a decline in exports. To account for variation in the demand for exports, they use country of destination-product-time dummies. We augment their analysis to assess whether a bank credit supply shock has a larger impact on exports to the bank's country of specialization.

The baseline reduced-form regression in PRSW compares exports by firms with different shares of credit received from *exposed* banks:

$$\ln X_{ipct} = \alpha_{ipc} + \alpha_{pct} + \beta \sum_b \omega_{ib} Exposed_b \times Post_t + \epsilon_{ipct}, \tag{9}$$

where X^c_{ipt} is the (volume) of exports of product p by firm i to country c during the intervals $t = \{Pre, Post\}$, Pre and $Post$ periods correspond to the 12 months before and after July 2008, $\omega_{ib} \equiv L_{ib}/\sum_b L_{ib}$ is the share of firm-i's credit from bank-b in the Pre period, and $Exposed_b$ is a dummy equal to 1 if the bank has a share of foreign debt above 10% in 2006. Then, $\sum_b \omega_{bi} Exposed_b$ is the share of credit received from exposed banks. The regression includes firm-product-country fixed effects, α_{ipc}, which control for all (time-invariant) unobserved heterogeneity across firms in exporting that product to that destination. It also includes a full set of country-product-time dummies, α_{pct}, that account for non-credit determinants of exports. In particular, these dummies account for demand shocks originated in narrowly defined export markets. Products are defined according to the four-digit categories of the Harmonized System. For example, product-country-time dummies account for changes in the demand for cotton T-shirts from Germany.

Column 3 in Table 10 shows the results of estimating 9 (in first differences). Exports by firms borrowing exclusively from exposed banks are, on average, 19% lower than those by firms borrowing from not-exposed banks. Because of the country-product-time dummies, α_{pct}, this coefficient has a supply interpretation: firms exposed to a credit supply shock through their lenders reduce their volume of exports.

To consider the heterogeneous effect of the credit supply shock across markets of bank specialization, we split the firm exposure measure $\sum_b \omega_{ib} Exposed_b$ into two components, depending on whether or not the exposed bank b specializes in the country of export destination c. The two resulting exposure measures, $\sum_b \omega_{ib} Exposed_b(\mathcal{S}_b^c > 0)$ and $\sum_b \omega_{ib} Exposed_b(\mathcal{S}_b^c = 0)$, vary at the firm-country level. The estimated coefficients on the two measures are presented in Table 10, column 4. If the exposed bank does not specialize in the destination country of the firm's exports ($\mathcal{S}_b^c = 0$), exports by related firms drop by 16% in response to the credit supply shock. The export decline is 33% larger if the exposed bank specializes in the destination country ($\mathcal{S}_b^c > 0$).

These results imply that banks' expertise in export markets, indeed, makes their debt difficult to replace, even by other lenders that also provide capital to exporters. A decline in the supply of credit by a specialized bank has a larger impact on firm exports to the country in which the lender specializes than to any other country. Combined with the results in the previous section of the paper, this implies that there are economically significant differences in bank advantages across export markets.

6 Conclusions

In this paper, we document novel patterns of specialization in bank lending. Using matched credit-export data for all firms in Peru between 1994 and 2010, we show that the share of funding that each bank allocates to exporters to a destination country is heavily right-skewed. We define a bank as specialized in a country if it is an outlier in the right tail of the exposure distribution of that country. Then, we adopt a revealed preference approach to demonstrate that bank specialization in a country is related to an advantage in providing new funding for export activities to that country. We show, in specifications that saturate all firm-time and bank-time variation, that firms that expand exports to a destination market tend to expand borrowing disproportionately more from banks that specialize in that destination market. We further find that firms that start exporting to a new destination are more likely to start borrowing from a bank specializing in the new market.

Our results suggest that banks acquire expertise in the activities of their related firms. By learning from monitoring and evaluating their clients' economic performance, banks gain an advantage in providing credit to other firms operating in the same market. Banks' expertise can be understood as real factor shaping the pattern of comparative advantages across products and export markets. The fact that banks' lending advantages are persistent over time, transmitted through mergers and acquisitions, and are independent of the bank's global presence are suggestive of advantages derived from expertise. As emphasized in the literature of relationship lending, banks *learn* from monitoring and evaluating the economic performance of their clients. The main novelty of our result is that, in contrast to the assumptions behind the relationship lending literature, the advantage conferred by this knowledge has spillovers outside the boundaries of the firm and affects all firms sharing the same economic activity.

