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ABSTRACT

We develop an empirical approach for identifying specialization in bank lending using granular data on borrower activities. We illustrate the approach by characterizing bank specialization by export market, combining bank, loan, and export data for all firms in Peru. We find that all banks specialize in at least one export market, that firms take the pattern of bank specialization into account when selecting their lending banks, and that credit supply shocks disproportionately affect a firm's exports to markets where the lender specializes in. Thus, bank specialization makes credit difficult to substitute, which has consequences for competition in credit markets and the transmission of credit shocks to the real economy.

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1 Introduction

A central function of banks is to monitor and screen borrowers. Banks invest in collecting borrower-specific information, often proprietary in nature, and evaluate new projects through repeated interactions with the same borrower. Over time, banks form relationships with borrowers that constitute an important source of a bank's comparative advantage. On the one hand, such relationship lending give banks an ex-ante incentive to invest in information collection on new borrowers. On the other hand, it creates an ex-post information monopoly that limits competition across banks and enables rent extraction. This trade-off is at the center of much theoretical and empirical work on financial intermediation and considered a primary reason why banks exist in the first place.[1]

In this paper, we explore a complementary, but theoretically distinct, source of comparative advantage of banks. We ask whether banks specialize by lending to firms in specific markets. We distinguish between bank specialization due to "market-specific" information, such as expertise in evaluating projects in a specific market or in a specific activity, and "firm-specific" information, such as the information gathered from relationship lending. Importantly, we analyze whether there is a distinct role for market-specific bank specialization *independent* of firm-specific information collected through relationship lending.

To provide compelling evidence of market-specific bank specialization, one needs to address several challenges. The first is deriving a theoretically sound measure of market-specific bank specialization that can be taken to the data. The second is to empirically identify the consequences of market-specific bank specialization separately from other bank characteristics that could affect lending directly. The third is to distinguish clearly between the impact of market-specific specialization and firm-specific information gathered through relationship lending.

[1] For the importance of relationship lending in financial intermediation see Bernanke, 1983; James, 1987; Hoshi et al., 1990; Petersen and Rajan, 1994; Petersen and Rajan, 1995; Berger and Udell, 1995; Degryse and Ongena, 2005; Chava and Purnanandam, 2011; Bolton et al., 2013; for surveys, see Boot, 2000 and Ongena and Smith, 2000.

Our analysis addresses these challenges using a new dataset that combines bank, loan, and export data on all firms in Peru. We start by constructing a new measure of market-specific bank specialization based on cross-country variation in firms' export activities. We define a bank to be specialized in a country if its portfolio share of lending to exporters to the country is a right-tail outlier in the distribution of portfolio shares of lending by all banks. We show that this measure 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 funding exports to specific countries). This approach captures market-specific bank specialization (e.g., better screening and monitoring of local risk, more value-added local services attached to credit issuances, etc.) that is independent of firm-specific information.

Using our new measure of bank specialization, we show that all banks are specialized in at least one export market. We further find that market-specific bank specialization is highly persistent. A bank that is specialized in a market today has a 50% probability of being specialized in the same market in ten years. These findings indicate that banks have market-specific expertise and knowledge regarding specific export markets.

We examine how firms' choice of lender is related to market-specific bank specialization. A direct implication of market-specific bank specialization is that firms will disproportionately fund exports to a specific country with credit from a bank specialized in that country. We develop a revealed preference approach that directly tests this implication. We exploit the disaggregated nature of the data to control for firm demand shocks (firm-time fixed-effects) and bank credit supply shocks (bank-time fixed-effects) that may affect lending for other reasons. Using our revealed preference approach, we find that when firms expand exports to a country, they increase borrowing by 79% more from banks that are specialized in the destination country relative to non-specialized banks, suggesting that firms value market-specific bank specialization.

We further analyze how market-specific bank specialization affects the impact of credit demand and supply shocks. On the demand side, we use macroeconomic innovations in export markets (changes in GDP and exchange rate) as country-specific export demand shocks while still saturating the model with firm-time and bank-time fixed effects. We find that the elasticity of credit demand to export shocks is 0.50 for banks specialized, 50% larger than the one from non-specialized banks (0.33). This shows that, for the *same* firm, the demand for credit from a specialized bank increases when the firm tilts its production towards the market of specialization. On the supply side, we use the reduction in bank credit induced by international capital flow reversals during the 2008 financial crisis and control for demand shocks by comparing changes in exports in narrowly defined product-destination export markets (e.g., cotton T-short exports to Germany).[2] We find that the elasticity of exports to a credit supply shock is 6.6 times larger to countries where the lender specializes in, relative to countries it does not, suggesting a direct effect of market-specific bank specialization on exports.

Next, we explore how market-specific bank specialization differs from firm-specific information gathered through relationship lending. Firm-specific information emerges because of private information collected as part of an ongoing lending interaction.[3] In contrast, market-specific bank specialization is tied to all firms operating in a market regardless of whether or not the bank has private information on each firm. We can thus distinguish these two sources of informational advantage by focusing on new firm-bank relationships (i.e., *extensive margin*) for which banks have no firm-specific information.

We find that the probability that a firm starts a new banking relationship after exporting to a new country is 6.9 times higher for a bank specialized in that country relative to a non-specialized bank. Moreover, a firm is 4.8 times more likely to start exporting to a new country the year after it starts borrowing from a bank specialized in that new market relative to a non-specialized bank. Starting a new relationship with a bank not specialized in that market, on the other hand, is not associated with any change in the probability of

[2]This identification strategy is based on the empirical setting in Paravisini et al. (2015).

[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.

export entry. These findings show that the impact of market-specific bank specialization is not driven by firm-specific information.

Market-specific bank specialization and firm-specific information also have different implications regarding bank size. Relationship lending is based on firm-specific information gathered through the lending process, which is difficult to scale and gets lost as banks grow larger.[4] Contrary to this prediction of relationship lending models, there is no reason to expect that market-specific bank specialization is lost as banks grow larger. Indeed, we find no evidence of a trade-off between bank size and market-specific bank specialization in export markets. Market-specific bank specialization does not vary systematically with bank size in the cross-section or in the time series. Moreover, using bank mergers as a source of variation in bank size and specialization, we find that market-specific 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.

As a final step, we consider the implications of market-specific bank specialization for the estimation of credit supply shocks. A large literature in economics and finance is concerned with estimating the economic impact of credit supply shocks such as bank failures, runs, liquidity shortages, or tighter monetary conditions. The now-standard approach of identifying the impact of banks' credit supply shocks, pioneered by Khwaja and Mian (2008), is to control for credit demand using firm-time fixed effects. The identifying assumption behind this approach is that changes in firms' credit demand are, in expectation, equally spread across all banks lending to the firm. In many settings this assumption is plausible assuming there is no market-specific bank specialization.

However, in the presence of market-specific bank specialization, this assumption holds only under restrictive conditions— e.g., for shocks to bank credit supply that are either uncorrelated with market-specific demand or that proportionally affect all activities in which banks may specialize. We illustrate how this identification assumption can

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

be tested using within-firm specifications that account for banks' pattern of export specialization using the empirical setting in Paravisini et al. (2015). We show that demand shocks can explain a larger amount of the within-firm variation in credit than bank funding shocks, which implies that ignoring market-specific bank specialization can lead to biased estimates.

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 to fund different projects by the same firm.[5] 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; Boyd and Prescott, 1986). However, diversification may prove costly when it implies expanding to markets in which the bank is not specialized.[6] It also implies that market-specific bank specialization directly affects the economy's pattern of comparative advantage across non-financial sectors.[7]

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; Drechsler

[5] Leading theories for multi-bank relationships hinge on arguments of ex post-renegotiation (Bolton and Scharfstein, 1996), information rents by relationship lenders (Rajan, 1992), and diversification of firms' exposure to bank failures (Detragiache et al., 2000), while existing explanations for loan syndicates include risk diversification and regulatory arbitrage (Pennacchi, 1988).

[6] Winton (1999) argues theoretically that there is a trade-off between diversification and the quality of loan monitoring. Acharya et al. (2006) find that more diversification leads to riskier lending among Italian banks. Berger et al. (2017) find that banks are more likely to rely on soft information in areas and industries to which they have high exposure. Granja et al. (2017) examine auctions of failed banks and show that banks specialize in certain business lines and geographic areas.

[7] 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), Manova (2013)).

et al., 2017; and Amiti and Weinstein, 2018). Our findings highlight the complementary role of market-specific bank specialization in the transmission of credit supply shocks. Market-specific bank specialization limits competition across banks, which amplifies the impact of financial crisis on the real economy. Our paper offers a way to separately identify the impact of market-specific bank specialization and credit supply shocks.

The rest of the paper proceeds as follows. Section 2 describes the data. In Section 3 we present a theoretical framework that guides our exercise and in Section 4, the empirical methodology to identify bank's lending advantage. The results are presented in Section 5. In Section 6 we discuss the difference between market-wide lending advantage and firm-specific relationship lending. In Section 7 we narrow down the potential sources of bank lending advantage. Finally, Section 8 concludes.

