Specialization in Bank Lending: Evidence from Exporting Firms

DANIEL PARAVISINI, VERONICA RAPPOPORT, and PHILIPP SCHNABL*

ABSTRACT

We develop an empirical approach for identifying specialization in bank lending with granular data on borrower activities. We use it to analyze export market specialization with loan and export data for all exporters in Peru. We measure a bank's market of specialization using its *relative concentration* of lending towards exporters to a given country. A bank's country of specialization strongly predicts the correlation between an exporter's credit from the bank and its volume of exports to the country. Also, new borrowers from a specialized bank are more likely to begin exporting to the country of specialization (and vice-versa). Finally, exports demand and credit supply shocks disproportionately affect borrowing from the specialized bank and exports to the specialization country, respectively. The results imply that bank specialization substantially curtails competition and augments the real economy effect of bank credit supply disruptions.

*Daniel Paravisini and Veronica Rappoport are at LSE and Philipp Schnabl is at NYU Stern. All authors are also with CEPR; additionally, Daniel Paravisini is with BREAD, Veronica Rappoport is with CEP, and Philipp Schnabl is with NBER. We thank Andrew Teodorescu and Luana Zaccaria for outstanding research assistance. We thank Luis Garicano, Asim Khwaja, Nicola Gennaioli, Rebecca Zarutskie, Johan Hombert, Gregor Matvos, and participants at Bank de France, Cambridge University, CEMFI, ERWIT, Financial Intermediation Research Society Conference, LBS Finance Symposium, LSE, NBER CF, NY Fed, Paris Trade Group, ICD Annual Conference in Financial Economics, SED, Stanford University, Stanford GSB, University of British Columbia Sauder School of Business, UC Berkeley, UC Berkeley Haas School of Business, UC San Diego, and University of Zurich seminars, workshops, and conferences for useful comments. All errors are our own. We have read the *Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Philipp Schnabl, New York University Stern School of Business; e-mail: pschnabl@stern.nyu.edu.

A LONGSTANDING VIEW IN FINANCIAL ECONOMICS is that competition in bank credit markets is curtailed by the informational monopoly obtained from interacting repeatedly with opaque borrowers.[1] Relationship lending confers an information advantage relative to other lenders that is firm-specific and developed over time. Absent this firm-specific advantage, it is often presumed that bank credit markets are competitive.

In this paper we challenge this view and posit that competition in bank credit markets can be substantially curtailed through an alternative mechanism: bank specialization. If banks develop skills, expertise, or technology in evaluating projects in a specific sector, geographical market, or economic activity, it may confer them with a *market-specific* advantage relative to other lenders. This market-specific advantage makes credit from one bank difficult to substitute with credit from another. Thus, in theory, bank specialization can segment credit markets, increase lender market power, and amplify the real economy effect of bank credit shortages. In this paper we develop an empirical framework to evaluate this conjecture.

We first develop an intuitive *relative debt concentration* measure of bank specialization, in the spirit of revealed comparative advantage indexes from international trade (Balassa (1965)), and use it to evaluate whether bank lending portfolios in the data are consistent with a credit market characterized by bank specialization. Then we examine how firms' choice of lender is related to this measure of specialization. Specifically, we test whether firm output in a market comoves disproportionately

[1]For the importance of relationship lending in financial intermediation see Bernanke (1983), James (1987), Hoshi, Kashyap, and Scharfstein (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).

with funding from the bank specialized in that market, both along the intensive and extensive margins. Finally, we assess the economic importance of specialization, evaluating how it shapes the choice of lender when firms face demand shocks and how it affects the impact of credit supply shocks on the real economy. Throughout, we distinguish which observed patterns can be attributed to market-specific specialization, as opposed to being driven by firm-specific information gathered through relationship lending.

The measure and methods we develop can be applied to analyze specialization along any sector or market dimension, but require very granular data on firm activities in each market or sector. We illustrate our approach in the context of the financing of exporting activities, for which such data are widely available. We combine bank, loan, and detailed customs data on the universe of exporters in Peru to examine bank specialization by geographic destination markets.

To motivate the relative concentration measure of specialization, consider the case of one bank in our data: Citibank. Citibank allocates about one third of its exporter loan portfolio to firms that export to Switzerland. This is a large share, considering that the average bank's portfolio share to Switzerland and the average weight of Swiss exports to total Peruvian exports are both close to 9%. Citibank's portfolio share in Switzerland is persistently in the top quartile of the Switzerland-share distribution for all banks over a 17-year sample period, which we interpret as a measure of Citibank's revealed comparative advantage in funding exports to Switzerland.[2]

In line with the example, we measure bank specialization in a country based on its export-value weighted portfolio share of lending to exporters to the country, relative to the portfolio shares of other banks to the same country. We show that this mea-

[2]The concept of revealed comparative advantage is borrowed from the literature in international economics, and it is used to measure the relative advantage or disadvantage of a country in a certain industry using the relative concentration of trade flows (see Balassa (1965)).

sure emerges naturally from a model in which firms operate across different markets (e.g., exports to multiple geographical markets), and each firm demands credit from banks that are differentiated in providing intermediation services across markets (e.g., banks have an advantage in financing exports to specific countries). Relative portfolio shares provide an intuitive measure of specialization, which is feasible with available granular data and has multiple desirable features that we discuss in detail below. For example, by comparing bank portfolio shares to the same destination, the measure is not biased by bank or export market size.

The Citibank example is not an exception. Every bank operating in Peru is persistently in the top quartile of the share distribution of some country during the sample period, regardless of bank size, ownership, or location. This stylized fact indicates that the export financing market is highly segmented, with certain banks specialized in certain destination markets. The revealed pattern of specialization is consistent with a market in which banks have market-specific expertise and knowledge. The core of the paper provides micro-econometric evidence that specialization confers a lending advantage to banks relative to other lenders that makes specialized bank debt difficult to substitute. For conciseness, we summarize the results below with comparisons between banks that are specialized in a country (top quartile of the country-share distribution) and those that are not (bottom quartile). Full comparisons across all quartiles are discussed in latter sections.

First we examine evidence regarding firms' choice of lender. If bank specialization relates with export market expertise or knowledge, then firms will disproportionately fund exports to a country with credit from a bank specialized in that country. We test this prediction using a specification that accounts for firm-specific and bank-specific shocks (firm-time and bank-time fixed-effects). We find that when firms expand exports to a country, they shift credit from non-specialized banks (with elasticity -0.013) towards specialized banks (with elasticity $+0.013$), suggesting that firms value market-specific bank specialization.

This pattern is also present in the extensive margin, which indicates that it is not driven by firm-specific lending relationships. When a firm starts exporting to a new country, the probability of starting a new relationship with a bank specialized in that country increases by 1.9 percentage points relative to the probability of starting a new relationship with a non-specialized bank. This magnitude is large relative to the unconditional probability of starting a new banking relationship, which is 0.74% per year. We also find the converse relationship to be true. During the year after a firm starts a new relationship with a specialized bank, the firm is 1.2 percentage points more likely to begin exporting to the bank's country of specialization, relative to a country in which the bank is not specialized. This magnitude is also economically significant, as the probability of exporting to a new destination is 0.69% per year unconditionally.

These findings are significant because they represent the first direct evidence that banks possess market-specific advantages in lending. These are distinct from the firm-specific advantage that emerges because of private information collected as part of an ongoing lending interaction.[3] The potential market power conferred by bank specialization has a broader reach, as it applies to all firms operating (or that intend to operate) in a market. We use bank mergers to document further that the observed patterns are unlikely to be driven by relationship lending. The advantage conferred by relationship lending diminishes with bank size.[4] In contrast, there is no reason to expect the advantage from market-specific bank specialization to be lost as banks ex-

[3]On the role of banks in collecting firm-specific information 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).

[4]The trade-off between relationship lending advantages and bank size is theorized in Stein (2002) and documented in Berger et al. (2005).

pand. We show that the advantage conferred by bank specialization before a merger carries over to the combined entity after the merger. These results indicate that market-specific bank specialization is scalable and not hindered by organizational constraints.

The results so far speak to the existence of lending advantages due to bank specialization, but they do not attest to their importance for the real economy. To assess this importance we analyze how market-specific bank specialization affects the impact of credit demand and supply shocks. To evaluate the impact of demand we use macroeconomic innovations in export markets (changes in GDP and exchange rate) as country-specific export demand shocks in an instrumental variable specification saturated with firm-time and bank-time fixed effects. We find that the credit demand elasticity to a change in the demand for exports from a given country is 50% larger for the bank specialized in the country than from a non-specialized bank. This implies that when a firm expands exports to a country, it substantially tilts its demand for credit towards the bank that is specialized in that country.

To evaluate the impact of credit supply we use the reduction in bank credit induced by international capital flow reversals during the 2008 financial crisis. Following Paravisini et al. (2015), we control for demand shocks by comparing changes in exports in narrowly defined product-destination export markets (e.g., cotton T-shirt exports to Germany) across firms heterogeneously exposed to the shock. We find that a 10% reduction in a bank's credit supply leads to a 4.5% decline in exports towards countries in which the bank specializes, while it does not affect exports towards other destinations. This is a very stark result, as it indicates that specialized bank credit is difficult to substitute, while non-specialized credit is not.

These results have significant implications for the interpretation of a broad academic literature that studies the transmission and amplification of shocks through the banking sector. The now-standard approach for the empirical identification of bank credit supply shocks, pioneered in Khwaja and Mian (2008), controls for changes in firm-specific credit demand using firm-time fixed effects. As discussed in Khwaja and Mian (2008), the fixed-effects approach does not solve the identification problem in general when firms' loan demand is bank-specific.[5]

Our setting represents a concrete example of where firms' loan demand is bank-specific. Our results imply that if an exporter faces a decline in the demand for its products in a certain country, the firm will reduce its demand for credit by 50% more from the bank specialized in that country than from non-specialized banks. The standard firm fixed-effects approach would incorrectly attribute this tilt in borrowing to a credit supply change by the specialized bank. We show that the magnitude of the bias can be evaluated by augmenting the standard firm-time fixed effects specification with measures of bank export specialization. Using the same capital flow reversals episode in 2008 described above, we find that demand shocks explain more than half of the same-firm tilts in credit across banks than bank funding shocks. The results imply that ignoring market-specific bank specialization can lead to severe biases in credit supply estimation with the commonly used firm-time fixed effects approach.

Our paper relates to two main strands in the literature. The first strand is the work on the industrial organization of bank credit markets and its consequences for the real economy. Market-specific bank specialization provides a rationale for why firms have multiple banking relationships and why banks form syndicates: multiple bank relationships and syndicates arise naturally when banks are differentially equipped

[5]Khwaja and Mian (2008) explain that firm-time fixed effects can fail to identify credit supply in their setting when: "(a) nuclear shocks disproportionately affect export/import demand, (b) firms get "export/import related" loans from banks that specialize in the tradeable sector, or (c) these export/import intensive banks had more dollar deposits and thus suffered a larger liquidity crunch as well." Khwaja and Mian (2008) show that their results are robust to accounting for these concerns.

to fund different projects by the same firm.[6] Our results also highlight the limits of bank diversification. Traditional banking theory argues that full diversification across sectors and projects is optimal (e.g., Diamond (1984) and Boyd and Prescott (1986)). However, diversification may prove costly when it implies expanding to markets in which the bank does not have expertise.[7] It also implies that market-specific bank specialization directly affects the economy's pattern of comparative advantage across non-financial sectors.[8]

The second strand is the work on the impact of credit supply shocks on the real economy. This work focuses on the role of shocks in the presence of firm-specific information gathered through relationship lending (e.g., Bernanke (1983); Khwaja and Mian (2008); Paravisini (2008); Gormley (2010); Amiti and Weinstein (2011); Chava and Purnanandam (2011); Schnabl (2012); Bolton et al. (2013); Jimenez et al. (2014); Chodorow-Reich (2014); and Drechsler, Savov, and Schnabl (2017)). Our findings highlight the complementary role of market-specific bank specialization in the

[6]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, Garella, and Guiso (2000)), while existing explanations for loan syndicates include risk diversification and regulatory arbitrage (Pennacchi (1988)).