The findings in this paper have important implications for the identification and assessment of credit supply shocks. First, we show that a bank's credit supply shock has a disproportionate effect on the activities in which it specializes. This implies that specialized bank credit cannot be freely substitutable by unspecialized sources of finance, and that the identified lending advantage is economically significant.

And, second, we illustrate the difficulty of disentangling demand from supply of credit in the presence of sectoral or aggregate shocks that affect the activity in which banks specialize. The results in this paper call for caution when applying the empirical strategy—now standard in identifying the lending supply channel—of absorbing the demand for credit with firm-time fixed effects. This methodology relies on firm credit demand to be, in expectation, spread equally across all banks lending to the firm. In other words, this methodology relies on banks being perfectly substitutable sources of funding for firms with whom they already have a credit relationship. Our results suggest that this assumption may not always hold.

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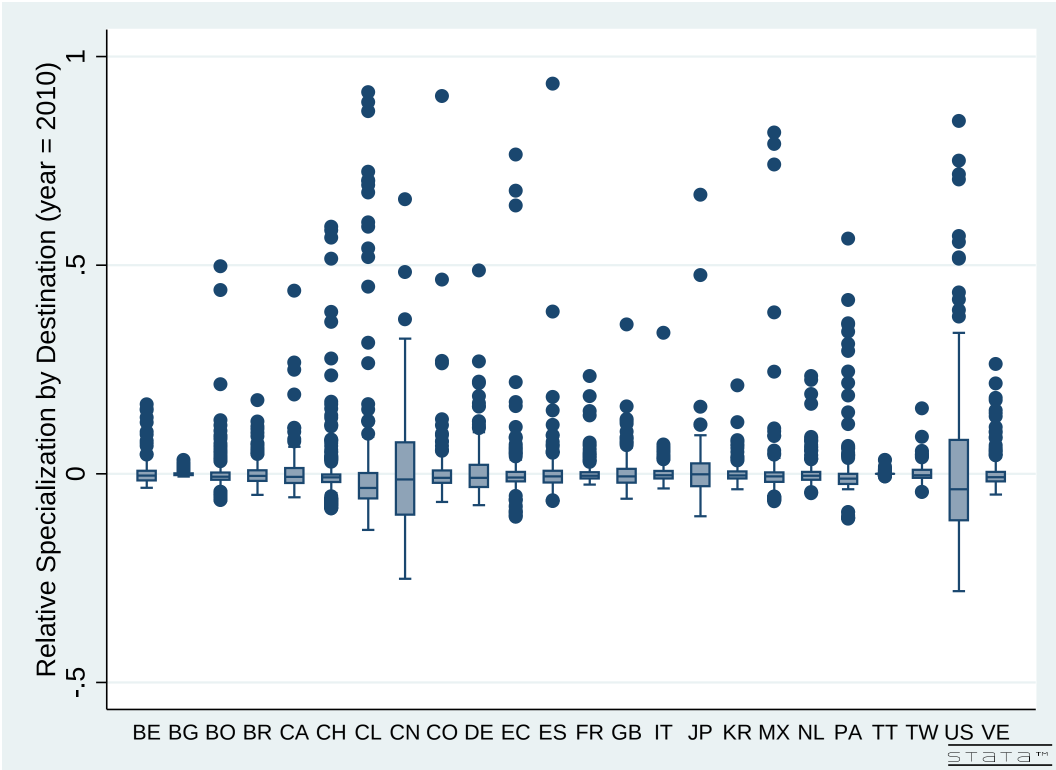
Figure 1: Distribution of Bank Lending Shares by Country



Note: The boxes encompass the interquartile range of the distribution of S^c_{bt} (defined in equation 3) for each country c, in year 2010. The limits of the lines encompass 4 times the interquartile rage.