2 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 1994-2010. 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 1 shows summary statistics describing the data. The unit of observation in our empirical analysis in Section 4 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.

We emphasize that all loan-level data is 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 1 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.[8] The share of Peruvian exports across the main ten destinations, during the entire sample, is shown in Figure 1.[9]

[8]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.

[9]We do not observe data on loan covenants. It is our understanding that loan covenants have limited

3 Specialization: Framework, Measurement, and Descriptive Statistics

To motivate our definition of bank specialization, we present a model in which: 1) funding from one bank is not perfectly substitutable with funding from another, and 2) banks are heterogeneous in their lending capabilities for specific economic activities. In the data, these activities will correspond to export markets, and bank specialization may come from providing credit at a lower cost, more credit for the same borrower characteristics, or more value added services attached to the issuance of credit than other lenders. Since the source of advantages is unobserved by the econometrician, we model specialization in reduced form. We use the model to derive observable and testable implications of the existence of market-specific bank specialization (whichever their source) on bank lending portfolios and the equilibrium relationship between credit from specialized banks and the economic activity in the sector they specialize in. This framework also guides the revealed preference approach used to assess whether our specialization measure (based on the stock of existing loans) is an indicator of an advantage in lending to exporters to that destination (based on the flow of new loans).

3.1 Theoretical Framework of Specialized Bank Lending

We use a nested logit model with deterministic second stage, adapted from Anderson et al. (1987). Each bank b is characterized by an interest rate r_b and a vector of absolute lending advantage for each economic activity $c = 1, ..., C$ (e.g., export destination country), $\gamma_b = [\gamma_b^1, ..., \gamma_b^C]$. Each firm i is defined as a collection of activities. For each activity c the firm proceeds in two steps. First, it chooses a bank, and then, how much to borrow from the chosen bank. If a given bank b is chosen in the first step, then the optimal amount of credit demanded for the activity c, L_{ib}^c, is the one that maximizes output in activity c,

economic significance in our setting because they are difficult and costly to enforce in the Peruvian judicial system.

q_i^c, given a total cost of credit for that activity, $r_b L_{ib}^c \leq E_i^c$.

We assume a log-production function: $q_i^c = \ln(\gamma_{ib}^c L_{ib}^c) + \mu\epsilon_{ib}^c$, where ϵ_{ib}^c is an idiosyncratic factor, unobserved to the econometrician. Since the production function is monotone in L_{ib}^c, the demand for credit that maximizes output, provided b is the chosen bank to finance activity c, is given, simply, by the cost of credit, r_b, and the size of the activity, E_i^c: $L_{ib}^c = \frac{E_i^c}{r_b}$.

Given this credit demand, firm i's choice of bank for each activity in the first stage is the one that maximizes output for a given credit cost:

$$q_i^c = \max_b \left\{\ln(\gamma_b^c L_{ib}^c) + \mu\epsilon_{ib}^c\right\} = \max_b \left\{\ln(\gamma_b^c) - \ln(r_b) + \ln(E_i^c) + \mu\epsilon_{ib}^c\right\}.$$

This firm-activity specific credit 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.

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.[10] 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.[11]

The within-firm distribution of credit across banks is driven, one-to-one, by the within-

[10] 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.

[11] 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 (2017), Buchak et al. (2018), Egan, Hortaçsu and Matvos (2017), Egan, Lewellen and Sunderam (2017), and Xiao (2017).

firm share of productive activities:

$$L_{ib} = \sum_c L_{ib}^c = \frac{1}{r_b} \sum_c \mathbb{I}_b^c \, E_i^c$$

where E_i^c is total cost associated with productive activity c and $\mathbb{I}_b^c$ is an indicator function equal to one if $\ln(\frac{\gamma_b^c}{r_b})\mu\epsilon_{ib}^c$ is the maximum across all banks.

The interpretation of the lending advantage parameter, γ_b^c, is broad. It could represent a bank service attached to credit issuances. Or, given that it determines the firm's choice through the ratio γ_b^c/r_b, it could refer to an activity-specific interest rate discount. Absent the idiosyncratic factor (i.e., $\mu = 0$), this *Ricardian* 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_b^c/r_b. This motivates the specialization measure defined in the next subsection.

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_b^c/r_b across activities, variations in E_i^c (size of activity c for firm i) would not predict a systematic shifts of credit across banks. This is the null hypothesis of the empirical tests that we develop in Section 4. The alternative hypothesis is that banks are heterogeneous in their activity-specific advantages. Under the alternative hypothesis, variations in E_i^c are associated with systematic shifts in credit composition towards banks the bank with high γ_b^c/r_b.

3.2 Specialization Measure

Our goal is to develop a measure of specialization that is consistent with the above framework and that can be implemented with micro-data. Absent noise, a bank is specialized in sector c if it has the maximum γ_b^c/r_b across all $\{\gamma_{b'}^c/r_{b'}\}_{b'}$. The first empirical challenge is to identify the bank(s) with the highest γ_b^c/r_b in the presence of noise. The second challenge derives from the limitations of the observable data, which do not differentiate the amount of c-specific credit from the chosen bank b, only total borrowing by each firm from each bank. We construct an outlier-based measure of specialization that meets these two challenges. A bank is specialized in a given activity c (export destination country) if it is an outlier of bank export-weighted lending across banks within a given activity.

The first step in constructing the specialization measure is to aggregate the firm-activity specific credit demands across all firms. The optimal amount of c-specific credit from the chosen bank b is $L_{ib}^{c} = E_i^c / r_b$ and firm i chooses bank b to fund activity c if:

$$b = \arg\max \left\{ \ln(\gamma_b^c) - \ln(r_b) + \mu \epsilon_{ib}^c \right\}. \tag{1}$$

Assuming that $\{\epsilon_{ib}^c\}_i$ are identically, independently Gumbel distributed, the probability that a firm chooses b for activity c is given by:

$$Pr_b^c = \frac{\exp\left\{\ln(\gamma_b^c) - \ln(r_b)\right\}/\mu}{\sum_{b'} \exp\left\{\ln(\gamma_{b'}^c) - \ln(r_{b'})\right\}/\mu} = \frac{\left(\frac{\gamma_b^c}{r_b}\right)^{1/\mu}}{\sum_{b'} \left(\frac{\gamma_{b'}^c}{r_{b'}}\right)^{1/\mu}}.$$

The second step, necessary to make the measure feasible, is to aggregate activity-specific demand across all destinations c (we do not observe activity-specific credit). Summing across c, we obtain the demand for the representative firm:[12]

$$E[L_{ib}] = \frac{1}{r_b} \sum_c \widetilde{\gamma}_b^c \, E_i^c \qquad where: \quad \widetilde{\gamma}_b^c \equiv \frac{\left(\frac{\gamma_b^c}{r_b}\right)^{\frac{1}{\mu}}}{\sum_{b'} \left(\frac{\gamma_{b'}^c}{r_{b'}}\right)^{\frac{1}{\mu}}}.$$

The parameter $\widetilde{\gamma}_b^c$ captures the comparative advantage of b in lending towards activity c. It compares the lending advantage of bank b (relative to the cost of lending), with those of the entire market $\{\gamma_{b'}^c / r_{b'}\}_{b'}$. As explained in the previous subsection, the strength of the pattern of comparative advantage (i.e., its skewness) is mediated by the importance of the idiosyncratic noise (μ).

The third step is to substitute total cost of goods exported to c, E_i^c, for its empirical

[12] This representative-agent demand function coincides with the one derived from CES preferences with elasticity of substitution $\rho \equiv \frac{1-\mu}{\mu}$, which we used in a previous version of this paper.

counterpart. Since in our setting activities $c = 1, ..., C$ correspond to export destination markets, this cost can be proxied by X_i^c, total exports to c. This approximation is exact ($E_i^c \propto X_i^c$) under perfect competition or constant markup, a good approximation for Peruvian exports (mostly commodities). Thus:

$$E[L_{ib}] = \frac{1}{r_b} \sum_c \widetilde{\gamma}_b^c \, X_i^c. \tag{2}$$

A direct implication of Equation 2 is that the elasticity of demand for loans with respect to the value of goods exported to country c is increasing in the comparative lending advantage of bank b in activity c. We use this result to develop a revealed preference approach to identify the effect of lending advantages in the next section.

A second implication of Equation 2 leads to our measure of specialization. Equation 2 implies that the bank with the highest lending advantage in activity c will have, all else equal, the highest share of lending associated with activity c, S_b^c, defined as:

$$S_b^c \equiv \frac{\sum_{i=1}^{I} L_{ib} X_i^c}{\sum_{k=1}^{C} \sum_{i=1}^{I} L_{ib} X_i^k}, \tag{3}$$

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.