[7]Winton (1999) argues theoretically that there is a trade-off between diversification and the quality of loan monitoring. Acharya, Hasan, and Saunders (2006) find that more diversification leads to riskier lending among Italian banks. Berger, Minnis, and Sutherland (2017) find that banks are more likely to rely on soft information in areas and industries to which they have high exposure. Granja, Matvos, and Seru (2017) examine auctions of failed banks and show that banks specialize in certain business lines and geographic areas. Antras and Foley (2015), Niepmann and Schmidt-Eisenlohr (2017), and Ahn and Sarmiento (2019) emphasize the importance of specialized financing in international trade.

[8]This mechanism is distinct from, and complementary to, the well documented pattern of comparative advantage across countries with different levels of development of the banking sector (e.g., Rajan and Zingales (1998) and Manova (2013)).

transmission of credit supply shocks. Market-specific bank specialization limits competition across banks, which amplifies the impact of bank failures on the real economy.

The rest of the paper proceeds as follows. Section I describes the data. In Section II we present our measure of bank specialization. Section III discusses the empirical methodology to identify a bank's lending advantage and presents results. Section IV evaluates the economic importance of bank specialization in the presence of demand and supply shocks. Section V examines potential sources of bank lending advantage. Section VI concludes.

I. Data

We use two datasets to construct our measure of bank specialization by export market: monthly loan-level data for each bank in Peru and customs data for Peruvian exports over the period 1994 to 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.

Peru is a highly bank-dependent country, with most firms relying on banks as the primary and only source of external capital. The Peruvian bank regulator (Superintendencia de Banca, Seguros and APF, or SBS) provides loan-level data covering the universe of firms. These data consist 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 by bank, 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 I shows summary statistics describing the data. The unit of observation in our empirical analysis in Section III 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 U.S. dollars. 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). As usual for this type of data, exports and debt are right-skewed. The median debt and exports are US$ 259,764 and US$ 87,218, respectively.

[**Table I about here**]

We emphasize that all loan-level data are reported at the bank-firm level, not the bank-firm-country level. This is a common limitation when using credit registry data because loans are recorded as being provided to firms, not firm-country pairs. Yet, even if information on credit by firm and country were available, it is not obvious that it should be used. The reason is that credit is fungible and can be used for other purposes than the stated loan objective. For those reasons, our paper proposes a measure of bank specialization that does not require information to directly link credit to countries within firms.

Panel 2 in Table I describes the 14,267 exporting firms in our data. The average number of banking relationships per firm is 2.42 and the average number of export countries is 2.65. We restrict the sample to include the export destination to the 22 main export markets, which represent 97% of Peruvian exports across the period of analysis.[9] The share of Peruvian exports across the main ten destinations, during the entire sample, is shown in Figure 1.[10]

[Figure 1 about here]

II. Specialization: Framework, Measurement, and Descriptive Statistics

In this section we present our new measure of bank specialization. The measure is based on the notion of revealed comparative advantage, borrowed from a long-standing tradition in international trade. The measure is intuitive and has several desirable properties, such as being impervious to the scale of the bank or the size of the specialization market. In the first subsection we present the measure and its properties, as well as examples. The following subsection, which may be skipped by the applied reader, provides a theoretical motivation for the specialization measure, based on the assumption that banks are heterogeneous in their lending capabilities towards certain activities, markets, products, or services of their borrowers. This heterogeneity implies that banks are not perfectly substitutable sources of funding. The final subsection presents the data and provides descriptive statistics of bank specialization in Peru.

[9] 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.

[10] We do not observe data on loan covenants. It is our understanding that loan covenants have limited economic significance in our setting because they are difficult and costly to enforce in the Peruvian judicial system.

II.A. *Specialization Measure*

Bank lending advantages towards certain export destination markets are unobservable. Our goal is to infer bank advantages by destination market from the pattern of loan portfolio specialization. Measuring specialization poses three challenges. First, the measure has to capture bank b's comparative advantage specific to activity c, and not bank-wide factors giving the bank an advantage on all sectors—for example, a bank-wide technological advantage in lending to all destinations, a lower cost of capital, etc. Second, the measure must not be mechanically driven by the size of the market or activity in which the bank specializes. And third, the measure of specialization must be constructed from observable data, which do not differentiate what fraction of a firm's borrowing from b is used to fund activity c.

Regarding the first challenge, a bank will be larger in overall lending if it charges lower interest rates or if it is more efficient irrespective of the activity. To cancel out these bank-wide factors affecting all activities, our starting point is to compare the lending of bank b towards activity c to all firms $i = 1, \ldots, I$ (i.e., $\sum_i L_{ib}^c$), relative to the lending of bank b towards all activities ($\sum_i L_{ib}$). That is, we start by using the portfolio share of lending of bank b towards activity c:

$$\widetilde{S}_b^c = \frac{L_b^c}{L_b} = \frac{\sum_{i=1}^{I} L_{ib}^c}{\sum_{k=1}^{C} \sum_{i=1}^{I} L_{ib}^k}.$$

Regarding the second challenge, notice that the proportion of lending towards activity c increases with the importance of this activity in the economy. To cancel out the size of the activity in the economy, we compare bank b's share with the country-c share of lending by other banks. As long as one compares lending shares to the same country, the measure is impervious to the size of the export destination market. Then, this within-country ideal index is reminiscent of the Balassa (1965) index of *Revealed Comparative Advantage* (*RCA*):

$$RCA_b^c = \frac{\widetilde{S}_b^c}{\widetilde{S}^c}, \tag{1}$$

where $\widetilde{S}^c = \frac{\sum_b \sum_i L_{ib}^c}{\sum_b \sum_{k=1}^{C} \sum_i L_{ib}^k}$ is the share of total credit towards activity c.

Regarding the third challenge, one cannot construct the ideal index RCA_b^c from available data. The reason is that activity-c specific credit (L_{ib}^c) is unobservable. The typical credit registry data will contain information on the credit from bank b to firm i (L_{ib}) but will not distinguish what fraction of that credit is used to fund exports by firm i to country c (X_i^c).[11] Therefore, as a second step, we proxy RCA_b^c with an empirically observable counterpart.

We use the observable variables L_{ib} (debt of firm i with bank b) and X_i^c (exports of firm i to country c) and define the following index:

$$S_b^c \equiv \frac{\sum_{i=1}^{I} L_{ib} X_i^c}{\sum_{k=1}^{C} \sum_{i=1}^{I} L_{ib} X_i^k} \tag{2}$$

which represents bank-b borrowers' exports to country c, weighted by their debt in bank b, as a share of bank-b borrowers' total debt-weighted exports. In the next subsection we show that the distribution of S_b^c across banks can be used to construct a measure of a bank's country-specific lending advantage.

Because the weighted portfolio share measure is based on the value of exports associated to a bank, it has another important desirable feature: bank specialization may be driven by both the number of firms and firm size. According to our definition, a bank is highly specialized in a country because it lends to a large number of exporters relative to other banks, or because it provides a large fraction of its credit

[11] There are some financial instruments associated with specific export markets, for example letters of credit. We discuss in Section V the limitations of using such instruments for identifying the pattern of lending advantage across countries.

to a few large exporters relative to other banks. Both situations are captured by the proposed specialization measure.

To illustrate the properties of our specialization measure, consider the average portfolio shares S_b^c depicted in Figure 2. The figure plots each bank's average portfolio share for the 2008 to 2010 period for the U.S. and Switzerland, two destination countries in our data. Each bank's share of exports to a country is impervious to the size of the bank because it is measured relative to its own portfolio. As an illustration, consider the nine banks in Figure 2 that have a negligible portfolio share to Switzerland. Among these banks is Interbank, one of the largest banks in Peru, with an exporter loan portfolio that is 179 times the loan portfolio of the smallest banks in this group (Financiera Cordillera).

[**Figure 2 about here**]

The measure is also impervious to the size of the export destination market because it captures the degree of specialization of bank b relative to other banks for the same country c. In the plot, Citibank has a very large portfolio share in Switzerland—more than twice as much as the portfolio share in Switzerland of any other bank. We interpret this as a revealed comparative advantage of Citibank in funding exports to Switzerland. The same bank, in contrast, has a very low portfolio share in the U.S. relative to other banks (the second lowest portfolio share after Banco Trabajo), which reveals that Citibank does not have a comparative advantage in lending to U.S. exporters. Instead, Financiera Cordillera, a small local financial intermediary, has the highest portfolio share in the U.S. amongst all banks, indicating a large degree of specialization and lending advantage.

This illustration highlights that the cardinal value of S_b^c does not, *per se*, capture specialization. Citibank's portfolio share in Switzerland does not tell us whether Citibank has a revealed comparative advantage unless we know the position of its portfolio share relative to the distribution of S_b^c for all banks in the same country.

Thus, in all the analysis that follows we use indicators for the quartile of the country-c distribution a bank belongs to as a single and simple measure of its relative specialization.

Specifically, we define the each variable in the set of dummies $D(S_b^c \in Q_q)$ as a dummy equal to 1 if the bank's portfolio share is in quartile $q = 1, \ldots, 4$ of the distribution of $\{S_{b'}^c\}_{b'}$ associated with country c. Using the above illustration, Citibank is in the top quartile of the portfolio share distribution for Switzerland, so $D(S_{Citi}^{Switzerland} \in Q_4) = 1$, and $D(S_{Citi}^{Switzerland} \in Q_q) = 0$ for $q \in \{1, 2, 3\}$. Aside from capturing the relative nature of our specialization measure, the quartile dummies also allow studying non-linearities in the relationship between our measure of specialization and different outcomes.

II.B. Theoretical Framework of Specialized Bank Lending

To motivate our definition of bank specialization, we present a model in which: (i) funding from one bank is not perfectly substitutable with funding from another, and (ii) banks are heterogeneous in their lending capabilities for specific economic activities. Since the source of advantages is unobserved by the econometrician, we model specialization in reduced form. We use the model to derive observable implications of the existence of market-specific bank lending advantage (whatever their source) on bank lending portfolios and the equilibrium relationship between credit from specialized banks and the economic activity in the sector in which they specialize.

B.1. Setup

We characterize the firms' demand of credit across banks with a nested logit model with deterministic second stage. Each bank b is characterized by an interest rate r_b and a vector of absolute lending advantage for each economic activity $c = 1, \ldots, C$

(e.g., export destination country), $\gamma_b = [\gamma_b^1, \ldots, \gamma_b^C]$, with $\gamma_b^c > 0$ for all c, b. We assume this vector γ_b to be independently distributed across banks. The interpretation of the lending advantage parameter, γ_b^c, is broad. For example, it could represent a bank service attached to credit issuances.

Each firm i is defined as a collection of activities. Firms use credit to fund each of those activities. The firm proceeds in two steps. First, it chooses the bank b that minimizes the cost of credit for the corresponding activity, c. And then, the optimal amount of credit demanded for the activity, L_{ib}^c, is the one consistent with the profit-maximizing output level q_i^c. For simplicity, we take the output q_i^c as given and focus on choice of credit in the first stage. Our results hold for any level of output q_i^c including the profit-maximizing one. We show in the internet appendix that the optimal level of q_i^c can be derived as the profit-maximizing solution in a setup with monopolistic competitive firms.