Table 1: Descriptive Statistics

	Mean (1)	S.D (2)	Min (3)	Median (4)	Max (5)
Panel 1: the unit of observation is firm-bank-country-time					
Outstanding Debt (US$ ’000)	2,044	6,804	0	260	235,081
Exports (US$ ’000)	2,148	19,821	0	87	1,470,300
$\mathcal{S}^c_{bt-1}$	0.16	0.30	-	-	1.00
$\mathcal{S}^c_{-ibt-1}$	0.17	0.33	-	-	1.00
Panel 2: the unit of observation is firm-time					
Total Debt (US$ ’000)	2,633	12,791	0	92	395,149
Number banks per firm	2.43	1.95	1.00	2.00	19.00
Total Exports (US$ ’000)	4,518	55,648	0	77	2,855,313
Number destinations per firm	2.65	2.84	1.00	1.00	22.00

Note: The statistics in Panel 1 describe the full firm-bank-country-time panel used in Section 4, which has 378,766 observations. $\mathcal{S}^c_{bt-1}$, defined in (5), is our measure of specialization of bank b in country c up to the year $t-1$. $\mathcal{S}^c_{-ibt-1}$ is defined as in (5) but removing firm-i from the computation. Panel 2 describes the firm-time panel, which has 45,762 observations. There are 14,267 firms in the dataset.

Table 2: Distribution of Bank Lending Shares by Country

		$S^c_{bt} - \overline{S}^c_t$				
		Min (1)	Median (2)	Max (3)	S.D (4)	Skewness (5)
Belgium	BE	-0.033	-0.004	0.166	0.027	3.172
Bulgaria	BG	-0.007	-0.001	0.033	0.006	2.379
Bolivia	BO	-0.063	-0.007	0.497	0.047	6.743
Brazil	BR	-0.050	-0.005	0.176	0.028	2.024
Canada	CA	-0.056	-0.007	0.439	0.044	4.691
Switzerland	CH	-0.083	-0.008	0.592	0.084	4.652
Chile	CL	-0.134	-0.034	0.914	0.155	3.983
China	CN	-0.251	-0.014	0.658	0.121	1.002
Colombia	CO	-0.068	-0.010	0.905	0.067	9.208
Germany	DE	-0.075	-0.010	0.487	0.056	3.186
Ecuador	EC	-0.103	-0.009	0.765	0.076	7.410
Spain	ES	-0.065	-0.006	0.935	0.064	10.619
France	FR	-0.026	-0.005	0.234	0.026	5.121
Great Britain	GB	-0.060	-0.006	0.358	0.040	3.041
Italy	IT	-0.035	-0.003	0.338	0.026	7.699
Japan	JP	-0.102	-0.001	0.669	0.062	5.451
South Korea	KR	-0.037	-0.004	0.212	0.023	3.787
Mexico	MX	-0.066	-0.006	0.818	0.086	7.701
Netherlands	NL	-0.047	-0.005	0.234	0.032	4.040
Panama	PA	-0.108	-0.012	0.564	0.068	4.725
Trinidad and Tobago	TT	-0.006	0.000	0.033	0.004	5.570
Taiwan	TW	-0.044	-0.003	0.157	0.019	2.338
USA	US	-0.281	-0.037	0.846	0.172	1.648
Venezuela	VE	-0.050	-0.008	0.263	0.036	3.602
Overall		-0.281	-0.005	0.935	0.071	5.480

Note: The statistics describe the distribution of the bank-country-time share S^c_{bt} (defined in equation 3) demeaned by the banking system's average $\overline{S}^c_t$.