To understand the intuition behind this measure and the definition of *specialization*, it is useful to consider the case of single-activity firms, which endogenously choose to have a single banking relationship. If the idiosyncratic component $\{\epsilon_{ib}^c\}_i$ plays no role in bank choice (i.e., $\mu = 0$), all firms in the same activity c would choose the same bank. The bank b with the highest γ_b^c / r_b in country c will have $S_b^c = 1$ and all other banks $-b$ will have $S_{-b}^c = 0$. If the importance of the idiosyncratic motive is not zero, the shares of other banks will be positive $S_{-b}^c > 0$. Importantly, for sufficiently small μ, the bank b with highest γ_b^c / r_b will have the largest share of lending associated with activity c, S_b^c. That is, the bank with highest advantage in c will appear as an outlier in the distribution of shares of weighted exports to country c across all banks in the data. We demonstrate this with simulated data in the Internet Appendix.

With panel data we can measure the lending share every period, S^c_{bt}. We propose a non-parametric approach to systematically identify the outlier banks in the distribution of $\{S^c_{bt}\}$ for each country-year. Formally:

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

Identifying outliers using percentiles and interquartile ranges has the advantage that it does not rely on any assumptions about the distribution of bank portfolio shares.[13] In a normally distributed sample, our definition would correspond to observations above the mean plus 2.7 times the standard deviation, which corresponds to observations in the 1st-percentile of the distribution.[14]

It is worth highlighting two additional features of the identifying bank specialization using share outliers. The first is that identification of outliers is not affected by the bank size distribution. Each bank's share of exports to a country is measured relative to its own portfolio, and thus impervious to scale. Second, the identification of outliers is also not affected by size of the export markets. The share of bank lending, S^c_{bt}, associated with large markets (e.g., China or U.S.) will be systematically higher across all banks, but outliers are identified by comparing bank shares for a given country. The dummy variable $O(S^c_{bt}) = 1$ captures whether bank b is specialized in country c, and not whether bank b is specialized in general. In fact, with as many banks as destination markets, all banks can be specialized, each bank in a different country. In other words, our proposed measure captures a bank's departure from the overall specialization pattern of exports.

[13] See Hodge and Austin (2004) for a survey of outlier detection methods.

[14] In an online appendix, we simulate data using a simple version of the discrete choice model in Subsection 3.1 and show that this measure of specialization correctly captures the underlying pattern of banks' lending advantage.

To illustrate the approach, we use a box-and-whisker plot to represent the distribution of $\{S_{bt}^c\}$ for two countries, Switzerland and the U.S., in 2010 (Figure 2). To facilitate the interpretation, we plot $\{S_{bt}^c - \overline{S}_t^c\}$ instead of $\{S_{bt}^c\}$, so that the share distributions are centered at zero for each country. The top and bottom edges of the box denote the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the distribution, and the size of the box is the interquartile range (IQR). The whiskers denote the highest (lowest) datum within 1.5 $\times$ IQR of the 75$^{\text{th}}$ (25$^{\text{th}}$) percentile. Then, for a given country and year, we consider a bank to be an outlier of the distribution if its share of portfolio lending to the country lies outside the whiskers (outliers are identified with dots in the plot). For example, according to our definition, in 2010 Citibank and Scotiabank are specialized in lending to firms exporting to Switzerland, while Santander is specialized in lending to firms that export to the U.S.

To summarize, our measure of specialization has three important and desirable features. First, a measure based on outliers of portfolio shares is consistent with a theory where banks have advantages in lending towards specific activities. Second, it is based on observable measures and thus straightforward to implement with available micro-data. For contrast, a measure of specialization based on the amount of credit from bank b to firm i devoted to activity c would be impossible to implement with existing data-sets. And third, a measure of specialization based on the value of exports to a market captures portfolio share outliers that are driven by both the number of firms and firm size. This is an important characteristic. According to our definition, a bank may become 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 to a few large exporters relative to other banks. Both extremes are captured by the proposed specialization measure.

3.3 Bank Specialization Descriptive Statistics

In our data, the firms $i = 1, ..., I$ are Peruvian exporters, $c = 1, ..., C$ 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 shares of lending associated with each export market using the outstanding debt of Peruvian firms in the 33 banks operating in Peru between 1994 and 2010, as well as the firm-level export data by shipment to the 22 largest destination markets.[15]

The values of S^c_{bt} defined in (3) provide information on the heterogeneity in lending shares by country across banks. In Table 2, we present descriptive statistics of S^c_{bt} by country, demeaned by the average share across all banks in the corresponding country, $\overline{S}^c_t$. The median of $S^c_{bt} - \overline{S}^c_t$ is negative for every country, indicating that the within-country distribution of $\{S^c_{bt}\}$ is right-skewed. This is confirmed in column 5, where we report a large and positive skewness for every country. This skewness implies that for every destination country in the sample, there is at least one bank that specializes in financing exports to that destination. Figure 3 confirms this finding. It shows the box-and-whisker plot of the distribution of $S^c_{bt} - \overline{S}^c_t$ for each country during the years 1995, 2000, 2005, and 2010. The dots outside the range of the whiskers, for each country-year, correspond to the specialized banks according to Definition 1.

Table 3, column 1, reports the number of countries in which each bank specializes at least once in the sample period. Banks specialize in several countries during the 17-year period, with one bank (code 73) reaching a maximum of 15 countries out of a total of 22. These numbers decline considerably once we count the countries in which each bank specializes for at least 25%, 50%, or 75% of the time that the bank appears in the sample (columns 2 to 4). Even using a stringent definition of specialization—in which the bank must be an outlier in the country for at least 75% of the observed sample period in order to be considered specialized—25 out of 33 banks in the sample specialize in at least one country. This is because the pattern of bank specialization is very persistent, as shown in Figure 4. The auto-correlation between bank-country specialization is constant at around 0.45 over a 10 year period.

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

[15]The bank panel is unbalanced because of entry, exit and M&A activity (we discuss M&A activity in more detail in subsection 6.3).

Whether this measure is associated with an underlying bank advantage in lending to the market of specialization is an empirical question. Our empirical approach, explained in the next section, tests not only whether banks have an advantage in lending towards specific destinations, but also whether this measure of specialization indeed provides information about such an advantage.[16]

4 Identifying Advantage in Lending

We use three different empirical strategies to characterize lending advantages. The first is aimed at testing in the data whether lending advantages *exist*, and is based on the prediction, derived from Equation 2 in Subsection 3.1. This approach to evaluate advantages is robust and generalizable, as it circumvents the problems involved in attempting to infer advantages from the direct observation of its potential sources or relying on instrumental variables.

The two other empirical approaches are aimed at identifying the magnitude of the advantages and their consequences for how demand shocks affect the health of the banking sector, and how credit supply shocks affect output. We measure how the following elasticities vary with the degree of bank specialization: the elasticity of firm's credit in response to a demand shock in the export markets, and the elasticity of exports to a credit supply shock. The estimation of these elasticities relies on using plausible exogenous variation to export demand and to the supply of credit, which we explain in more detail below.

[16]Our work focuses on bank specialization in export activities. In related work, Granja et al. (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.

4.1 Revealed Preference Identification

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

$$L_{ibt} = L\left(L^{S}_{bt}, L^{D}_{it}, \mathcal{L}_{ibt}\right). \tag{4}$$

Bank-firm outstanding credit is an equilibrium outcome at time t, determined by the overall supply of credit by the bank, L^{S}_{bt}, which varies with bank-level variables such as overall liquidity, balance-sheet position, etc.; the firm's overall demand for credit L^{D}_{it}, which varies with firm-level productivity, demand for its products, investment opportunities, etc.; and, finally, a firm-bank specific component, $\mathcal{L}_{ibt}$, 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, $\mathcal{L}_{ibt}$, using saturated regressions. Specifically, we account for the bank-specific credit supply shocks L^{S}_{bt} (common in expectation across all firms) and all firm-specific credit demand shocks L^{D}_{it} (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, our baseline specification is:

$$\ln L_{ibt} \quad = \quad \alpha^{c}_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \, \ln X^{c}_{it} + \beta_2 \, S^{c}_{ibt} + \beta_3 \, S^{c}_{ibt} \times \ln X^{c}_{it} + \epsilon^{c}_{ibt}, \tag{5}$$

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, $\beta_3 = 0$, meaning that firm exports to a country are not systematically correlated with borrowing from banks specialized in that country.

[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).

The measure of specialization used in this analysis, S^c_{ibt}, is based on a rolling period of three years up to the year of the loan: for every year t, it corresponds to the fraction of years between $t-2$ and t in which bank b is an outlier in the loan distribution associated with country c.[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:

$$S^c_{(-i)b\tau} \equiv \frac{\sum_{k\neq i}^{I} L_{bk\tau} X^c_{k\tau}}{\sum_{c=1}^{C}\sum_{k\neq i}^{I} L_{bk\tau} X^c_{k\tau}}, \tag{6}$$

Using this leave-one-out share in our measure of specialization in Definition 1 leads to the following firm-varying measure of bank specialization:

$$S^c_{ibt} = \frac{1}{3}\sum_{\tau=t-2}^{t} O(S^c_{(-i)b\tau}), \tag{7}$$

Note that although outstanding debt is a firm-bank-year value, L_{ibt}, there are 22 relationships like the one in (5) for each firm-bank-year—one for each country c in our analysis sample. To estimate the parameters of (5), 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 the revealed preference approach for identifying the existence of lending advantages is that it can 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 following joint hypothesis: that

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

banks have advantages in lending, and that our measure of specialization captures it. The disadvantage is that the magnitude of the covariance measure, β_3, requires careful interpretation. Thus, we turn next to estimating elasticities to demand and supply shocks, which have direct economic meaning and provide information on the magnitude of lending advantages.[19]

4.2 Elasticity of Credit Demand to Exports

To obtain the elasticity of credit to changes in the demand for exports we use again specification (5), 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.[20] This exercise is similar to the gravity equation 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.[21]

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 is to expect 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

[19] An equivalent approach to test for bank specialization is to regress lending on firm and bank time effects and examine whether the residuals are persistent. Our test is more stringent, as it requires the residuals to be correlated with our measure bank-industry specialization interacted with exports.