To focus on the choice of credit, we assume that credit is the single factor of production used to produce the commodity exported to country c. Specifically, we assume a linear production function: $q_i^c = \gamma_b^c L_{ib}^c \ \exp\{\mu \epsilon_{ib}^c\}$, where ϵ_{ib}^c is an idiosyncratic factor unobserved to the econometrician.

The firm chooses the bank that minimizes the cost of production for each activity c. Given the production function and any output level q_i^c, the cost of production is given by $r_b L_{ib}^c = [\frac{r_b}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}] q_i^c$. The optimal bank b for firm i and activity c is such that:

$$b = \arg\min_{b'} \quad \frac{r_{b'}}{\gamma_{b'}^c} \exp\{-\mu \epsilon_{ib'}^c\}.$$

The choice of the optimal bank follows a *bang-bang* solution. For each activity c, the firm i chooses a single bank depending on the interest rate r_b, the absolute advantage γ_b^c, and its idiosyncratic motive ϵ_{ib}^c. For the chosen bank b, the activity-specific demand of credit is $L_{ib}^c = [\frac{1}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}] q_i^c$. We can therefore rewrite the optimal loan amount in terms of marginal cost such that $L_{ib}^c = \frac{MC_i^c}{r_b} q_i^c$ where

$$MC_i^c = \frac{r_b}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}. \tag{3}$$

For any other bank $b' \neq b : L_{ib'}^c = 0$.

The discrete-choice micro-foundation highlights two features of the framework. First, firms may have multiple banking relationships because they may choose different banks to fund different activities. Thus, our analysis provides a rationale for multiple banking relationships as a consequence of the multi-activity nature of the firm and the activity-specific advantage of banks.[12] Second, firms in the discrete-choice model do not establish banking relationships with all banks. Instead, they choose one bank per activity (although this is not hard-wired, as it may well be that the same bank is chosen for more than one activity). The discrete model with differentiated banks delivers this result without having to introduce a fixed cost of establishing a relationship with a bank.[13]

The total amount of credit taken by firm i from bank b is the sum across all activities for which bank b is optimal:

$$L_{ib} = \sum_c L_{ib}^c = \frac{1}{r_b} \sum_c \mathbb{I}_{ib}^c \cdot MC_i^c \cdot q_i^c, \tag{4}$$

where L_{ib}^c is the loan amount for activity c taken from bank b, q_i^c is total output associated with productive activity c, MC_i^c is the marginal cost of activity c and

[12] In a previous version of the paper we derived this result from a love-of-variety utility function. We are grateful to the associate editor and an anonymous referee to encourage us to provide a micro-foundation for this result.

[13] This assumption is consistent with the new structural literature in banking in which banks provide differentiated services and these services are imperfect substitutes (e.g., Benetton (2021); Buchak et al. (2018); Egan, Hortaçsu, and Matvos (2017); Egan, Lewellen, and Sunderam (2022); and Xiao (2020).

bank b defined in equation ((3)), and $\mathbb{I}^c_{bi}$ is an indicator function equal to 1 if bank b is optimal for activity c and zero otherwise.

Assuming that $\{\epsilon^c_{ib}\}_i$ are identically, independently Gumbel distributed across firms $i \in I$, the probability that a firm chooses b for activity c is given by :

$$Pr^c_b = \frac{\exp\left\{\ln(\gamma^c_b) - \ln(r_b)\right\}/\mu}{\sum_{b'} \exp\left\{\ln(\gamma^c_{b'}) - \ln(r_{b'})\right\}/\mu} = \frac{\left(\frac{\gamma^c_b}{r_b}\right)^{1/\mu}}{\sum_{b'}\left(\frac{\gamma^c_{b'}}{r_{b'}}\right)^{1/\mu}}. \tag{5}$$

We note that the probabilities depend only on the ratio of $\frac{\gamma^c_b}{r_b}$. Hence, banks can give activity-specific interest rate discounts that are isomorphic to a higher lending advantage γ^c_b. Absent the idiosyncratic factor (i.e., $\mu = 0$), this differentiation naturally implies that all firms would choose the same bank to fund an activity. Any given activity would be fully funded by the bank with highest lending advantage in that activity, relative to its cost of credit, γ^c_b/r_b. The idiosyncratic factor adds noise to the choice. If this idiosyncratic noise is predominant (i.e., μ is large) or if banks do not differ in γ^c_b/r_b across activities, variations in q^c_i (size of activity c for firm i) would not predict systematic shifts of credit across banks.

In our setting, activities correspond to export destination markets, so we substitute $MC^c_i \cdot q^c_i$ in equation (4) for exports of firm i to c (i.e., $X^c_i = p^c_i q^c_i$). This approximation is exact under perfect competition or constant markup (marginal cost is proportional to price, $MC^c_i \propto p^c_i$), a good description of Peruvian exports, mostly commodities. Then, in expectation, a firm i that exports X^c_i to each country $c = 1, \ldots, C$ would have the following overall standing credit with bank b:

$$E[L_{ib}] = \frac{1}{r_b} \sum_c Pr^c_b X^c_i. \tag{6}$$

A direct implication of equation (6) is that the elasticity of demand for bank-b loans with respect to the value of goods exported to country c, vis-a-vis other destinations

k, is increasing in the relative lending advantage, embedded in the probability Pr_b^c. We use this result to test the existence of lending advantages in the next section.

B.2. Specialization Measure

The ideal index of *Revealed Comparative Advantage* discussed above, $RCA_b^c = \frac{1}{\widetilde{S}^c}\frac{\sum_{i=1}^{I} L_{ib}^c}{\sum_{k=1}^{C}\sum_{i=1}^{I} L_{ib}^k}$, has a natural correspondence with the proposed theoretical framework. In expectation, a firm i that exports X_i^c to country c borrows $L_{ib}^c = 1/r_b \cdot Pr_b^c X_i^c$ from bank b. Then:

$$RCA_b^c = \widetilde{\gamma}_b^c \, \frac{\sum_{i=1}^{I} X_i^c}{\sum_{k=1}^{C}\sum_{i=1}^{I} X_i^k} \, \frac{\nu_b}{\widetilde{S}^c} \qquad \widetilde{\gamma}_b^c \equiv \frac{Pr_b^c}{\sum_{k=1}^{C} Pr_b^k},$$

where $\widetilde{S}^c \equiv \frac{\sum_{i=1}^{I} L_i^c}{\sum_{k=1}^{C}\sum_{i=1}^{I} L_i^k}$ recovers the importance of the activity in the overall banking sector and $\nu_b \equiv \frac{\sum_k Pr_b^k \sum_k X^k}{\sum_k Pr_b^k X^k}$ is a bank-wide constant equal to 1 in expectation, given our assumption of independence between the distribution of the γ parameters and exports across countries.[14] Comparing RCA_b^c across-banks and within-destination, this index successfully captures our theoretical object of interest, $\widetilde{\gamma}_b^c$, the relative advantage of bank b in activity c.

Since the ideal index RCA_b^c cannot be constructed from available data, we proposed the observable empirical proxy S_b^c (equation (2)), which represents bank-b borrowers' exports to country c, weighted by their debt in bank b, as a share of bank-b borrowers' total debt-weighted exports. Under mild assumptions, S_b^c is a good proxy for a bank's c-specific lending advantage $\widetilde{\gamma}_b^c$, in the sense that the covariance between the two variables across-banks within-activity is positive.

For example, if lending advantages across activities are not correlated, and neither

[14]This independence assumption is not crucial. The constant ν_b accounts for the correlation between the bank's pattern of lending advantage and cross-country market size. Intuitively, the bank's overall lending is larger if it has a relative advantage in lending towards larger export markets.

are export across destinations, then this *observable* index is positively correlated with $\tilde{\gamma}_b^c$, our *unobservable* object of interest, for any destination c (formally, $\text{cov}(X_i^k; X_i^c) = \text{cov}(\gamma_b^k; \gamma_b^c) = 0$ for $k \neq c$):

$$\text{cov}(S_b^c; \tilde{\gamma}_b^c) = (X^c)^2 E\left[(\tilde{\gamma}_b^c - \overline{\gamma}^c)^2\right] > 0,$$

where X^c stands for aggregate exports to country c, and $\overline{\gamma}^c$ is the average value of the lending advantage towards c across all banks, and $E[\cdot]$ is the expectation across banks. More generally, we show in the internet appendix that the covariance across-banks within-activity between S_b^c and $\tilde{\gamma}_b^c$ is positive under mild and intuitive conditions.

To summarize, our measure of specialization is consistent with a theory where banks have advantages in lending towards specific activities, it is straightforward to implement with available micro-data, and it is not driven mechanically by bank or export market size.

II.C. Bank Specialization Descriptive Statistics

In our data, firms $i = 1, \ldots, I$ are Peruvian exporters, $c = 1, \ldots, C$ are the destination country of exports, X_{it}^c are exports by firm i to destination country c in year t, and L_{ibt} is the outstanding debt of exporting firm i with bank b in year t. We compute the portfolio shares that constitute the basis for our specialization measure, S_b^c, 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-level export data by shipment to the 22 largest destination markets.[15]

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

Table II presents descriptive statistics of S_{bt}^{c} by country. Large export destination countries have large average shares (e.g, the average U.S. share is 21% and the average Switzerland share is 2.7%). Within-country shares are very heterogeneous: for the mean country, the standard deviation of the shares across banks is 1.77 times the country's average share. The within-country share distribution across banks is also right-skewed for every country, and the mean country's share skewness is 5.3.

[**Table 2 about here**]

The observed skeweness in the same-country share distribution is also a feature of specialization, as it implies that some banks have abnormally large portfolio shares in a country relative to the banking sector as a whole. In fact, we find that every bank in Peru has a portfolio share in the top quartile of the distribution for at least one country. That is, $D(S_b^c \in Q_4) = 1$ for every bank b in at least one country c. This is not a mechanical feature of how the quartiles are constructed: a fully diversified bank that holds the *average* portfolio would not feature a portfolio share in the top quartile in any country. The data indicate that banks systematically deviate from full diversification and tilt their loan portfolios towards firms that export to certain destination markets.

Table III presents the transition probability matrix of $D(S_b^c \in Q_q)$ calculated over all pairs of consecutive years between 1994 and 2010 for the full country and bank sample. The transition probabilities on the upper-left and bottom-right corners of the matrix are above 60%, indicating that banks with a large (small) portfolio share in a country relative to other banks are likely to retain a large (small) share over time. More generally, the heavy weight on the diagonal of the transition probability matrix indicates that portfolio shares are very persistent over time. The persistent lending portfolio tilts towards certain countries is consistent with a bank credit market for exporters that is segmented by export destination country.

[**Figure III about here**]

To summarize, we consider a bank to be specialized in a export destination market if it exhibits a portfolio share that is persistently in the top quartile of the share distribution across all banks for that destination market. All banks in our data specialize in at least one country. We interpret bank portfolio specialization as a revealed comparative advantage in lending to exporters to a given destination market. In the next section we develop an empirical approach to test whether banks indeed have a lending advantage towards destinations in which they exhibit large and persistent portfolio shares.[16]

III. Identifying Advantage in Lending

In this section, we evaluate whether bank specialization indeed corresponds to a lending advantage. If bank specialization relates with export market expertise or knowledge, then firms will finance exports to a country with credit from a bank specialized in that country. We test whether firm output in a given market comoves disproportionately with funding from the bank specialized in that market using a specification that accounts for firm-specific and bank-specific variation in credit with firm-time and bank-time fixed effects.