Table 3: Patterns of Bank Specialization

	Number of countries in which the bank is an outlier for at least X% of the years in the sample			
	X = 0% (1)	X = 25% (2)	X = 50% (3)	X = 75% (4)
Bank Code				
1	7	4	2	1
2	7	3	2	2
4	6	2	2	1
6	7	3	2	1
7	5	3	2	2
9	4	2	2	1
22	8	2	1	0
25	5	3	2	2
26	4	2	1	1
31	5	3	2	1
36	5	4	1	1
52	11	3	1	0
54	5	2	2	1
55	7	4	2	1
61	13	7	2	1
68	3	2	0	0
72	13	5	3	1
73	15	7	2	1
77	5	3	2	1
78	3	3	1	1
80	3	3	0	0
81	4	3	2	1
82	5	3	2	1
120	9	4	2	0
121	11	4	1	1
122	1	1	1	1
123	12	3	2	1
124	6	3	1	0
125	9	3	2	2
126	6	3	1	1
127	5	3	3	1
130	10	6	3	1
140	4	4	1	1

Note: A bank b is an outlier if S^c_{bt} is above the Upper Extreme Value, defined by the 75$^{\text{th}}$ percentile plus 1.5 interquartile ranges of the distribution of $\{S^c_{bt}\}$ across banks for a given country-year (Definition 1).

Table 4: Exports, Lending, and Specialization. Baseline Results

Dep. Variable	$\ln(L_{ibt})$ Intensive Margin		$(L_{ibt} > 0 \vert L_{ibt-1} = 0)$ Extensive Margin
	(1)	(2)	(3)
$\mathcal{S}^c_{bt-1} \times \ln(X^c_{it})$	0.014**		
	(0.006)		
$\mathcal{S}^c_{-ibt-1} \times \ln(X^c_{it})$		0.009*	
		(0.005)	
$(X^c_{it-1} > 0 \vert X^c_{it-2} = 0)$			0.060*** $\cdot 10^{-2}$
			(0.006 $\cdot 10^{-2}$)
$\mathcal{S}^c_{bt-1} \times (X^c_{it-1} > 0 \vert X^c_{it-2} = 0)$			0.386*** $\cdot 10^{-2}$
			(0.065 $\cdot 10^{-2}$)
$\mathcal{S}^c_{bt-1}$	0.039*		-0.022*** $\cdot 10^{-2}$
	(0.022)		(0.003 $\cdot 10^{-2}$)
$\mathcal{S}^c_{-ibt-1}$		0.020	
		(0.030)	
$\ln(X^c_{it})$	0.026***	0.027***	
	(0.005)	(0.005)	
Bank-Country FE	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes
Observations	366,696	366,696	144,313,112
$R^2 adj$	0.310	0.310	0.280

Note: L_{ibt} is the credit of firm i with bank b in year t. X^c_{it} is annual exports of firm i to country c in year t. And $\mathcal{S}^c_{bt-1}$, defined in (5), is our measure of specialization of bank b in country c up to the year $t-1$. $\mathcal{S}^c_{-ibt-1}$ is defined as in (5) but removing firm-i from the computation. Columns 1 and 2 report the *intensive-margin* results of specification 6, demeaned. Column 3 reports the *extensive-margin* results of specification 7. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 5: Specialization and Bank Size

Dep. Variable	$\mathcal{S}^c_{bt}$		$\ln(L_{ibt})$	
	between	within		
	(1)	(2)	(3)	(4)
$\ln(Size_{bt})$	-0.006	0.004		
	(0.006)	-0.004		
$Foreign_{bt}$	-0.021**	0.017***		
	(0.010)	(0.002)		
$\mathcal{S}^c_{bt-1} \times \ln(X^c_{it}) \times SmallBank_b$			-0.016	
			(0.030)	
$\mathcal{S}^c_{bt-1} \times SmallBank_b$			0.056	
			(0.059)	
$\ln(X^c_{it}) \times SmallBank_b$			-0.026*	
			(0.015)	
$\mathcal{S}^c_{bt-1} \times \ln(X^c_{it}) \times Foreign_{bt}$				-0.010
				(0.017)
$\mathcal{S}^c_{bt-1} \times Foreign_{bt}$				0.064*
				(0.035)
$\ln(X^c_{it}) \times Foreign_{bt}$				-0.042***
				(0.009)
$\mathcal{S}^c_{bt-1} \times \ln(X^c_{it})$			0.014**	0.013*
			(0.006)	(0.006)
$\ln(X^c_{it})$			0.033***	0.035***
			(0.006)	(0.004)
$\mathcal{S}^c_{bt-1}$			0.026	0.017
			(0.025)	(0.025)
Bank FE	No	Yes		
Country FE	Yes	Yes		
Year FE	Yes	Yes		
Bank-year FE			Yes	Yes
Firm-year FE			Yes	Yes
Country-Bank FE			Yes	Yes
Observations	7,560	7,560	366,696	366,696
R-squared	0.49	0.51	0.31	0.31