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

[21] 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 et al. (2012) for the effect of real exchange rate shocks on exports using firm-country panel data for French firms.

the bank-time fixed effects. Therefore, coefficient β_3 in this specification can be interpreted as the elasticity of the firm-bank credit component ($\mathcal{L}_{ibt}$ in equation 2) to destination-specific export variation for banks specialized in the destination country, relative to non-specialized banks (for which the elasticity is β_1).

4.3 Elasticity of Exports to Credit Supply

The goal is to 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:

$$\ln X^c_{ipt} = \alpha^c_{ibp} + \alpha^c_{pt} + \beta_1 \ln L_{ibt} + \beta_2 S^c_{ibt} + \beta_3 \; S^c_{ibt} \times \ln L_{ibt} + \epsilon^c_{ibpt} \tag{8}$$

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 moths after July 2008.[22] Together with the results, we show in Subsection 5.3, that this instrumental approach is still valid in the context of specialized banks. The coefficient β_3 in specification 8 can be interpreted as the elasticity of exports to credit sup-

[22]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.

ply for banks specialized in the market of export destination, relative to other banks (for which with elasticity is β_1).

The regression includes firm-product-bank-country fixed effects, α^c_{ipb}, which control for all (time-invariant) unobserved heterogeneity across firms and banks in exporting that product to that destination.[23] 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.[24] Note that although export is a firm-product-country-year value, X^c_{ipt}, the right-hand side of the relationship (8) varies also at the bank level. To estimate the parameters in (8), 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.

A coefficient estimate $\beta_3 > 0$ indicates that, for a given firm, the elasticity of exports to a bank credit supply shock is larger for exports to countries in which the bank specializes in. This specification tests 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. The importance of the last component of the joint hypothesis lies in that if it were rejected, then differences in bank advantages would have no impact on the patterns of exporting activity. Finding $\beta_3 > 0$ implies that bank advantages do affect exports and competition across lenders.

5 Bank Specialization, Lending, and Exports

This section presents the estimates from the three empirical specifications described in Section 4: 1) a test of whether the correlation between credit and exports is larger for

[23]Our approach is stringent in that we control for time-invariant bank specialization at the firm-product-bank-country level and only use variation over time. We examine time-invariant bank specialization in our analysis of global banks in section 7.1.

[24]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.

banks specialized in the market of destination (revealed preference), 2) an estimate of the effect of demand shocks to product markets on the demand for credit of specialized banks, and 3) an estimate of the effect of a supply shock from a specialized bank on output in the market of specialization.

5.1 Revealed Preference Results

We present in Table 4, column 1, the estimates of specification 5. Our coefficient of interest on the interaction of exports and the specialization measure is positive and significant at the 1% level. This result shows that when a firm expands its exports to a country, it increases its borrowing disproportionately from banks that specialize in the same country. The inclusion of firm-time fixed effects implies 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.[25] 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 magnitude of the effect, we compare the estimates for specialized and non-specialized lenders in the same specification. The coefficient on exports with non-specialized lenders is 0.024, while the point estimate on the interaction term of exports and the specialization measure is 0.019. The relative size of the coefficients implies that, for the same change in exports to a country, the increase in borrowing is 79% larger for banks specialized in that country, relative to non-specialized banks.

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 in. The results also validate that our measure of specialization captures lending advantages.

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

5.2 Export Demand and Credit

Table 4, columns 2 and 3, present the first-stage and instrumental variables (IV) estimation of specification 5, using GDP growth and real exchange rate in the destination country (and their interaction with specialization) as an instrument for export demand (and its interaction with specialization).

The first stage (Table 4, Column 2) is a regression of exports to country i 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 30. The same is true for the second first-state regression (not shown for brevity), in which the left hand-side variable is the interaction of exports to country i with the specialization measure.

The IV estimates of the elasticity of credit from specialized and non-specialized banks to an export demand shock (Table 4, Column 3) are both positive. However, the credit elasticity from non-specialized banks is noisily estimated and not statistically different from zero. In contrast, the point estimate of the credit elasticity from specialized banks (relative to non-specialized ones) is 0.169 and statistically different from zero.[26]

The elasticity to an export demand shock of credit from specialized banks is 50% larger than from non-specialized banks. The order of magnitude of the effect of specialization on the elasticity is similar to the effect of specialization on the covariance of exports and credit obtained in the revealed preference approach above (79%). This result is important because it implies that 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 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 OLS estimates discussed in the previous subsection (column 1). The IV approach isolates the variation in exports and credit due to market-specific export demand shocks. In contrast, the OLS estimates of the revealed preference approach capture

[26] A one-standard deviation in specialization is 0.17. Hence, a one-standard deviation increase in specialization raises the credit elasticity by 2.9%.

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.

5.3 Credit Supply and Exports

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.

Table 4, columns 5 and 6, presents the OLS and IV estimates of specification 8. The endogenous variable, credit by bank b to firm i, and its interaction with bank specialization, are instrumented with the bank exposure instrument, $Exposed_b \times Post_t$, and its interaction with specialization measures. Table 4, column 4, shows the bank exposure instrument is negatively and significantly correlated with lending, implying that banks with more exposure to foreign liabilities reduced lending more after the crisis. The two first stage regressions have F-statistics of 7.1 and 16.

The IV estimate in column 6 measures the elasticity of exports to a market to a credit supply shock and how this elasticity varies with the specialization of the bank in that market. The point estimates imply that a 10% reduction in a bank's credit supply leads to a 7% decline in exports to countries in which the bank specializes in, and a 1% decline in exports to countries in which the bank does not specialize in. All point estimates are precisely estimated and the difference between the export elasticities across specialized and non-specialized lenders is statistically significant at the 10%-level.[27]

These elasticity estimates and their variation with bank specialization imply that lending advantages make specialized bank credit difficult to substitute. It implies that 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.

5.4 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] Put simply, the approach assumes that credit demand shocks *cannot* induce firms to systematically shift their borrowing from one bank to another, and thus can be controlled for with firm-time fixed effects. This assumption is only true in general if banks do not have lending advantages and do not specialize, an assumption that is shown not to hold in our setting. The assumption may hold under restricted circumstances: if the source of the credit supply shock is uncorrelated with anything affecting specialized demand. We can illustrate in our setting how regressions saturated with firm fixed effects and augmented with specialization measures can be used to evaluate the validity of this identification assumption.

[27] As in the previous subsection, the elasticity estimates (column 6) are much larger than the OLS estimates in (column 5), indicating that a small fraction of the total variation in bank credit during the 2008 financial crisis was driven by credit supply.

[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.

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 $Exposed_b$ –i.e., 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 2008-2009. Using credit data we estimate the following specification:

$$\ln(L_{ibt}) = \alpha_{ib} + \alpha_{it} + \beta \cdot Exposed_b \times Post_t + \nu_{ibt}, \tag{9}$$

where the definition of the variables and time periods coincide with those in (8). The regression includes firm-bank fixed effects, α_{ib}, which control for all (time-invariant) unobserved heterogeneity in the demand and supply of credit. It also includes a full set of firm-time dummies, α_{it}, that control for the firm-specific evolution in 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 5, 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 absorb credit demand variation *only if* a change in firm credit demand is, in expectation, equally spread across all banks lending to the firm, an assumption that may not hold in the presence of bank specialization.

We augment specification 9 with the variable $(C(X_i^c > 0) \bigcap C(S_{ib}^c > 0)) \times Post_t$. The dummy $(C(X_i^c > 0) \bigcap C(S_{ib}^c > 0))$ is equal to one if the set of countries supplied by firm i, $C(X_i^c > 0)$, has at least one country that belongs to the set of specialization of bank b, $C(S_{ib}^c > 0)$—i.e., countries for which S_{ib}^c defined in (7) is positive in the Pre period. The coefficient on this additional term measures the change in the equilibrium amount of credit to firms that export to the country in which bank b specializes, relative to the change in credit to firms that do not. The estimated coefficients of the augmented specification are shown in Table 5, column 2. The estimated coefficient on the additional term, -0.199, 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 20% during the sample period. Thus, the variable $(C(X_i^c > 0) \bigcap C(S_{ib}^c > 0))$ recovers bank-specific credit demand shocks that *are not* accounted for by the firm-time dummies in specification 9.[29]

Adding $(C(X_i^c > 0) \bigcap C(S_{ib}^c > 0))$ to specification 9 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 2.3 —i.e, $(0.199 + 0.155)/0.155$.[30]

We emphasize that the results are estimated in the context of the 2008 financial crisis. In a financial crisis banks are likely to be credit constrained, which may strengthen the effect of bank specialization on lending outcomes. Even though the coefficient may be different during regular times, the estimate in a crisis period is an important parameter for policy analysis because it is during a financial crisis that the welfare cost of credit

[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.

supply shocks may be the largest.