We empirically distinguish this market-specific lending advantage from firm-specific information gathered through relationship lending. We test whether specialization predicts decisions at the extensive margin of where to export and from whom to bor-

[16]Our work focuses on bank specialization in export activities. In related work, Granja, Matvos, and Seru (2017) use bidding data from failed bank auctions to document bank specialization in asset business lines and geographic areas. Though different in focus, the common thread across both papers is a focus on bank specialization.

row. Specifically, we test whether the probability that a firm starts a new banking relationship increases for specialized banks, when the firm starts exporting to the market of specialization. By construction, this extensive margin comovement cannot be explained by relationship lending. Finally, we use bank mergers and test whether the advantage conferred by bank specialization before a merger carries over to the combined entity after the merger. The advantage conferred by relationship lending is expected to diminish with bank size. In contrast, there is no reason to expect the advantage from market-specific bank specialization to be lost as banks expand.

III.A. Baseline Empirical Strategy

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

$$L_{ibt} = L\left(L_{bt}^{S}, L_{it}^{D}, \mathscr{L}_{ibt}\right). \tag{7}$$

Bank-firm outstanding credit is an equilibrium outcome at time t, determined by the overall supply of credit by the bank, L_{bt}^{S}, which varies with bank-level variables such as overall liquidity, balance-sheet position, etc.; the firm's overall demand for credit L_{it}^{D}, which varies with firm-level productivity, demand for its products, investment opportunities, etc.; and, finally, a firm-bank specific component, $\mathscr{L}_{ibt}$, our object of interest: the component of bank b's lending that depends on its relative advantage in markets supplied by the firm i.

Our baseline empirical specification isolates the bank-firm pair component of lending, $\mathscr{L}_{ibt}$, using saturated regressions. Specifically, we account for the bank-specific credit shocks L_{bt}^{S} (common in expectation across all firms) and all firm-specific credit shocks L_{it}^{D} (common in expectation across all banks) by saturating the empirical model with a full set of bank-time and firm-time dummies, α''_{bt} and α'_{it}.[17] Thus, for each country-bank-firm-year, we estimate:

$$\ln L_{ibt} \quad = \quad \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \ln X^c_{it} + \beta_2 \, S^c_{ibt} + \beta_3 \, S^c_{ibt} \times \ln X^c_{it} + \epsilon^c_{ibt}, \tag{8}$$

where L_{ibt} is the observed amount of debt of firm i from bank b at time t, X^c_{it} are exports from firm i to country c, and S^c_{ibt} is a measure of bank specialization in country c. Under the null hypothesis that funding across banks is perfectly substitutable we have $\beta_3 = 0$, meaning that firm exports to a country are not systematically correlated with borrowing from banks specialized in that country.

We allow for the effect of specialization on lending to be non-linear in specialization. To capture non-linearities, we divide the specialization measure into four quartiles, according to the country-specific distribution at time t: $D(S^c_{ibt} \in Q_q)$ is a dummy equal to 1 if the bank is in the quartile $q = 1, \ldots, 4$ of the distribution of S^c_b across banks for export destination c. Then, our baseline specification is:

$$\ln L_{ibt} = \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \ln X^c_{it} + \sum_{q=2}^{4} \beta_{2q} D(S^c_{ibt} \in Q_q) + \sum_{q=2}^{4} \beta_{3q} \, D(S^c_{ibt} \in Q_q) \times \ln X^c_{it} + \epsilon^c_{ibt}. \tag{9}$$

The bottom quartile $D(S^c_{ibt} \in Q_1)$ is omitted. So our results are based on the coefficient β_{3q}, which captures the elasticity for banks with q-levels of specialization, relative to non-specialized banks (i.e., the bottom quartile).

Our measure of specialization, S^c_{ibt}, is based on a rolling period of three years up

[17] This methodology builds 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)). Estimation based on demeaning the dependent variable instead of using fixed effects yields biased results (Gormley and Matsa, 2014).

to the year of the loan.[18] To avoid any potential spurious correlation between lending by bank b to firm i (L_{ibt}) and the specialization measure of bank b, we employ the following *leave-one-out* measures of the share of bank b's borrower exports to country c to construct the specialization measure:

$$S^c_{(-i)b\tau} \equiv \frac{\sum_{k\neq i}^{I} L_{bk\tau} X^c_{k\tau}}{\sum_{c=1}^{C} \sum_{k\neq i}^{I} L_{bk\tau} X^c_{k\tau}}, \tag{10}$$

Using this leave-one-out share in our measure of specialization leads to the following firm-varying measure of bank specialization:

$$S^c_{ibt} = \frac{1}{3} \sum_{\tau=t-2}^{t} S^c_{(-i)b\tau}, \tag{11}$$

Note that although outstanding debt is a firm-bank-year value, L_{ibt}, there are 22 relationships like the one in equation (9) for each firm-bank-year—one for each country c in our analysis sample. To estimate the parameters of equation (9), 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_{ibt} is constant across countries for a given bank-firm-time triplet. The set of time-invariant firm-bank-country fixed effects, α^c_{ib}, accounts for all unobserved heterogeneity in the firm-bank-country lending relationship, such as the distance between bank headquarters and the destination country.

The advantage of this approach for identifying the existence of lending advantages is that it can be generalized to other settings. Our framework can be used as long as there is variation across activities and banks have lending advantages across activities (e.g., bank specialization by industry). Moreover, our framework does not require parametric assumptions. We are testing the joint hypothesis that banks have advan-

[18]As an alternative, we also constructed estimates based on two-year and four-year rolling windows. The results are qualitatively and quantitatively unchanged.

tages in lending and that our measure of specialization captures these advantages.

III.B. Baseline Results

Column 1 of Table IV presents results for the the baseline specification with quartiles (equation (9)) . We find that lending is more sensitive to changes in exports for more specialized banks. The effect is increasing in specialization and largest for highly specialized banks in the top quartile of the country-specific distribution. Column 2 shows that the effect is robust to estimating a linear specification (equation (8)). These results show that when a firm expands its exports to a country, it increases its borrowing disproportionately from banks that specialize in the same country.

We note that our estimation includes firm-time and bank-time fixed effects. It means that this correlation holds within a firm: if a firm's export composition shifts from country A to country B, its borrowing composition shifts from a bank specialized in country A to a bank specialized in country B.[19] The bank-time fixed effects imply that this correlation is not driven by generic shocks to credit supply that affect all firms in the same manner.

To interpret the role of bank specialization, we compare the estimates for specialized (top quartile) and non-specialized (bottom quartile omitted) lenders from Column 1. For the same change in exports to a given country, the firm shifts lending from non-specialized (elasticity -0.013) towards a bank highly specialized in that

[19]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 (bottom quartile of the distribution). Note that there is independent bank-firm variation in exports—variation that is not captured by the firm-time dummies—because banks differ in their pattern of specialization across countries, so not all banks are in the top quartile for the same countries.

destination (elasticity $+0.013 = -0.013 + 0.026$). These results reject the hypothesis that debt is perfectly substitutable across banks and confirm that banks have advantages in lending to the countries in which they specialize. The results also validate that our measure of specialization captures lending advantages.

[**Table IV about here**]

III.C. New Banking Relationships and Export Entry

The basic premise behind the firm-specific advantages gained through relationship lending is the following: banks gather private information through repeated interactions with a firm, which implies an advantage vis-à-vis other uninformed banks. If the observed patterns of specialization in export markets and their associated advantages are firm-specific, then our specialization measure should not predict firm behavior at the extensive margin. We begin by testing whether 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 (parallel to specification (9)):

$$\begin{aligned}(L_{ibt} > 0 \mid L_{ibt-1} = 0) \quad = \quad & \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1\,(X^c_{it-1} > 0 \mid X^c_{it-2} = 0) + \sum_{q=2}^{4} \beta_{2q}\, D(S^c_{bt} \in Q_q) \\ & + \sum_{q=2}^{4} \beta_{3q}\, D(S^c_{bt} \in Q_q) \times (X^c_{it-1} > 0 \mid X^c_{it-2} = 0) + \epsilon^c_{ibt}, \qquad (12)\end{aligned}$$

where $(L_{ibt} > 0 | L_{ibt-1} = 0)$ is a dummy equal to 1 if firm i borrows from bank b in year t, but not in year $t-1$; and, correspondingly, $(X^c_{it-1} > 0 \mid X^c_{it-2} = 0)$ is a dummy equal to 1 if firm i exports to country c in year $t-1$, but not in year $t-2$. In this case, the specialization measure, S^c_{bt}, is not specific to firm i.

We also test an alternative extensive margin: whether the probability that a firm starts exporting to country c increases after the firm starts borrowing from a bank specialized in that destination:

$$
\begin{aligned}
(X_{ibt} > 0 \mid X_{ibt-1} = 0) \quad = \quad & \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \, (L^c_{it-1} > 0 | L^c_{it-2} = 0) + \sum_{q=2}^{4} \beta_{2q} \, D(S^c_{bt} \in Q_q) \\
& + \sum_{q=2}^{4} \beta_{3q} \, D(S^c_{bt} \in Q_q) \times (L^c_{it-1} > 0 \mid L^c_{it-2} = 0) + \epsilon^c_{ibt}. \qquad (13)
\end{aligned}
$$

Our coefficient of interest in specifications (12) and (13) is β_{3q} for increasing quartiles q of the specialization measures (bottom quartile Q_1 is omitted in both regressions).

Table V presents the OLS estimates of the entry margin specifications in (12) and (13).[20] The coefficient estimates in column (1) indicate that exporting to a new destination decreases the probability of starting a banking relationship with a non-specialized bank (bottom quartile omitted) by 1.07 percentage points, and increases with the degree of specialization. The probability of starting a new banking relationship increases by 0.82 p.p. (1.89 − 1.07) the year after first exporting, for banks in the top quartile of specialization in the new destination market. This is an economically large effect given that the unconditional probability that an exporter starts a new relationship with a bank at any point in time is 0.74%. Then, this probability doubles for banks specialized in a given country the year after first exporting to this new destination.

[Table V about here]

The probability of exporting to a new country decreases by 0.55 percentage points the year after a firm starts borrowing from a bank not specialized in that destination

[20]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 (the large sample size and the low probability of a new relationship).

(column (2)). On the other extreme, this probability increases by 0.6 p.p. (1.15 − 0.55) for countries in which the bank specializes. To assess the economic importance of this effect, we compare the magnitude of the coefficient with the unconditional probability that an exporting firm with positive credit adds a new destination in any given year (0.69%). It follows that the likelihood of exporting to a new destination doubles after a firm starts borrowing from a specialized bank.

Taken together, these results indicate that bank specialization plays an important role in financing export activity even when the firm and the bank have no prior lending relationship. The extensive margin results underline the presence of *market-specific* bank advantages in lending, as opposed to *firm-specific* ones emphasized by prior work on relationship lending.

III.D. Transmission of Lending Advantage into Merged Banks

We explore the connection between lending advantage and bank mergers. This is motivated by the theoretical framework in Stein (2002), which suggests that relationship lending is associated with soft firm-specific information that is difficult to systematize. This informational advantage is lost in the hierarchical structure of the banks, is not easily scalable, and is difficult to transmit to an acquiring bank. We explore the lending patterns of banks before and after a merger or acquisition. We test whether the pattern of lending advantage that characterized the two banks prior to the M&A is preserved and expanded to the entire corporation after the merger.

We modify the data and specification (9) 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 and four years after the event—are drawn from the original data and stacked to perform a single estimation. We use as a measure of bank specialization the variable S^c_{ib}, defined in equation (2) and computed the year before the merger. We combine the merging entities into a single one before the merger, and, conservatively, we use the maximum of the two banks as a measure of their combined specialization (e.g., if, before the merger, bank-1 and bank-2 were in the top and 3rd quartile of specialization in country A respectively, then the combined entity is considered to be in the top-quartile before the merger, irrespectively of the relative size of the two banks).