Note: L_{ibt} is the credit of firm i with bank b in year t. X^c_{it} is annual exports of firm i to country c in year t. And $\mathcal{S}^c_{bt}$, defined in (5), is our measure of specialization of bank b in country c up to the year t. In columns 1 and 2, the dependent variable is $\mathcal{S}^c_b$. $Size_{bt}$ is total lending of bank b at time t and $Foreign_{bt}$ is a dummy equal to 1 if the bank if foreign-owned. In column 3, results of specification 6 (demeaned) are augmented with an interaction $SmallBank_b$, a dummy equal to 1 for banks outside the top 10, measured in average total (real) lending over the entire sample. In column 4, the interacting term is the time-varying dummy $Foreign_{bt}$. Standard errors are two-way clustered at the bank and firm levels. ***p< 0.01, **p < 0.05, and *p < 0.1.

Table 6: Persistence of Specialization after a Merger

Dep. Variable	$\ln(L_{ibt})$			
	(1)	(2)	(3)	(4)
$\mathcal{S}^c_{bPreMerger} \times \ln(X^c_{it})$	0.014***	0.017**	0.012**	0.016**
	(0.004)	(0.007)	(0.004)	(0.008)
$\mathcal{S}^c_{bPreMerger} \times \ln(X^c_{it}) \times Target_b$		-0.007		-0.008
		(0.011)		(0.012)
$\mathcal{S}^c_{bPreMerger} \times \ln(X^c_{it}) \times Merger_{bt}$			0.023*	0.015
			(0.013)	(0.013)
$\mathcal{S}^c_{bPreMerger} \times \ln(X^c_{it}) \times Merger_{bt} \times Target_b$				0.037**
				(0.017)
$\ln(X^c_{it}) \times Merger_{bt} \times Target_b$				0.086***
				(0.024)
$\mathcal{S}^c_{bPreMerger} \times Merger_{bt}$			0.045***	0.038**
			(0.015)	(0.017)
$Merger_{bt}$			-0.045*	-0.045*
			(0.023)	(0.023)
$\ln(X^c_{it}) \times Merger_{bt}$			-0.024***	-0.024***
			(0.009)	(0.009)
$\ln(X^c_{it})$	0.011***	0.011***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Bank-Merger-year FE	Yes	Yes	Yes	Yes
Firm-Merger-year FE	Yes	Yes	Yes	Yes
Country-bank-Merger FE	Yes	Yes	Yes	Yes
Observations	586,097	586,097	586,097	586,097
R-squared	0.288	0.288	0.288	0.288

Note: L_{ibt} is the credit of firm i with bank b in year t. X^c_{it} is annual exports of firm i to country c in year t. And the index of specialization $\mathcal{S}^c_{bPreM}$, defined in (5), is computed the year before the merger for both banks participating in the Merger. Results of specification 6 (demeaned) with data rearranged around event time (Merger). Column 1 replicates specification 6. Column 3 adds the interaction term $Merger_{bt}$, a post-merger dummy. Similarly, column 2 replicates specification 6 with the interaction term $Target_b$, a dummy that signals the target bank (as opposed to the acquirer), and column 4 adds the interaction term $Merger_{bt}$. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 7: Specialization and Global Banks