The role of market-specific bank specialization is also important when considering alternative methods for estimating the impact of credit supply shocks. For example, Amiti and Weinstein (2018) develop a methodology to separate firm borrowing shocks from bank supply shocks with matched bank-firm data. The paper notes that the approach is based on the assumption that all variation in lending is either firm or bank specific, as is often assumed in the financial intermediation literature. However, this assumption may not hold in a setting with market-specific bank specialization because market-specific shocks affect only certain lending relationship within bank and only certain activities within a firm, thereby violating the identification assumption. Similar to the setting above, one therefore needs to adjust for market-specific bank specialization when applying this methodology.

6 Market Advantage vs Relationship Lending

In our analysis so far we have assumed that banks may have advantages in lending to firms operating in a market or sector of economic activity. This type of market- or sector-specific advantages are potentially distinct from the firm-specific advantages in lending emphasized by the existing literature on banking and relationship lending.[31] The distinction is important because market-specific and firm-specific advantages have different implications for the industrial organization of bank credit markets but may lead to the same observed phenomena. For example, consider the following two rationales for firms borrowing from multiple lenders. In the presence of market-specific advantages, the firm borrows from lenders specialized in each market it operates in to exploit the lending advantages. In the presence of firm-specific advantages, in contrast, firms borrow from multiple lenders to avoid the monopoly rents that a privately inform bank extracts from

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

it.

In this section we explore whether the lending advantages uncovered here are market-specific or firm-specific, through three approaches: 1) by estimating whether specialization predicts extensive margin decision of where to export and whom to borrow from, 2) by exploring the connection between lending advantage and the size of firms and banks, and 3) by exploring the lending advantage patterns of banks before and after a merger or acquisition.

6.1 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 a 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 in 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.[32] We estimate the following linear probability model (parallel to specification 5):

$$\begin{aligned}(L_{ibt} > 0 | L_{ibt-1} = 0) \;\; &= \;\; \alpha^c_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \, (X^c_{it-1} > 0 | X^c_{it-2} = 0) + \beta_2 \, S^c_{ibt} \\ &\quad + \beta_3 \, S^c_{ibt} \times (X^c_{it-1} > 0 | X^c_{it-2} = 0) + \epsilon^c_{ibt}, \end{aligned} \tag{10}$$

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, $(X^c_{it-1} > 0 | X^c_{it-2} = 0)$ 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 is not firm-i specific.

We also test an alternative extensive margin: whether the probability that a firm starts

[32] As shown below, we also examine the situation where the firm first borrows and then starts exporting. We think that either timing is plausible

exporting to country c increases after the firm starts borrowing from a bank specialized in that destination.

$$
\begin{aligned}
(X_{ibt} > 0 | X_{ibt-1} = 0) \;\; &= \;\; \alpha^{c}_{ib} + \alpha'_{it} + \alpha''_{bt} + \beta_1 \, (L^{c}_{it-1} > 0 | L^{c}_{it-2} = 0) + \beta_2 \, S^{c}_{ibt} \\
&\quad + \beta_3 \, S^{c}_{ibt} \times (L^{c}_{it-1} > 0 | L^{c}_{it-2} = 0) + \epsilon^{c}_{ibt}, \qquad (11)
\end{aligned}
$$

Our coefficient of interest in specifications 10 and 11 is β_3. A coefficient $\beta_3 > 0$ indicates that the probability of starting to borrow from a bank increases after the firm starts exporting to the bank's country of specialization (equation 10), or that the probability of starting exporting to a given destination increases after the firm starts borrowing from a bank specialized in that country (equation 11).

Table 6, columns 1 and 2, present the OLS estimates of the entry margin specifications in (10) and (11) respectively.[33] The coefficient estimates in column 1 indicate that exporting to a new destination increases the probability of starting a banking relationship with a non-specialized bank (S^{c}_{ibt}=0) by 0.06 percentage points. Instead, the probability of starting a banking relationship with a bank that has specialized in that destination for the full sample period up to t (S^{c}_{ibt}=1) increases by 0.40 percentage points, almost seven times more than with a non-specialized bank. 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%.

The probability of exporting to a new country increases by 2.6 percentage points the year after a firm starts borrowing from a bank specialized in that destination (column 2). There is no effect for non-specialized lenders. 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 increases 4.8 times

[33] The sample for this estimation is the combination of all possible bank-firm relationships—meaning all the bank-firm pairs that do not have a positive outstanding balance in any given year (thus the large sample size and the low probability of a new relationship).

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.

6.2 Specialization and Bank and Firm Size

We explore the connection between lending advantage and the size of firms and banks. This is motivated by the theoretical framework in Stein (2002), which suggests that there is a trade-off between bank and firm size and the firm-specific advantage generated through relationship lending. The informational wedge between insider and outsider banks is understood to be more acute for small firms, which are more opaque than large corporations. Moreover, this firm-specific information is understood to be lost in large banks, as it is communicated across more hierarchical layers of the organization (*soft* information). In contrast, if the source of the lending advantage is scalable, not only will the advantage persist for large banks and firms, but the banks with larger advantages will be larger.

Table 7, columns 1 and 2, show the correlation between our measure of specialization, defined in (7), and bank size, measured by total (real) lending in Peru. Since foreign-owned banks are much larger than implied by their lending in Peru, we also include the dummy $Foreign_{bt}$ to capture this global size difference. Larger and foreign-owned banks are not more likely, in the cross-section, to specialize in export markets (column 1). For a given bank over time (column 2), the number of countries in which banks specialize does not grow with size, but banks do increase their set of specialization after being acquired by a foreign bank.

We are interested in whether the patterns obtained from estimating the baseline regressions in Table 4 are similar in the cross-section of bank size and foreign ownership status. We estimate specification 5 augmented with interactions of the right-hand-side variables with $Foreign_{bt}$ and $SmallBank_b$, a dummy equal to 1 if b is not one of the ten largest institutions measured in total loans over the full sample period.[34] The results are reported in Table 7, columns 3 and 4. The coefficient on exports interacted with specialization is similar to that in the baseline specification in Table 4. This implies that the ten largest banks in Peru have a significant advantage in lending to the countries in which they specialize. The coefficient on the interaction with $SmallBank_b$ is negative but statistically insignificant (column 3). Although the point estimate is noisily estimated, its magnitude suggests that smaller banks may have a smaller lending advantage or none at all. Similarly, the lending advantages of foreign and domestic banks are not significantly different from each other (column 4). In column 5 we analyze whether the lending advantage is related to the firm size, measured by total exports. The correlation between export flows and credit is larger for firms in the top 10% of the total exports distribution during at least one year in our sample. But the lending advantage, measured by the interaction term $S^c_{ibt} \times \ln X^c_{it}$, does not vary across firm size.

6.3 Transmission of Lending Advantage into Merged Banks

To further explore the transmission and communication of the lending advantage within the financial institution, 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 5 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 defined in Definition 1, $S^c_{ib} = O(S^c_{ibt})$, computed the year before the

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

merger. We combine the merging entities into a single one before the merger, and we use the maximum of the outlier indicators of the two banks as a measure of their combined specialization (e.g., if, before the merger, bank 1 specialized in country A and bank 2 specialized in country B, then the combined entity is considered to specialize in A and B before the merger).

We first replicate our baseline estimation in (5) without the merger interaction term to corroborate that the point estimates are robust to the change in sample and specification (Table 8, column 1). The coefficients on the term $S^c_{ib} \times \ln(X^c_{it})$ are positive and significant, similar in magnitude to those in our baseline result in Table 4. The relationship between exports and lending is somewhat smaller (0.012 vs. 0.024 in the baseline regression), which implies that, in this subsample, the elasticity between exports and bank credit of specialized banks is about 130% larger than for non-specialized banks (it was 79% in the baseline regression).

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, $S^c_{ib} \times \ln(X^c_{it}) \times Merger_{bt}$, measures whether the link between the specialization and lending is affected by the merger. The point estimate in column 2 is positive and statistically significant at the 5% level. That is, the merged entity inherits, and even deepens, the specialization of the original banks.

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

7 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 3.2. 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.

In this section we use our empirical methodology to characterize the lending advantage in our data, which narrows down potential mechanisms. First, we explore whether bank specialization patterns are related to the international presence of global banks such as the country of ownership and the location of international subsidiaries. Second, we examine whether the local distribution of bank branches is correlated with the geographical distribution of firms exporting to same destinations. And finally, we explore an alternative source of lending specialization based on the mix of products exported by the firms.