[**Table VI about here**]

We first replicate our baseline estimation in equation (9) without the merger interaction term to corroborate that the point estimates are robust to the change in sample and specification (Table VI, column (1)). The coefficient on the term $D(S^c_{ib} \in Q_4) \times \ln(X^c_{it})$ is positive and significant, larger in magnitude that that in our baseline result in Table IV (0.051 vs. 0.026 in the baseline regression). Also, the correlation between exports and credit for non-specialized size is negative and significant, larger in magnitude than in the baseline results (−0.023 vs. −0.013).

In column (2), 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, $D(S^c_{ib} \in Q_q) \times \ln(X^c_{it}) \times Merger_{bt}$, measures whether the link between the specialization and lending is affected by the merger. The point estimate in column (2) is positive but not statistically significant. That is, the merged entity inherits the specialization of the original banks.

These results imply that banks retain their capabilities in their markets of specialization even as they are acquired or merged 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.

IV. Economic Relevance

The results so far speak to the existence of market-specific lending advantages, but they do not attest to their importance for the real economy. To assess this importance we analyze how bank specialization affects the impact of credit demand and supply shocks. To evaluate the effect of real shocks to firms on credit, we use macroeconomic innovations in export markets (changes in GDP and exchange rate) as country-specific export demand shocks in an instrumental variable specification saturated with firm-time and bank-time fixed effects. And, to evaluate the impact of credit supply shocks on exports, we follow Paravisini et al. (2015) and use the reduction in bank credit induced by international capital flow reversals during the 2008 financial crisis.

IV.A. Elasticity of Credit Demand to Exports

To obtain the elasticity of credit to changes in the demand for exports we use again specification (9), and estimate it by instrumenting exports to country c, X_{it}^{c}, with two macroeconomic performance measures in the destination country: real appreciations and variation in GDP growth in the country of destination. We implement this strategy by adding the destination country exchange rate and GDP growth as instruments in the first stage regression.[21] This exercise is similar to the gravity equation

[21] The fixed-effects specification implies that our estimates derive from changes in the exchange rate level and changes in the growth rate of GDP.

estimates in Fitzgerald and Haller (2014), which uses firm-destination-year export data from Ireland and absorbs any firm-level change in costs or productivity with firm-time fixed effects.[22]

The exclusion restriction is that foreign export demand variation and its interaction with bank specialization only affect firm borrowing through its effect on export activity. This assumption is plausible given that any direct effect of international macroeconomic shocks on bank lending is controlled for through bank-time and firm-time fixed effects, α_{it} and α_{bt}. In fact, it can be expected that, given bank abnormal exposure towards the country of specialization, destination-country innovations in macroeconomic performance may be correlated with credit supply. This general variation in bank credit supply is absorbed by the bank-time fixed effects.

Table VII, column (1), shows evidence of the existence of a first stage. It shows the estimated coefficients from a regression of exports on GDP growth and real exchange rate in the destination country. The coefficients on both variables are positive and significant, and the F-statistic exceeds 20.

[**Table VII about here**]

Table VII, column (2) shows the instrumental variables (IV) estimation of specification (9), using GDP growth and real exchange rate in the destination country as instruments for export demand. Since the exports variable is interacted with three portfolio share quartile dummies, we also interact the two instruments with the quartile dummies for a total of eight instruments.[23] The IV estimates indicate

[22]Fitzgerald and Haller (2014) also analyze the effect of tariffs on export because they want to compare the effect of low-frequency tariff changes with high-frequency exchange rate changes. Tariffs are less useful in our setting because they tend to be uniform across destination countries and only change infrequently. See also Berman, Martin, and Mayer (2012) for the effect of real exchange rate shocks on exports using firm-country panel data for French firms.

[23]Estimates of the four first stages are omitted for brevity and available from the authors.

that the elasticity of credit to an export demand shock is positive for all levels of specialization. Even for non-specialized banks, this elasticity is 0.227 (bottom quartile omitted). However, the credit elasticity from banks in the top two quartiles of specialization is 50% larger. This result is important because it implies that the lending advantages have a first order impact on firms' marginal credit demand decisions. The result also implies that the same export market shock will have a very heterogeneous impact across banks with different markets of specialization.

We note that the point estimates of the credit elasticities are an order of magnitude larger than the baseline OLS estimates discussed in the previous subsection. The IV approach isolates the variation in exports and credit due to market-specific export demand shocks. In contrast, the baseline OLS estimates in Table IV capture covariances between exports to a country and borrowing from specialized banks that may be driven by export-demand shocks, firm shocks (e.g., productivity, credit, etc.) and product shocks (e.g, changes in world prices, cost). The comparison of the two estimates indicates that a small fraction of the total variation in exports is driven by aggregate demand shocks in the country of destination.

IV.B. Elasticity of Exports to Credit Supply

The results so far indicate that banks have lending advantages across different markets and that firms demand credit disproportionately from specialized banks to expand output in their market of specialization. These results, however, do not answer the question of whether differences in bank lending advantages are large or whether they have important implications for output. The reason is that even small differences in lending advantages may lead to large swings in demand across banks if banks are close substitutes as capital suppliers. To shed light on this issue we turn to exploring how a firm's output in a market responds to changes in the supply of credit from specialized and non-specialized banks.

We now evaluate how shocks to the credit supply of specialized banks affect firm output in the market of specialization (relative to other markets). To isolate bank-specific credit supply shocks, we use the empirical setting in Paravisini et al. (2015) (hereafter, PRSW): bank-level heterogeneity in the exposure to the 2008/09 financial crisis as an instrument for changes in credit supply. In 2008, international portfolio capital inflows to Peru decreased sharply, and, as a result, funding to banks with a high share of international liabilities dropped substantially. To account for variation in the demand for exports PRSW 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:

$$\ln X^c_{ipt} = \alpha^c_{ibp} + \alpha^c_{pt} + \beta_1 \ln L_{ibt} + \sum_{q=2}^{4} \beta_{2q} D(S^c_{ibt} \in Q_q) + \sum_{q=2}^{4} \beta_{3q} D(S^c_{ibt} \in Q_q) \times \ln L_{ibt} + \epsilon^c_{ibpt} \tag{14}$$

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. L_{ibt} is firm-i's credit from bank b in the period t. We instrument the change in credit supply in $t = Post$ with $Exposed_b \times Post_t$, where $Exposed_b$ is a dummy equal to 1 if the bank has a share of foreign debt above 10% in 2006, and $Post_t$ is a dummy equal to 1 during the 12 months after July 2008.[24] In the next subsection we show that this instrumental approach is still valid in the context of specialized banks. The coefficient β_{3q} in specification (14) captures the elasticity differential of exports towards countries the bank specializes (quartile q) relative to destinations in which the banks does not (bottom quartile omitted).

The regression includes firm-product-bank-country fixed effects, α^c_{ipb}, which con-

[24]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.

trol for all (time-invariant) unobserved heterogeneity across firms and banks in exporting that product to that destination. It also includes a full set of country-product-time dummies, α^c_{pt}, that accounts for non-credit determinants of exports. In particular, these dummies account for demand shocks originated in narrowly defined export markets.[25] Note that although export is a firm-product-country-year value, X^c_{ipt}, the right-hand side of specification (14) varies also at the bank level. To estimate the parameters in specification (14), we stack the observations for all banks and adjust the standard errors for clustering at the product-country level to account for the fact that X^c_{ipt} is constant across banks for a given product-country-firm-time combination.

[**Table VIII about here**]

Table VIII, column (1), shows evidence of the existence of a first stage for the IV estimation. The coefficient of a regression of bank credit on the bank exposure instrument is negative and statistically significant (F-statistic exceeds 10), implying that banks with more exposure to foreign liabilities reduced lending more after the crisis.

Table VIII, columns (2) through (5), present the OLS and IV estimates of specification (14), where the endogenous variable, credit by bank b to firm i, is instrumented with bank exposure, $Exposed_b \times Post_t$. Columns (4) and (5) augment the regression with interactions of credit with the bank specialization quartile dummies, and the instrument set is augmented to include bank exposure interacted with the specialization quartile dummies.[26]

The IV estimate of the overall elasticity of exports to the credit supply shock is shown in column (3). On average, a 10% reduction in credit supply results in a 1.9%

[25] 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.

[26] Estimates of the four first stages are omitted for brevity.

drop in the volume of exports. Column 5 shows how this elasticity varies depending on whether the destination country corresponds to the bank's set of specialization countries. These results suggest that the entire effect of the credit supply shock on export is in destination markets where the bank specializes. The point estimates imply that a 10% reduction in a bank's credit supply leads to a 4.5% decline in exports towards countries in which the bank specializes (top quartile), while it does not affect exports towards destinations in which the bank does not. The difference between the top and bottom quartiles is statistically significant at the 5% level. This shows that the effect on credit supply during a financial crisis is non-linear, with the effect being concentrated among specialized banks.[27]

These results corroborate an augmented joint hypothesis: that banks have advantages in lending, that our measure of specialization captures it, and that firms cannot easily substitute credit from specialized banks to sustain export activities. Even isolated shocks to the balance sheet of one bank may have a large impact on output in the market where the bank has lending advantages. It also implies that market-specific lending advantages hinder competition across seemingly similar lenders. Thus, lending advantages have important implications for the equilibrium outcomes in credit markets and their real outcomes. Our proposed measure of specialization provides a useful tool to analyzing these implications.

[27]As in the previous subsection, the elasticity estimates are significantly larger than the OLS estimates, indicating that a small fraction of the total variation in bank credit during the 2008 financial crisis was driven by credit supply.

IV.C. *Identifying Credit Supply Shocks*

In this subsection we discuss the implications of our findings for the empirical identification and measurement of bank credit supply shocks. The state-of-the-art methodology to empirically identify credit supply shocks relies on the assumption that credit demand shocks may be accounted for by using empirical models that saturate all firm-time variation.[28] The main idea behind this approach is that using firm fixed effects controls for the endogenous matching of banks and firms (Khwaja and Mian (2008)). This assumption does not hold in general (in the absence of a proper instrument) when banks are specialized, but it may still hold under restricted circumstances: if the source of the credit supply shock is uncorrelated with bank-specific loan demand. We provide a formal derivation of this result in the internet appendix.

We use regressions saturated with firm-time fixed effects and augmented with specialization measures to evaluate the validity of the identification assumptions behind the fixed-effects approach in our setting. We begin by estimating the standard saturated regression using our dummy measure of bank exposure to the financial crisis as a source of variation. That is, that $Exposed_b$—a dummy equal to 1 if the bank has a share of foreign liabilities above 10% in 2006—is a predictor of bank-specific credit supply shock during 2008 to 2009. Using firm-bank-year credit data we estimate the following specification:

$$\ln(L_{ibt}) = \alpha_{ib} + \alpha_{it} + \beta \cdot Exposed_b \times Post_t + \nu_{ibt}, \tag{15}$$

where the definition of the variables and time periods coincide with those in specification (14). The regression includes firm-bank fixed effects, α_{ib}, which control for

[28] For examples of recent papers using this approach, see Khwaja and Mian (2008), Paravisini (2008), Schnabl (2012), Jimenez et al. (2014), Chodorow-Reich (2014). An alternative approach is to estimate a structural model of the banking sector, see Egan, Hortaçsu, and Matvos (2017).

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 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 typically interpreted as the effect of the capital flow reversals on the supply of credit. The estimated coefficient is presented in Table IX, 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. However, firm-time dummies may not fully absorb credit demand variation in the presence of bank specialization.