Dep. Variable	$\mathcal{S}_b^c$	$\ln(L_{ibt})$	
	(1)	(2)	(3)
$CountryOwnership_{bc}$	0.095***		
	(0.018)		
$DistanceToHeadquarters_{bc}$	0.005*		
	(0.003)		
$CommonLanguage_{bc}$	0.027***		
	(0.010)		
$CountrySubsidiary_{bc}$	-0.002		
	(0.008)		
$\mathcal{S}_{bt-1}^c \times \ln(X_{it}^c)$		0.014**	0.017*
		(0.006)	(0.009)
$CountryOwnership_b^c \times \ln(X_{it}^c)$		-0.020	-0.030
		(0.023)	(0.023)
$ln(DistancetoHeadquarters_b^c) \times \ln(X_{it}^c)$			-0.002
			(0.006)
$CommonLanguage_b^c \times \ln(X_{it}^c)$			0.010
			(0.007)
$CountrySubsidiary_b^c \times \ln(X_{it}^c)$			0.015
			(0.010)
$\ln(X_{it}^c)$		0.027***	0.038
		(0.005)	(0.052)
$\mathcal{S}_{bt-1}^c$		0.039*	0.036
		(0.022)	(0.023)
Bank FE	Yes		
Country FE	Yes		
Year FE	Yes		
Firm-year FE		Yes	Yes
Bank-year FE		Yes	Yes
Country-Bank FE		Yes	Yes
Observations	7,560	366,696	366,696
$R^2 adj$	0.51	0.31	0.31

Note: In column 1, the dependent variable is $\mathcal{S}_b^c$, defined in (5), over the entire sample period. Columns 2 and 3 show the results of an augmented version of specification 6 (demeaned). $CountryOwnership_b^c$ is a dummy equal to 1 if the destination country of the export flow coincides with the country of ownership of the bank. Similarly $CountrySubsidiary_b^c$ is equal to 1 if the bank has a subsidiary in the destination country of the export flow. The variables distance (in (log) km) and common language (dummy variable) refer to the connection between the bank's country of ownership and the export destination. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 8: Specialization and Bank Local Presence

Dep. Variable	$\ln(L_{ibt})$	
	(1)	(2)
$\mathcal{S}^c_{bt-1} \times \ln(X^c_{it})$	0.016*	0.015*
	(0.008)	(0.008)
$\ln(X^c_{it})$	0.023***	0.011
	(0.006)	(0.013)
$\mathcal{S}^c_{bt-1}$	0.183	0.181
	(0.153)	(0.153)
$BranchDistrict_{ib} \times \ln(X^c_{it})$		0.013
		(0.015)
$N\ BranchDistrict_{ib} \times \ln(X^c_{it})$		0.001
		(0.001)
$BranchDistrict_{ib}$		0.000
		(0.054)
$N\ BranchDistrict_{ib}$		-0.008
		(0.006)
Firm-year FE	Yes	Yes
Bank-year FE	Yes	Yes
Country-Bank FE	Yes	Yes
Observations	228,911	228,911
$R^2 adj$	0.33	0.33

Note: Columns 1 and 2 show the results of specification 6 (demeaned) for the period 2001-2010, for which the bank branch locations in Peru are available. $BranchDistrict_{ib}$ is a dummy equal to 1 if the firm is located in a district where the bank has a branch. $N\ BranchDistrict_{ib}$ is the number of branches of the bank in the district where the firm is located. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 9: Specialization in Export Products and Destinations

Dep. Variable	$\ln(L_{ibt})$	
	(1)	(2)
$\mathcal{S}^p_{bt-1} \times \ln(X^p_{it})$	0.031*	
	(0.017)	
$\mathcal{S}^c_{bt-1} \times \ln(X^{pc}_{it})$		0.012**
		(0.005)
$\mathcal{S}^p_{bt-1} \times \ln(X^{pc}_{it})$		0.013
		(0.012)
$\ln(X^p_{it})$	0.030***	
	(0.004)	
$\ln(X^{pc}_{it})$		0.018***
		(0.005)
$\mathcal{S}^p_{bt-1}$	0.201*	0.608***
	(0.104)	(0.163)
$\mathcal{S}^c_{bt-1}$		-0.004
		(0.019)
Observations	177,236	437,791
R-squared	0.34	0.29

Note: Column 1 shows the results of specification 6 (demeaned) based on firm exports by product, X^p_{it}. Correspondingly, bank specialization $\mathcal{S}^p_{bt-1}$, defined in (5), is computed based on the share of lending to firms exporting a given product:

$$S^p_{bt} \equiv \frac{\sum_{i=1}^{I} L_{bit} X^p_{it}}{\sum_{p=1}^{P} \sum_{i=1}^{I} L_{bit} X^p_{it}}.$$