7.1 International Presence of Global Banks

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 9, column 1, shows the cross-sectional correlation between the bank-country specialization index and: 1) $CountryOwnership_b^c$, a dummy equal to 1 if bank b's headquarters are located in country c; 2) $CountrySubsidiary_b^c$, a dummy equal to 1 if bank b has a subsidiary in country c in 2004;[35] 3) $CommonLanguage_b^c$, a dummy equal to 1 if the language in bank b's headquarters coincides with that in country c; and 4) $DistanceToHeadquarters_b^c$ between the country of ownership and the export destination c.[36] For this cross-sectional analysis, we use the measure of specialization in Definition 1, $O(S_{bt}^c)$, averaged during the entire life of the bank.[37] We find that, indeed, there is a connection between the bank's country of ownership and the set of specialization. Banks are more likely to specialize in the country of their headquarters or in countries with the same language.

We then explore whether the bank's country of ownership is a sufficient statistic of the market-specific lending advantages found in our baseline regressions in Table 4. If lending advantages were driven exclusively by the location and network of the headquarters, including the above variables in our baseline revealed preference regression would make the specialization measure redundant. We explore this possibility by expanding the baseline regression in (5) with the four indicators 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 9, columns 2 and 3. None of these interaction terms is statistically significant, and their inclusion in the re-

[35]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).

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

[37]That is, S_{ibt}^c, as defined in equation 7, up to the last year the bank appears in our dataset (t_F): $S_{ibt}^c = \frac{1}{t_F - t_0} \sum_{\tau=t_0}^{t_F} O(S_{b\tau}^c)$.

gression does not change the magnitude or the significance of the interaction of exports and specialization.[38]

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.

7.2 Geographical Distribution of Local Branches

Another potential source of destination-specific lending advantage is the geographical proximity between exporters and banks in Peru. If firms that export to a specific country are geographically clustered, then banks that have a larger presence in that area may end up specializing in funding exports to this country.

There are 1,853 districts in Peru and each denotes a relatively small geographical area. Exporter location, obtained from the tax authority web page (SUNAT), is concentrated in 305 districts, and the top ten districts account for 52.3% of the exporters. Bank branch location data are from the bank supervision agency in Peru and are only available after 2001, so we restrict the sample to the 2001 to 2010 period for this analysis. Bank branch location is also geographically concentrated. The 1,455 bank branches in Peru in 2010 were located in only 144 districts.

We test whether the destination-specific lending advantage can be explained by local clustering. To do so, we augment the baseline regression 5 with two measures of proximity between firm i and bank b (and their interaction with firm exports, $\ln(X_{it}^{c})$): 1) a dummy if bank b has a branch in year t in the district in Peru where firm i is located, and 2) the number of branches that bank b has in year t in the district where firm i is located. Table 10, column 1, replicates the baseline regression estimates on the 2001 to 2010 and obtains very similar estimates to those in Table 4. Column 2, shows the estimated coefficients on the specification augmented with the local distance variables and their in-

[38]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.

teraction with firm exports. We find that the coefficient on the interaction between the bank specialization measure and exports does not change after the inclusion of the local geography variables. This implies that local distance to a branch does not explain the bank advantages related to specialization.

7.3 Product or Destination Advantage?

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

We test for industry-specific lending advantage in Table 10, column 3. We further disaggregate firms' annual exports into product-destination flows, X_{it}^{pc} (products defined according to 2-digit categories of the Harmonized System). We can therefore analyze whether the baseline measure of bank specialization based on country of destination (S_{ibt}^{c}) or the one based on export products (S_{ibt}^{p}) is a better predictor of the pattern of credit. When both interactions are included, the baseline results are maintained. The elasticity of credit to exports, at the product-destination level, is 53% larger for a bank that has been specialized in the country of destination during the whole sample relative to a non-specialized bank. The interaction with product-specialization, on the other hand, turns insignificant when the two measures of specialization are included. We conclude that in our sample, although both measures of specialization are highly correlated, bank specialization on export destination is a better predictor of bank lending patterns.

8 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 an 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 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.

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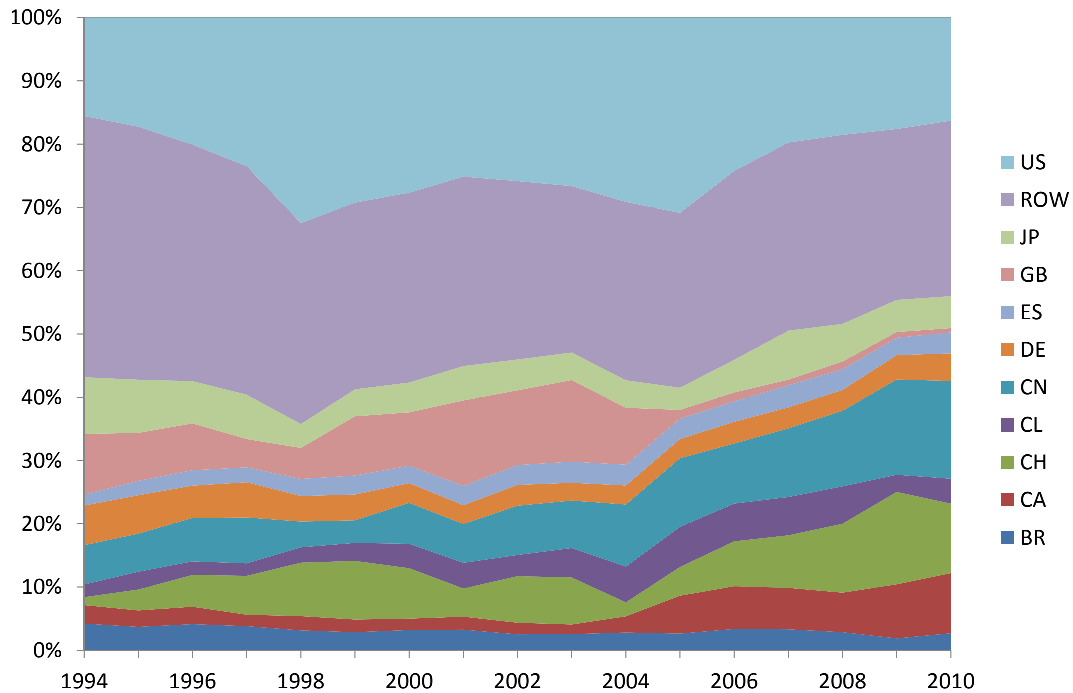
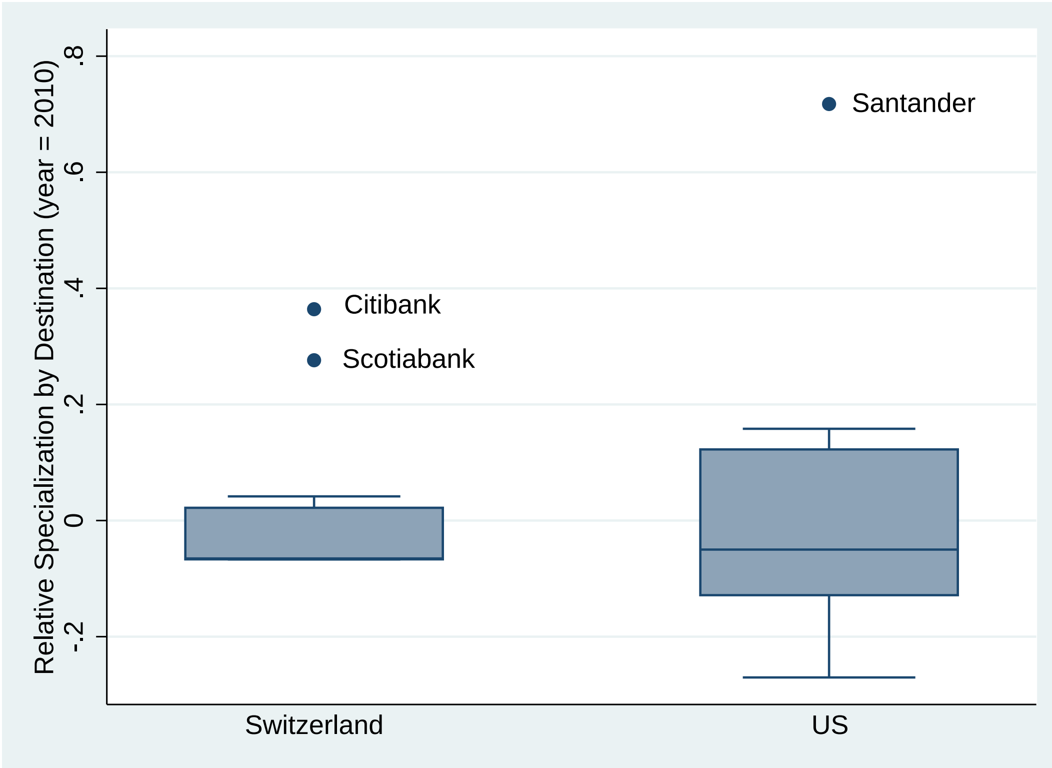
Figure 1: Export Composition by Destination