[Table IX about here]

We augment specification (15) with the variable $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q)) \times Post_t$, for $q = 2, \ldots, 4$ (bottom quartile Q_1 omitted). The dummy $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q))$ is equal to 1 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 countries in which bank b is in the q-th quartile of the specialization, $C(S_{ib}^c \in Q_q)$—that is, countries for which S_{ib}^c defined in equation (11) is in the q-th quartile of the country-specific distribution 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 has some level of specialization, relative to the change in credit to firms that do not (bottom quartile). The estimated coefficients of the augmented specification are shown in Table IX, column (2). The estimated coefficient on the additional term is largest (in absolute terms) for the top quartile, -0.158. This result has 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

16% during the sample period. Thus, the variable $(C(X_i^c > 0) \bigcap C(S_{ib}^c \in Q_4))$ recovers bank-specific credit demand shocks that *are not* accounted for by the firm-time dummies in specification (15).[29]

Adding $(C(X_i^c > 0) \bigcap C(S_{ib}^c \in Q_q))$ to specification (15) 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 in the case of banks in the top quartile of specialization—that is, $(0.158 + 0.158)/0.158$.[30]

The large potential bias may be specific to our application in the context of the 2008 financial crisis, when large and heterogenous export demand shocks occurred concurrently with the variation in bank credit supply. The result calls for caution when using the saturated regression approach for the identification of credit supply

[29]An alternative explanation for the negative coefficient is that bank specialization is correlated with loan losses, which reduced bank equity and therefore affected lending. We believe this explanation is unlikely to explain our findings since Peruvian banks were not directly exposed to the U.S. financial crisis and loan delinquencies were in line with historical standards.

[30]We focus on comparing the coefficients rather than the marginal R^2 because most variation in bank specialization is controlled for by fixed effects.

shocks in contexts when sector-specific demand is fluctuating, as the identification assumptions are less likely to hold.

V. Characterization of the Bank Lending Advantage

Banks provide a variety of services supporting firms' export activities. Bartoli et al. (2011) report the results of a survey on Italian firms precisely about this question. They find that, beyond ordinary services such as online payments or insurance and guaratees, there is a substantial request of advisory services, in the form of legal and financial advisory, in loco support during fairs, and investment opportunities abroad. These services and the cross-bank advantage in providing them are typically unobservable. And, even if they were observable, one cannot conclude that specialization implies an underlying bank advantage on the provision of that specific service.

To illustrate this point, consider for example the case of letters of credit, which is an observable financial instrument that can be associated to a specific export destination. Niepmann and Schmidt-Eisenlohr (2014) document that U.S. banks are specialized in export countries when issuing letters of credits, which coincides with the specialization patterns in Subsection II.A. However, one cannot conclude whether the bank specialization implies an advantage in the issuing of letters of credit towards a specific destination, or whether the demand for such instrument is a consequence of another underlying destination-linked bank advantage. Then, although our methodology can identify the existence and importance of a lending advantage associated to an export destination, the specific source of the bank lending advantage is unknown.

[Table X about here]

In this section we use our empirical methodology to characterize the lending advantage in our data and, in doing so, narrow down potential mechanisms. 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 X, column (1), shows the cross-sectional correlation between the bank-country specialization index and: (i) $CountryOwnership_b^c$, a dummy equal to 1 if bank b's headquarters are located in country c; (ii) $CountrySubsidiary_b^c$, a dummy equal to 1 if bank b has a subsidiary in country c in 2004;[31] (iii) $CommonLanguage_b^c$, a dummy equal to 1 if the language in bank b's headquarters coincides with that in country c; and (iv) $DistanceToHeadquarters_b^c$, the distance between the country of ownership and the export destination c.[32] For this cross-sectional analysis, we use the measure of specialization in equation (2), S_{bt}^c, averaged during the entire life of the bank.[33] We find that, indeed, there is a connection between the bank's country of ownership and the bank's set of specialization countries. Banks are more likely to specialize in the country of their headquarters. We find no correlation between our measure of country-specialization and the language in headquarters nor the location of subsidiaries.

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 IV. 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

[31]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).

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

[33]That is, S_{ibt}^c, as defined in equation (2), up to the last year the bank appears in our dataset (t_F): $S_{ibt}^c = \frac{1}{t_F - t_0} \sum_{\tau=t_0}^{t_F} S_{b\tau}^c$.

this possibility by expanding the baseline regression in equation (9) with the four variables defined above, interacted with exports (i.e., $CountryOwnership_b^c \times \ln(X_{it}^c)$, $CountrySubsidiary_b^c \times \ln(X_{it}^c)$, $CommonLanguage_b^c \times \ln(X_{it}^c)$, $DistanceToHeadquarters_b^c \times \ln(X_{it}^c)$). Results are presented in Table X, columns (2) and (3). None of the interaction terms are statistically significant, and their inclusion in the regression does not change the magnitude or the significance of the interaction of exports and specialization.[34]

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.

VI. Conclusions

Our paper proposes a new measure of market-specific bank specialization that captures a bank's expertise in evaluating projects in specific markets. Using data on all Peruvian firms and exports between 1994 and 2010, we measure market-specific bank specialization for each bank and export market and show that market-specific bank specialization is an important determinant of the supply of bank credit and export activity, independent of firm-specific information gathered through relationship lending.

The findings in this paper have important implications for the industrial organization of bank credit markets. Market-specific bank specialization provides a new rationale for why firms have multiple banking relationships and why banks form

[34] Our results are different from those in Bronzini and D'Ignazio (2012). Using a different methodology and data from Italian firms, they find that the geographical distribution of the bank foreign subsidiaries affects the export performance of related firms.

syndicates. The reason is that firms borrow from more than one bank because they value banks' market-specific specialization across different markets. Hence, multiple lending relationships naturally emerge in a setting with specialized banks and multi-market firms. Market-specific bank specialization can also explain why there are limits to bank diversification.

The paper also has important implications for the assessment of credit supply shocks such as those caused by bank failures, runs, liquidity shortages, or tight monetary conditions. If bank expertise varies across markets or activities, then a credit supply shortage by a single bank may have first-order effects on the real output of the market or activity in which the bank specializes. Hence, 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 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 hold in the presence of market-specific bank specialization.

Initial submission: XXXX ; Accepted: XXXX

Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

REFERENCES

Acharya, Viral V., Iftekhar Hasan, and Anthony Saunders, 2006, Should banks be diversified? Evidence from individual bank loan portfolios, *The Journal of Business* 79, 1355–1412.

Ahn, JaeBin, and Miguel Sarmiento, 2019, Estimating the direct impact of bank liquidity shocks on the real economy: Evidence from letter-of-credit import transactions in Colombia, *Review of International Economics* 27, 1510–1536.

Amiti, Mary, and David Weinstein, 2011, Exports and Financial Shocks, *The Quarterly Journal of Economics* 126, 1841–1877.

Antras, Pol, and C. Fritz Foley, 2015, Poultry in motion: A study of international trade finance practices, *Journal of Political Economy* 123, 853–901.

Balassa, Bela, 1965, Trade liberalisation and "revealed" comparative advantage, *The Manchester School* 33, 99–123.

Bartoli, Francesca, Giovanni Ferri, Enrico Maccarone, and Zeno Rotondi, 2011, Can banks help small business export performance?, in Giampio Bracchi, and Donato Masciandaro, eds., *L'Europa e Oltre. Banche e Imprese Nella Nuova Globalizzazione* (EDIBANK, Italy).

Benetton, Matteo, 2021, Leverage regulation and market structure: A structural model of the UK mortgage market, *The Journal of Finance* 76, 2997–3053.

Berger, Allen, Nathan Miller, Mitchell Petersen, Raghuram Rajan, and Jeremy Stein, 2005, Does function follow organizational form? Evidence from the lending practices of large and small banks, *Journal of Financial Economics* 76, 237–269.

Berger, Allen, and Greg Udell, 1995, Relationship lending and lines of credit in small firm finance, *Journal of Business* 68, 351–381.

Berger, Philip G., Michael Minnis, and Andrew Sutherland, 2017, Commercial lending concentration and bank expertise: Evidence from borrower financial statements, *Journal of Accounting and Economics* 64, 253–277.

Berman, Nicolas, Philippe Martin, and Thierry Mayer, 2012, How do different exporters react to exchange rate changes?, *Journal of Banking and Finance* 127, 437–492.

Bernanke, Ben, 1983, Non monetary effects of the financial crisis in the propagation of the Great Depression, *The American Economic Review* 73, 257–276.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo E. Mistrulli, 2013, Relationship and transaction lending in a crisis, BIS Working Paper No. 417.

Bolton, Patrick, and David Scharfstein, 1996, Optimal debt structure and the number of creditors, *Journal of Politocal Economy* 104, 1–25.

Boot, Arnoud W. A., 2000, Relationship banking: What do we know?, *Journal of Financial Intermediation* 9, 7–25.

Boyd, John H., and Edward C. Prescott, 1986, Financial intermediary coalitions, *Journal of Economic Theory* 38, 211–232.

Bronzini, Raffaello, and Alessio D'Ignazio, 2012, Bank internationalization and firm exports: Evidence from matched firm-bank data, EFIGE Working Paper No 59.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Chava, Sudheer, and Amiyatosh Purnanandam, 2011, The effect of banking crisis on bank-dependent borrowers, *Journal of Financial Economics* 99, 116–135.

Chodorow-Reich, Gabriel, 2014, The employment effects of credit market disruptions: Firm-level evidence from the 2008-09 financial crisis, *Quarterly Journal of Economics* 129, 1–59.

Degryse, Hans, and Steven Ongena, 2005, Distance, lending relationships, and competition, *Journal of Finance* 60, 231–266.

Detragiache, Enrica, Paolo Garella, and Luigi Guiso, 2000, Multiple versus single banking relationships: Theory and evidence, *The Journal of Finance* 55, 1133–1161.

Diamond, Douglas W., 1984, Financial intermediation and delegated monitoring, *Review of Economic Studies* 51, 393–414.

Diamond, Douglas W., 1991, Monitoring and reputation: The choice between bank loans and directly placed debt, *Journal of Political Economy* 8, 689–721.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The deposits channel of monetary policy, *The Quarterly Journal of Economics* 132, 1819–1876.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, 2017, Deposit competition and financial fragility: Evidence from the US banking sector, *American Economic Review* 107, 169–216.

Egan, Mark, Stefan Lewellen, and Adi Sunderam, 2022, The cross-section of bank value, *The Review of Financial Studies* 35, 2101–2143.

Fama, Eugene F., 1985, What's different about banks?, *Journal of Monetary Economics* 15, 29–39.

Fitzgerald, Doireann, and Stefanie Haller, 2014, Exporters and shocks: Dissecting the international elasticity puzzle, Federal Reserve Bank of Minneapolis Working Paper.

Gormley, Todd A., 2010, The impact of foreign bank entry in emerging markets: Evidence from India, *Journal of Financial Intermediation* 19, 26–51.

Gormley, Todd A., and David A. Matsa, 2014, Common errors: How to (and not to) control for unobserved heterogeneity, *The Review of Financial Studies* 27, 617–661.

Granja, Joao, Gregor Matvos, and Amit Seru, 2017, Selling failed banks, *The Journal of Finance* 72, 1723–1784.

Holmstrom, Bengt, and Jean Tirole, 1997, Financial intermediation, loanable funds, and the real sector, *Quarterly Journal of Economics* 112, 663–691.

Hoshi, Takeo, Anil Kashyap, and David Scharfstein, 1990, The role of banks in reducing the costs of financial distress in Japan, *Journal of Financial Economics* 27, 67–88.

James, Christopher, 1987, Some evidence on the uniqueness of bank loans, *Journal of Financial Economics* 19, 217–235.

Jimenez, Grabriel, Steven Ongena, Jose Luis Peydro, and Jesus Saurina, 2014, Hazardous times for monetary policy: What do 23 million loans say about the impact of monetary policy on credit risk-taking?, *Econometrica* 82, 463–505.