There are 33 product categories. They correspond to 2-digit categories of the Harmonized System with at least 0.25% of total Peruvian exports in the pool sample. In column 2, firm exports are disaggregated at the product-destination level, X^{pc}_{it}. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 10: Credit Supply Shocks

	ΔL_{ib}		$\Delta \ln X_{icp}$	
	(1)	(2)	(3)	(4)
$Exposed_b$	-0.168***	-0.157***		
	(0.046)	(0.049)		
$C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0)$		-0.222***		
		(0.083)		
$\sum_b \omega_{ib}\ Exposed_b$			-0.193***	
			(0.063)	
$\sum_b \omega_{ib}\ Exposed_b\ (\mathcal{S}_b^c > 0)$				-0.165***
				(0.061)
$\sum_b \omega_{ib}\ Exposed_b\ (\mathcal{S}_b^c = 0)$				-0.220**
				(0.086)
Firm FE	Yes	Yes	No	No
Country-Product FE	–	–	Yes	Yes
Obs	10,334	10,334	14,208	14,208
R^2 adj	0.63	0.63	0.44	0.44

Note: Columns 1 and 2 show results of the within-firm specification in 8. $\Delta L_{ib} \equiv \ln L_{ibPost} - \ln L_{ibPre}$ is the change in bank-firm credit; $Exposed_b$ is a dummy equal to 1 for exposed banks–i.e., bank-b's share of foreign debt in 2006 is above the system's mean; and $C(X_i^c > 0) \bigcap C(\mathcal{S}_b^c > 0)$ is a dummy equal to one if, in the Pre period, the set of countries supplied by the firm has at least one country that belongs to the set of specialization of the bank (i.e., set of countries with positive $\mathcal{S}_b^c$)). Standard errors clustered at the bank level. Columns 3 and 4 show results of specification in 9. $\sum_b \omega_{ib} Exposed_b$, with $\omega_{bi} \equiv L_{ib}/\sum_b L_{ib}$, is firm-$i$'s share of credit with exposed banks. In column 4, $\sum_b \omega_{ib} Exposed_b(\mathcal{S}_b^c = 0)$ is the share of firm-i's share of credit with exposed banks non-specialized in country c, and $\sum_b \omega_{ib} Exposed_b(\mathcal{S}_b^c > 0)$ is the share of credit with exposed banks, with positive specialization in country c. Standard errors clustered at the product-destination level. ***p< 0.01, **p < 0.05, and *p < 0.1.

Appendix: Proof of Result 1

Proof. Notice that $\sum_{k=1}^{J} S_b^k = 1$. Since $\gamma_b^k = \gamma_{b'}^k$ for all $k \neq j, j'$, it follows that $S_b^j + S_b^{j'} = S_{b'}^j + S_{b'}^{j'}$. Then,

$$\frac{\sum_{i=1}^{I} L_{ib}\left(X_i^j + X_i^{j'}\right)}{\sum_{i=1}^{I} L_{ib'}\left(X_i^j + X_i^{j'}\right)} = \frac{\sum_{k=1}^{J}\sum_{i=1}^{I} L_{ib} X_i^k}{\sum_{k=1}^{J}\sum_{i=1}^{I} L_{ib'} X_i^k}.$$

It follows that:

$$\frac{S_b^j}{S_{b'}^j} = \frac{\sum_{i=1}^{I} L_{ib} X_i^j}{\sum_{i=1}^{I} L_{ib'} X_i^j} \cdot \frac{\sum_{i=1}^{I} L_{ib'}\left(X_i^j + X_i^{j'}\right)}{\sum_{i=1}^{I} L_{ib}\left(X_i^j + X_i^{j'}\right)},$$

which is bigger than one as long as $\sum_{i=1}^{I} L_{ib} X_i^j \cdot \sum_{i=1}^{I} L_{ib'} X_i^{j'} > \sum_{i=1}^{I} L_{ib'} X_i^j \cdot \sum_{i=1}^{I} L_{ib} X_i^{j'}$. This condition is always satisfied for $\gamma_b^j = \gamma_{b'}^{j'} > \gamma_b^{j'} = \gamma_{b'}^j$. $\square$