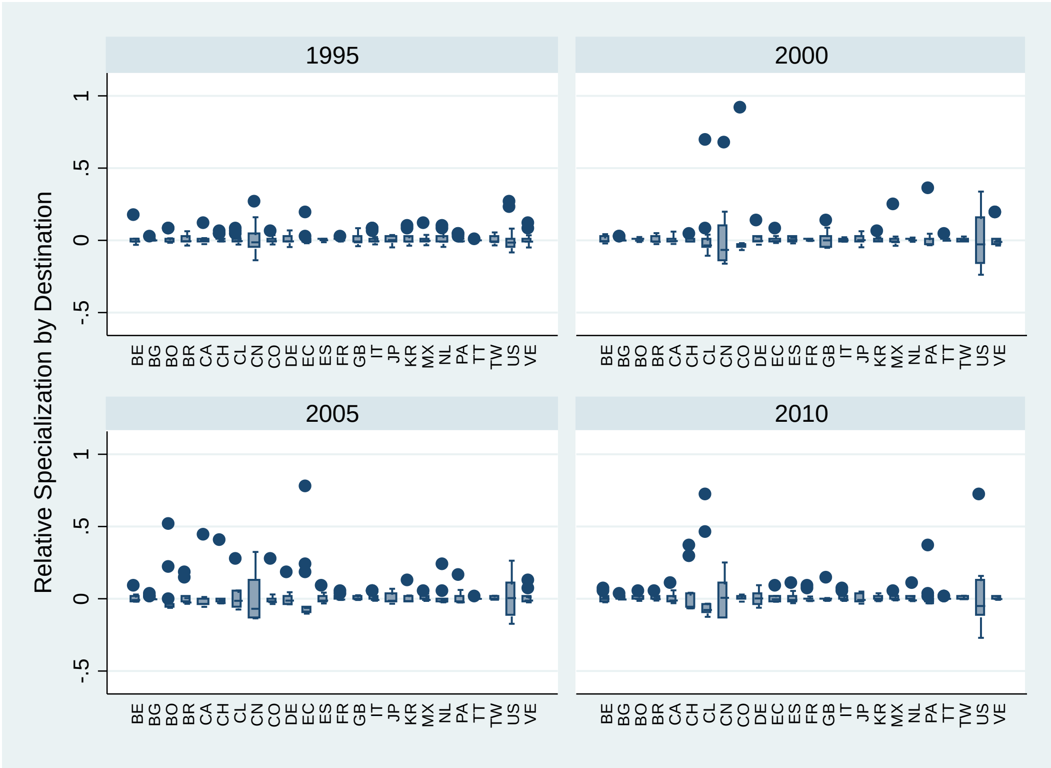
Note: Export shares according to export values. The ten main destinations included in the figure are United States, Japan, Great Britain, Spain, Germany, China, Chile, Switzerland, Canada and Brazil.

Figure 2: Outlier Definition: Example



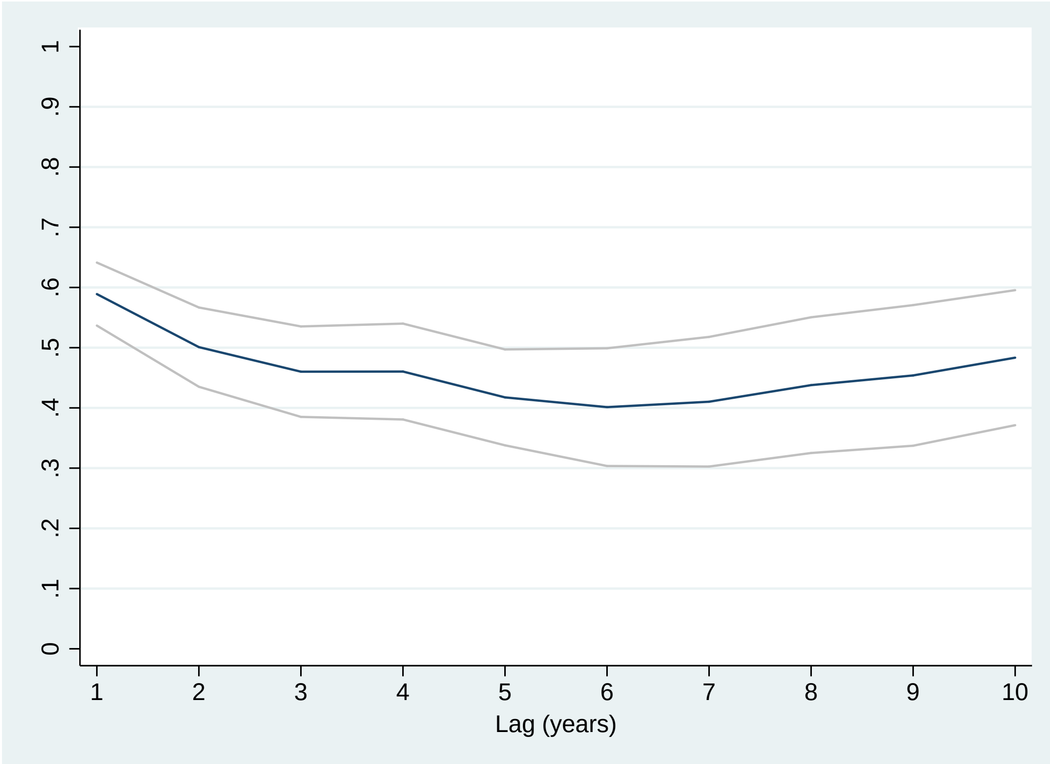
Note: The boxes encompass the interquartile range of the distribution of S^c_{bt} (defined in equation 3) for each country in 2010. The limits of the lines encompass 4 times the interquartile range. The dots outside that range, for each country-year, correspond to the specialized banks according to Definition 1.

Figure 3: Distribution of Bank Lending Shares by Country



Note: The boxes encompass the interquartile range of the distribution of S^c_{bt} (defined in equation 3) for each country c, in years 1995, 2000, 2005, and 2010. The limits of the lines encompass 4 times the interquartile range. The dots outside that range, for each country-year, correspond to the specialized banks according to Definition 1.

Figure 4: Persistence of Bank Specialization



Note: Auto-correlation in the bank set of specialization over a 10 year period: $corr(O(S_{bct}), O(S_{bct-\tau}))$ for $\tau = 1, ..., 10$ and 95% confidence interval. $O(S_{bct})$ defined in Definition 1.

Table 1: Descriptive Statistics

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

Note: The statistics in Panel 1 describe the full firm-bank-country-time panel used in Section 5, which has 378,766 observations. S^{c}_{ibt}, defined in (7), is our leave-i-out measure of specialization of bank b in country c in the last three years up to t. The variable Outstanding Debt has the same value across all destinations within the same firm-bank-time and, similarly, the variable Exports has the same value across all banks for the same firm-country-time. Panel 2 describes the firm-time panel, which has 45,762 observations. There are 14,267 firms in the dataset.

Table 2: Distribution of Bank Lending Shares by Country

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

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

Table 3: Patterns of Bank Specialization

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

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

Table 4: Lending Advantage and Specialization

	Revealed Preference (Baseline)	Export Demand Shock		Credit Supply Shock		
Dep. Variable	$\ln(L_{ibt})$	$\ln(X_{it}^c)$	$\ln(L_{ibt})$	$\ln(L_{ibt})$	$\ln(X_{ipt}^c)$	
	OLS	First Stage	IV	First Stage	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$S_{ibt}^c \times \ln(X_{it}^c)$	0.019***		0.169**			
	(0.006)		(0.063)			
$\ln(X_{it}^c)$	0.024***		0.329			
	(0.006)		(0.194)			
S_{ibt}^c	0.000		-0.003		-0.073**	-0.156
	(0.030)		(0.011)		(0.038)	(0.106)
$GDPGrowth_t^c$		0.010**				
		(0.004)				
$\ln(RER_t^c)$		0.499***				
		(0.066)				
$Exposed_b \times Post_t$				-0.181***		
				(0.064)		
$\ln(L_{ibt}) \times S_{ibt}^c$					-0.004	0.630*
					(0.019)	(0.324)
$\ln(L_{ibt})$					0.016	0.095**
					(0.012)	(0.042)
Firm-Bank-Country FE	Yes	Yes	Yes	–	–	–
Firm-Year FE	Yes	Yes	Yes	No	No	No
Bank-Year FE	Yes	Yes	Yes	No	No	No
Bank-Firm-Product-Country FE	–	–	–	No	Yes	Yes
Product-Country-Year FE	–	–	–	No	Yes	Yes
Observations	334,432	303,942	303,942	51,024	51,024	51,024
R^2 adj	0.31	0.27		0.19	0.19	