Khwaja, Asim, and Atif Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *The American Economic Review* 98, 1413–1442.

Leland, Hayne E., and David H. Pyle, 1977, Informational asymmetries, financial structure, and financial intermediation, *Journal of Finance* 32, 371–387.

Manova, Kalina, 2013, Credit constraints, heterogeneous firms, and international trade, *Review of Economic Studies* 80, 711–744.

Mayer, Thierry, and S. Zignago, 2011, Notes on CEPII's distances measures: the GeoDist Database, CEPII Working Paper No. 25.

Niepmann, Friederike, and Tim Schmidt-Eisenlohr, 2014, Banks in international trade finance: Evidence from the U.S., Federal Reserve Bank of New York Working Paper.

Niepmann, Friederike, and Tim Schmidt-Eisenlohr, 2017, No guarantees, no trade: How banks affect export patterns, *Journal of International Economics* 108, 338–350.

Ongena, Steven, and David C. Smith, 2000, *Performance of Financial Institutions*, chapter Bank Relationships: A review, 221–258 (Cambridge University Press).

Paravisini, Daniel, 2008, Local bank financial constraints and firm access to external finance, *The Journal of Finance* 63, 2160–2193.

Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon, 2015, Dissecting the effect of credit supply on trade: Evidence from matched credit-export data, *Review of Economic Studies* 82, 333–359.

Pennacchi, George G., 1988, Loan sales and the cost of bank capital, *The Journal of Finance* 43, 375–396.

Petersen, Mitchell, and Raghuram Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3–37.

Petersen, Mitchell, and Raghuram Rajan, 1995, The effect of credit market competition on lending relationships, *Quarterly Journal of Economics* 5, 407–443.

Rajan, Raghuram, 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *Journal of Finance* 47, 1367–400.

Rajan, Raghuram, and Andrew Winton, 1995, Covenants and collateral as incentives to monitor, *Journal of Financ* 50, 1113–1146.

Rajan, Raghuram, and Luigi Zingales, 1998, Financial dependence and growth, *American Economic Review* 88, 559–586.

Ramakrishnan, Ram T. S., and Anjan V. Thakor, 1984, Information reliability and a theory of financial intermediation, *Review of Economic Studies* 51, 415–432.

Schnabl, Philipp, 2012, The international transmission of bank liquidity shocks: Evidence from an emerging market, *The Journal of Finance* 67, 897–932.

Sharpe, Steven A., 1990, Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships, *Journal of Finance* 45, 1069–1087.

Stein, Jeremy, 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *The Journal of Finance* 57, 1891–1921.

Winton, Andrew, 1999, Don't put all your eggs in one basket? Diversification and specialization in lending, Working paper, Carlson School of Management, University of Minnesota.

Xiao, Kairong, 2020, Monetary transmission through shadow banks, *The Review of Financial Studies* 33, 2379–2420.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Internet Appendix.

Replication code.

Table I

Descriptive Statistics

This table presents summary statistics at the firm and firm-bank-country level for the years 1994 to 2010. The data are reported monthly and cover 14,267 firms, 33 banks, and 22 countries. Outstanding debt is a firm's total bank debt with a given bank. Exports are a firm's total exports for a given export market. Total debt is a firm's total bank debt. Number of banks per firm is the number of banks from which a firm is borrowing. Total exports are a firm's total exports. Number of destinations per firm is the numbers of market to which a firm is exporting.

Panel A: Firm-bank-country-time level (N = 378,766)					
	Mean (1)	St. Dev. (2)	Min (3)	Median (4)	Max (5)
Outstanding debt (US$ '000s)	2,044	6,804	0	260	235,081
Exports (US$ '000s)	2,148	19,821	0	87	1,470,300

Panel B: Firm-time level (N = 45,762)					
	Mean (1)	St. Dev. (2)	Min (3)	Median (4)	Max (5)
Total debt (US$ '000s)	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$ '000s)	4,518	55,648	0	77	2,855,313
Number destinations per firm	2.65	2.84	1.00	1.00	22.00

Table II

Descriptive Statistics for Country Portfolio Share

This table provides statistics on the portfolio shares by country. We calculate portfolio shares following the definition in equation (2) using firm-bank level data on all debt with 33 banks for the years 1994 to 2010, as well as firm-level export data by shipments to the 22 largest export markets.

		S_{bt}^{c}			
Country	Code	Mean (1)	St. Dev. (2)	Median (3)	Skewness (4)
Belgium	BE	0.023	0.027	0.0180	3.4
Bulgaria	BG	0.003	0.006	0.0008	3.0
Bolivia	BO	0.022	0.049	0.0100	7.7
Brazil	BR	0.025	0.030	0.0140	2.3
Canada	CA	0.033	0.046	0.0230	5.1
Switzerland	CH	0.027	0.088	0.0014	5.2
Chile	CL	0.083	0.160	0.0390	4.2
China	CN	0.150	0.130	0.1200	1.1
Colombia	CO	0.035	0.069	0.0250	9.7
Germany	DE	0.055	0.059	0.0470	3.0
Ecuador	EC	0.029	0.079	0.0130	8.2
Spain	ES	0.031	0.066	0.0190	11.0
France	FR	0.014	0.026	0.0069	5.5
Great Britain	GB	0.035	0.043	0.0210	3.0
Italy	IT	0.019	0.027	0.0130	7.7
Japan	JP	0.061	0.065	0.0590	5.7
South Korea	KR	0.017	0.025	0.0094	3.9
Mexico	MX	0.030	0.088	0.0130	8.2
Netherlands	NL	0.023	0.034	0.0130	3.6
Panama	PA	0.024	0.072	0.0030	5.4
Trinidad and Tobago	TT	0.001	0.004	0.0001	5.8
Taiwan	TW	0.021	0.023	0.0180	2.4
USA	US	0.210	0.180	0.1700	1.7
Venezuela	VE	0.028	0.038	0.0170	3.5
Overall		0.042	0.087	0.0150	5.3

Table III

Portfolio Share Quartile Transition Probability Matrix

This table reports the probability that a bank's portfolio share in a given country transitions from quartile q (rows) to quartile r (columns) between consecutive years. We calculate portfolio shares, quartiles, and transition probabilities using firm-bank level data on all debt with 33 banks for the years 1994 to 2010 and firm-level export data by shipments to the 22 largest export markets.

To portfolio share quartile:	Q_1	Q_2	Q_3	Q_4	Sum
From portfolio share quartile:					
Q_1	0.64	0.17	0.10	0.10	1.00
Q_2	0.13	0.48	0.28	0.11	1.00
Q_3	0.06	0.24	0.46	0.24	1.00
Q_4	0.06	0.11	0.23	0.60	1.00

Table IV

Lending Advantage and Specialization

This table examines the impact of bank specialization on lending. We denote the natural logarithm of total debt of firm i with bank b at time t as $\ln(L_{ibt})$, the natural logarithm of exports of firm i to country c as $\ln(X^c_{it})$, and bank specialization (defined in equation (11)) as S^c_{ibt}. We construct indicator variables equal to 1 if specialization S^c_{ibt} is in quartile Q_2, Q_3, or Q_4, respectively, and 0 otherwise. Column (1) reports the results from estimating equation (8). Column (2) reports the results from estimating equation (9). All specifications include bank-country, firm-year and bank-year fixed effects. Standard errors are clustered at the bank and firm levels. ***p <0.01, **p <0.05, and *p < 0.1.

	$\ln(L_{ibt})$	
	(1)	(2)
$\ln(X^c_{it})$	−0.013*	−0.003**
	(0.007)	(0.002)
$\ln(X^c_{it}) \times (S^c_{ibt} \in Q_2)$	0.010	
	(0.009)	
$\ln(X^c_{it}) \times (S^c_{ibt} \in Q_3)$	0.016	
	(0.010)	
$\ln(X^c_{it}) \times (S^c_{ibt} \in Q_4)$	0.026**	
	(0.012)	
$\ln(X^c_{it}) \times S^c_{ibt}$		0.053**
		(0.025)
Observations	327,727	327,727
Adjusted R^2	0.569	0.569

Table V

Specialization and New Banking Relationships

This table examines the impact of bank specialization on new banking relationships. All variables are defined in Table IV. Column (1) reports the results from estimating equation (12). Column (2) reports the results from estimating equation (13). All specifications include bank-country, bank-year and firm-year fixed effects, and the interaction terms $(S_{ibt} \in Q_q)$, $q = 2, \ldots, 4$ (not shown). Standard errors are two-way clustered at the bank and firm levels. ***p <0.01, **p <0.05, and *p < 0.1.

	$(L_{ibt} > 0 \mid L_{ibt-1} = 0) \times 100$	$(X^c_{it} > 0 \mid X^c_{it-1} = 0) \times 100$
	(1)	(2)
$(X^c_{it-1} > 0 \mid X^c_{it-2} = 0)$	−1.07***	
	(0.02)	
$(X^c_{it-1} > 0 \mid X^c_{it-2} = 0) \times (S^c_{ibt} \in Q_2)$	1.15***	
	(0.03)	
$(X^c_{it-1} > 0 \mid X^c_{it-2} = 0) \times (S^c_{ibt} \in Q_3)$	1.25***	
	(0.03)	
$(X^c_{it-1} > 0 \mid X^c_{it-2} = 0) \times (S^c_{ibt} \in Q_4)$	1.89***	
	(0.03)	
$(L_{ibt-1} > 0 \mid L_{ibt-2} = 0)$		−0.55***
		(0.03)
$(L_{ibt-1} > 0 \mid L_{ibt-2} = 0) \times (S^c_{ibt} \in Q_2)$		0.13***
		(0.03)
$(L_{ibt-1} > 0 \mid L_{ibt-2} = 0) \times (S^c_{ibt} \in Q_3)$		0.82***
		(0.03)
$(L_{ibt-1} > 0 \mid L_{ibt-2} = 0) \times (S^c_{ibt} \in Q_4)$		1.15***
		(0.03)
Observations	158,463,338	158,713,474
Adjusted R^2	0.267	0.248

Table VI
Persistence of Specialization after a Merger

This table examines the persistence of specialization after a merger. The sample is constructed as follows. Eight-year interval subsamples centered around the time of the merger are drawn from the original data. The merging entities are combined into a single one before the merger, and $S^c_{ibPreMerger}$ is computed as the maximum of the two banks' specialization measures in the year before the merger. All other variables are defined in Table IV. Column (1) estimates equation (9) on the revised sample. Column (2) adds the interaction of $Merger_{bt}$, a dummy equal to 1 during the four years after a merger event for the merging entity, to equation (9). All specifications include bank-merger-year, firm-merger-year and country-bank-merger fixed effects, and the interaction terms ($S_{ibPreMerger} \in Q_q$) and, for column (2), ($S_{ibPreMerger} \in Q_q$) $\times$ $Merger_{bt}$ for $q = 2, \ldots, 4$ (not shown). Standard errors are two-way clustered at the bank and firm levels. ***p <0.01, **p <0.05, and *p < 0.1.

	$\ln(L_{ibt})$	
	(1)	(2)
$\ln(X^c_{it})$	−0.023*	−0.022
	(0.013)	(0.013)
$Merger_{bt}$		0.325
		(0.238)
$\ln(X^c_{it}) \times Merger_{bt}$		−0.024
		(0.024)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_2)$	0.013	0.012
	(0.013)	(0.013)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_3)$	0.031*	0.032*
	(0.016)	(0.016)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_4)$	0.051**	0.051**
	(0.025)	(0.024)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_2) \times Merger_{bt}$		0.014
		(0.016)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_3) \times Merger_{bt}$		0.012
		(0.016)
$\ln(X^c_{it}) \times (S^c_{ibPreMerger} \in Q_4) \times Merger_{bt}$		0.021
		(0.015)
Observations	539,885	539,885
R^2	0.5677	0.5677

Table VII

Lending Advantage and Specialization (Instrumental Variables)

This table examines the impact of bank specialization on lending and exports using instrumental variables (IV). Column (1) presents results from the first stage regression of exports on GDP growth, $GDPGrowth_t^c$, and the natural logarithm of the real exchange rate in the destination country, $\ln(RER_t^c)$. Column (2) shows the IV estimation of specification (9) using $GDPGrowth_t^c$ and $\ln(RER_t)$ as instruments for export demand. All other variables are defined in Table IV. The specification includes firm-year, bank-year and bank-country fixed effects, and all interaction terms (not shown). Standard errors are clustered at the bank and firm levels. ***p <0.01, **p <0.05, and *p < 0.1.

	$\ln(X_{it}^c)$	$\ln(L_{ibt})$
	First Stage	IV
	(1)	(2)
$\ln(X_{it}^c)$		0.227***
		(0.047)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_2)$		0.011
		(0.051)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_3)$		0.123***
		(0.041)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_4)$		0.114**
		(0.055)
$GDPGrowth_t^c$	0.013***	
	(0.004)	
$\ln(RER_t^c)$	0.413***	
	(0.067)	
Observations	328,224	328,219
Adjusted R^2	0.316	

Table VIII

Credit Supply Shock and Specialization

This table examines the impact of credit supply shocks in the presence of bank specialization. The variable 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. L_{ibt} is firm-i's credit from bank b in period t. $Exposed_b$ is a dummy equal to 1 if the bank has a share of foreign debt above 10% in 2006, and $Post_t$ is a dummy equal to 1 during the 12 months after July 2008. Column (1) presents the first stage results for the IV estimation in specification (14). Columns (2) and (3) present the OLS and IV estimates of specification (14), where the endogenous variable, credit by bank b to firm i, is instrumented with bank exposure, $Exposed_b \times Post_t$. The specifications in columns (4) and (5) include the interaction terms $(S_{ibt} \in Q_q)$, not shown. All other variables are defined in Table IV. All specifications include product-country-year and bank-firm-product-country fixed effects (HS 4-digits). Standard errors are clustered at the bank and product-destination level. ***p <0.01, **p <0.05, and *p < 0.1.

	$\ln(L_{ibt})$	$\ln(X^c_{ipt})$			
	First Stage (1)	OLS (2)	IV (3)	OLS (4)	IV (5)
$Exposed_b \times Post_t$	−0.195**				
	(0.083)				
$\ln(L_{ibt})$		0.025**	0.195***	0.011	0.035
		(0.010)	(0.046)	(0.012)	(0.070)
$\ln(L_{ibt}) \times (S^c_{ibt} \in Q_2)$				−0.009	−0.596
				(0.015)	(0.542)
$\ln(L_{ibt}) \times (S^c_{ibt} \in Q_3)$				0.031**	−0.063
				(0.015)	(0.231)
$\ln(L_{ibt}) \times (S^c_{ibt} \in Q_4)$				−0.016	0.446**
				(0.010)	(0.173)
Observations	33,214	51,024	51,024	51,024	51,024
Adjusted R^2	0.197	0.438		0.609	

Table IX

Identification of Credit Supply Shocks

This table examines the effect of capital flow reversals on the supply of credit. *Pre* and *Post* periods correspond to the 12 months before and after July 2008. $Exposed_b$ is a dummy equal to 1 if the bank has a share of foreign debt above 10% in 2006. All other variables are defined in Table IV. Column (1) reports the results of regression specification (15) in within-firm differences (*Post* vs. *Pre*). Column (2) presents the results from specification (15), augmented with the variable $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q)) \times Post_t$ for $q = 2, \ldots, 4$ (bottom quartile Q_1 omitted). The dummy $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q))$ is equal to 1 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 countries in which bank b is in the q-th quartile of the specialization. All specifications include firm fixed effects. Standard errors clustered at the bank level. ***p <0.01, **p <0.05, and *p < 0.1.

	$\Delta \ln(L_{ib})$	
	(1)	(2)
$Exposed_b$	−0.168***	−0.158***
	(0.046)	(0.055)
$C(X_i^c > 0) \cap C(S_b^c \in Q_2)$		−0.137***
		(0.050)
$C(X_i^c > 0) \cap C(S_b^c \in Q_3)$		−0.137
		(0.089)
$C(X_i^c > 0) \cap C(S_b^c \in Q_4)$		−0.158**
		(0.075)
Observations	10,334	10,334
Adjusted R^2	0.261	0.263

Table X

Specialization and Global Banks

The table examines the relationship between bank specialization in a country and geographical advantages conferred by the ownership country and subsidiary network. The variables are defined as follows: (i) $CountryOwnership_b^c$ is a dummy equal to 1 if bank b's headquarters are located in country c; (ii) $CountrySubsidiary_b^c$ is a dummy equal to 1 if bank b has a subsidiary in country c in 2004; (iii) $CommonLanguage_b^c$ is a dummy equal to 1 if the language in bank b's headquarters coincides with that in country c; and (iv) $DistanceToHeadquarters_b^c$ is the distance between the country of ownership and the export destination c. All other variables are defined in Table IV. Column (1) reports the results of a regression of S_b^c on these four variables above (estimated the bank-country level). Columns (2) and (3) estimate equations (8) and (9) at the firm-bank-time level, respectively, augmented with the four variables above. Column (1) includes bank, country and year fixed effects. Columns (2) and (3) include firm-year, bank-year and country-bank fixed effects, and the interactions terms $(S_{ibt} \in Q_q)$ (not shown). Standard errors are two-way clustered at the bank and firm levels. ***p <0.01, **p <0.05, and *p < 0.1.

	S_b^c	$\ln(L_{ibt})$	
	(1)	(2)	(3)
$CountryOwnership_b^c$	0.067***		
	(0.006)		
$DistanceToHeadquarters_b^c$	0.001		
	(0.001)		
$CommonLanguage_b^c$	0.002		
	(0.003)		
$CountrySubsidiary_b^c$	−0.008***		
	(0.003)		
$\ln(X_{it}^c)$		0.011	0.001
		(0.025)	(0.028)
$\ln(X_{it}^c) \times CountryOwnership_b^c$		0.002	0.002
		(0.008)	(0.008)
$\ln(X_{it}^c) \times DistanceToHeadquarters_b^c$		0.000	−0.001
		(0.003)	(0.003)
$\ln(X_{it}^c) \times CommonLanguage_b^c$		−0.006	−0.005
		(0.005)	(0.005)
$\ln(X_{it}^c) \times CountrySubsidiary_b^c$		−0.005	−0.005
		(0.004)	(0.004)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_2)$			0.01
			(0.009)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_3)$			0.016
			(0.010)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_4)$			0.026**
			(0.013)
Observations	7,560	327,727	327,727
Adjusted R^2	0.418	0.570	0.570

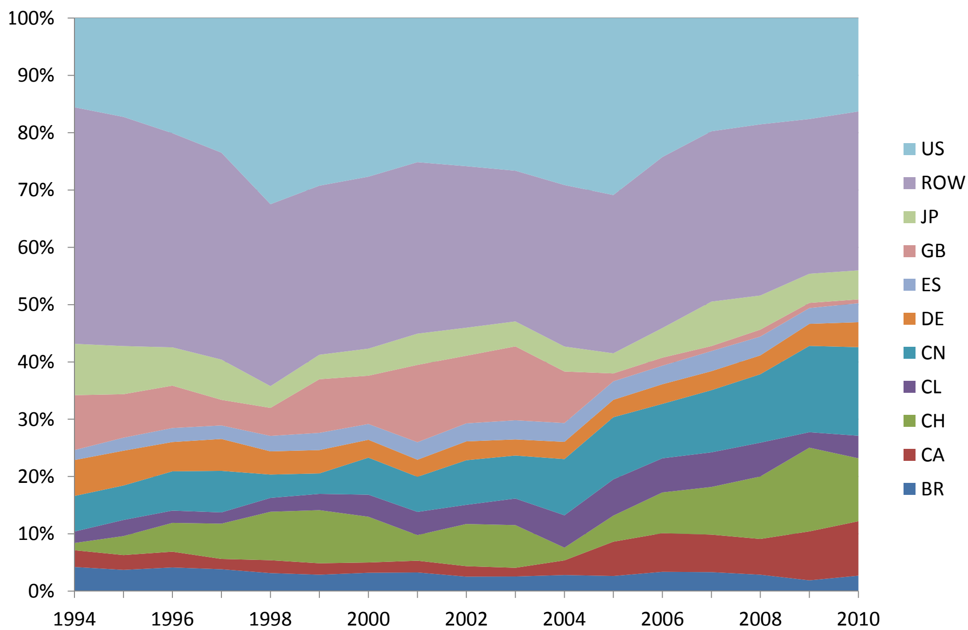

Figure 1. **Export composition by destination**. The figure presents the share of exports to the top 10 export destinations according to export values. The dataset covers 14,267 firms, 33 banks, and 22 export markets for the years 1994 to 2010. Country names are abbreviated by the country codes listed in Table II. The 12 countries that are not in the top 10 export destinations are pooled under the code "ROW".

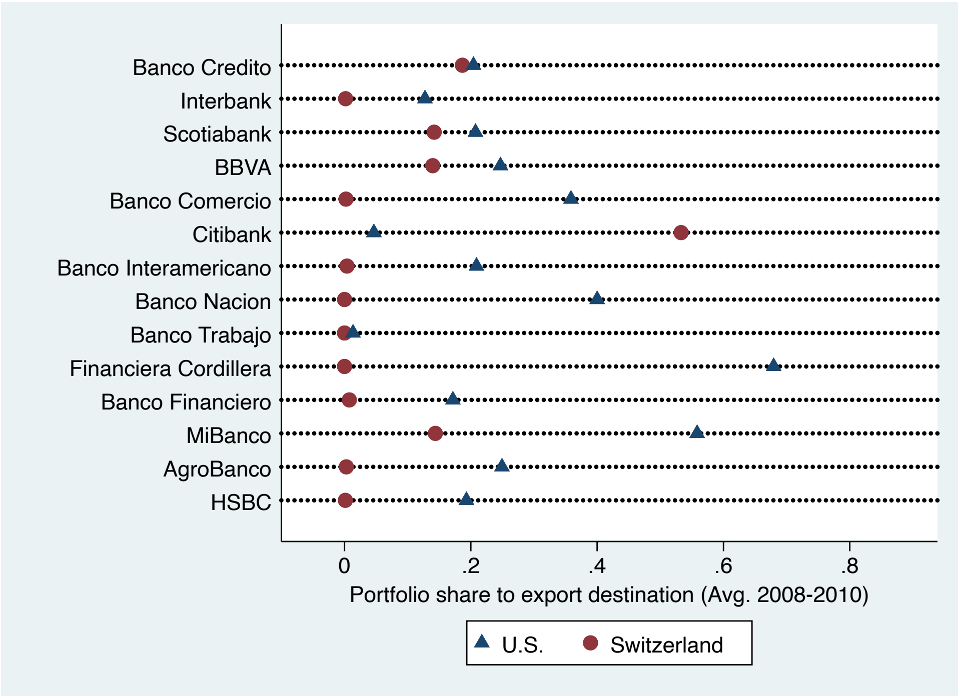

Figure 2. **Specialization measure: example**. The figure reports the average (2008–2010) portfolio share S^c_{bt} by bank for two countries, the United States and Switzerland. Portfolio shares are calculated according to the definition in equation (2).