Note: L_{ibt} is the credit of firm i with bank b in year t, X_{it}^c is annual exports of firm i to country c in year t, and X_{ipt}^c is annual exports of firm i to country c and product p (HS 4-digits). S_{ibt}^c is the measure of specialization of bank b in country c in the three years up to year t, defined in 7. Column 1 shows the Revealed Preference estimation 5. Column 3 shows results of specification 5 using GDP growth ($GDPgrowth_t^c$) and real exchange rate (RER_t^c), and the corresponding interactions, to instrument for $ln(X_{it}^c)$ and $ln(X_{it}^c) \times S_{ibt}^c$. Column 6 shows the results of estimation 8 using $Exposed_b \times Post_t$, and the corresponding interactions, as an instrument for L_{ibt} and $L_{ibt} \times S_{ibt}^c$ in years $t = \{Pre, Post\}$, 12 months before and after July 2007. $Exposed_b$ is a dummy equal to 1 for exposed banks– i.e., bank-b's share of foreign debt in 2006 is above the system's mean. $Post_t$ is a dummy equal to 1 if $t = Post$. Standard errors are clustered at the bank and firm levels in columns 1 to 3, and at the bank and product-destination level in columns 4 to 6. ***p< 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 5: Identification of Credit Supply Shocks

	$\Delta \ln L_{ib}$	
	(1)	(2)
$Exposed_b$	-0.168***	-0.155***
	(0.046)	(0.049)
$C(X_i^c > 0) \bigcap C(S_b^c > 0)$		-0.199**
		(0.079)
Firm FE	Yes	Yes
Obs	10,334	10,334
R^2 adj	0.261	0.262

Note: Results of the within-firm specification in (9). $\Delta L_{ib} \equiv \ln L_{ibPost} - \ln L_{ibPre}$ is the change in bank-firm credit; $Exposed_b$ is a dummy equal to 1 for exposed banks–i.e., bank-b's share of foreign debt in 2006 is above the system's mean; and $C(X_i^c > 0) \bigcap C(S_{ib}^c > 0)$ is a dummy equal to one if, in the Pre period, the set of countries supplied by the firm has at least one country that belongs to the set of specialization of the bank (i.e., set of countries with positive S_{ibt}^c). Standard errors clustered at the bank level. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 6: Specialization and New Banking Relationships

Dep. Variable	$(L_{ibt} > 0 \mid L_{ibt-1} = 0)$ (x100) (1)	$(X^c_{it} > 0 \mid X^c_{it-1} = 0)$ (x100) (2)
$S^c_{ibt} \times (X^c_{it-1} > 0 \mid X^c_{it-2} = 0)$	0.400***	
	(0.065)	
$(X^c_{it-1} > 0 \mid X^c_{it-2} = 0)$	0.058***	
	(0.006)	
$S^c_{ibt} \times (L_{ibt-1} > 0 \mid L_{ibt-2} = 0)$		2.578***
		(0.155)
$(L_{ibt-1} > 0 \mid L_{ibt-2} = 0)$		-0.006
		(0.005)
S^c_{ibt}	-0.003**	-0.190***
	(0.002)	(0.015)
Bank-Country FE	Yes	Yes
Bank-year FE	Yes	Yes
Firm-year FE	Yes	Yes
Observations	145,599,237	145,869,772
$R^2 adj$	0.28	0.26

Note: L_{ibt} is the credit of firm i with bank b in year t. X^c_{it} is annual exports of firm i to country c in year t. And S^c_{ibt} is the measure of specialization of bank b in country c leaving-i-out, in the three years up to year t, defined in (7). Columns 1 and 2 report the *extensive-margin* results of specifications 10 and 11, respectively. Standard errors are two-way clustered at the bank and firm levels. ***p< 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 7: Specialization and Bank Size

Dep. Variable	S^c_{bt}		$\ln(L_{ibt})$		
	between (1)	within (2)	(3)	(4)	(5)
$\ln(Size_{bt})$	-0.006	0.004			
	(0.006)	-0.004			
$Foreign_{bt}$	-0.021**	0.017***			
	(0.010)	(0.002)			
$S^c_{ibt} \times \ln(X^c_{it})$			0.019**	0.016**	0.019**
			(0.007)	(0.007)	(0.008)
$\ln(X^c_{it})$			0.031***	0.034***	0.015***
			(0.006)	(0.005)	(0.005)
S^c_{ibt}			-0.003	-0.003	-0.027
			(0.030)	(0.028)	(0.032)
$S^c_{ibt} \times \ln(X^c_{it}) \times SmallBank_b$			-0.010		
			(0.028)		
$\ln(X^c_{it}) \times SmallBank_b$			-0.028*		
			(0.015)		
$S^c_{ibt} \times SmallBank_b$			0.018		
			(0.011)		
$S^c_{ibt} \times \ln(X^c_{it}) \times Foreign_{bt}$				0.009	
				(0.015)	
$\ln(X^c_{it}) \times Foreign_{bt}$				-0.045***	
				(0.010)	
$S^c_{ibt} \times Foreign_{bt}$				0.02	
				(0.016)	
$S^c_{ibt} \times \ln(X^c_{it}) \times LargeFirm_i$					-0.004
					(0.014)
$\ln(X^c_{it}) \times LargeFirm_i$					0.024***
					(0.005)
$S^c_{ibt} \times LargeFirm_i$					0.055***
					(0.011)
Bank FE	No	Yes			
Country FE	Yes	Yes			
Year FE	Yes	Yes			
Bank-year FE			Yes	Yes	Yes
Firm-year FE			Yes	Yes	Yes
Country-Bank FE			Yes	Yes	Yes
Observations	7,560	7,560	334,432	334,432	334,432
$R^2 adj$	0.49	0.51	0.31	0.31	0.31

Note: $Size_{bt}$ is total lending of bank b at time t, $Foreign_{bt}$ is a dummy equal to 1 if the bank if foreign-owned, $SmallBank_b$ is a dummy equal to 1 for banks outside the top 10, measured in average total (real) lending over the entire sample, and $LargeFirm_i$ is a dummy equal to 1 if the firm belongs to the top 10% of the total exports during at least one year in our sample. In columns 1 and 2, S^c_{ibt} is computed over all firms. Columns 3 to 5 correspond to specification 5. Standard errors are two-way clustered at the bank and firm levels. ***p< 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 8: Persistence of Specialization after a Merger

Dep. Variable	$\ln(L_{ibt})$	
	(1)	(2)
$S^c_{ibPreMerger} \times \ln(X^c_{it})$	0.016***	0.013**
	(0.005)	(0.005)
$S^c_{ibPreMerger} \times \ln(X^c_{it}) \times Merger_{bt}$		0.051**
		(0.019)
$\ln(X^c_{it})$	0.012***	0.015***
	(0.003)	(0.003)
$\ln(X^c_{it}) \times Merger_{bt}$		-0.022***
		(0.008)
$S^c_{ibPreMerger} \times Merger_{bt}$		-0.009
		(0.019)
$Merger_{bt}$		-0.021
		(0.024)
Bank-Merger-year FE	Yes	Yes
Firm-Merger-year FE	Yes	Yes
Country-bank-Merger FE	Yes	Yes
Observations	543,788	543,788
R^2	0.29	0.29

Note: L_{ibt} is the credit of firm i with bank b in year t. X^c_{it} is annual exports of firm i to country c in year t. And the index of specialization leaving-i-out, S^c_{ibPreM} defined in (7), is computed the year before the merger for both banks participating in the Merger. Results of specification 5 (demeaned) with data rearranged around event time (Merger). Column 1 replicates specification 5. Column 2 adds the interaction term $Merger_{bt}$, a post-merger dummy. Standard errors are two-way clustered at the bank and firm levels. ***p< 0.01, **p < 0.05, and *p < 0.1.

Table 9: Specialization and Global Banks

Dep. Variable	S_b^c	$\ln(L_{ibt})$	
	(1)	(2)	(3)
$CountryOwnership_{bc}$	0.095***		
	(0.018)		
$DistanceToHeadquarters_{bc}$	0.005*		
	(0.003)		
$CommonLanguage_{bc}$	0.027***		
	(0.010)		
$CountrySubsidiary_{bc}$	-0.002		
	(0.008)		
$S_{ibt}^c \times \ln(X_{it}^c)$			0.021**
			(0.008)
$CountryOwnership_b^c \times \ln(X_{it}^c)$		-0.031	-0.028
		(0.022)	(0.024)
$ln(DistancetoHeadquarters_b^c) \times \ln(X_{it}^c)$		-0.002	-0.004
		(0.006)	(0.006)
$CommonLanguage_b^c \times \ln(X_{it}^c)$		0.007	0.008
		(0.006)	(0.007)
$CountrySubsidiary_b^c \times \ln(X_{it}^c)$		0.016	0.012
		(0.010)	(0.010)
$\ln(X_{it}^c)$		0.042	0.050
		(0.052)	(0.056)
S_{ibt}^c			0.000
			(0.030)
Bank FE	Yes		
Country FE	Yes		
Year FE	Yes		
Firm-year FE		Yes	Yes
Bank-year FE		Yes	Yes
Country-Bank FE		Yes	Yes
Observations	7,560	366,696	366,696
$R^2 adj$	0.51	0.31	0.31

Note: In column 1, the dependent variable is S_{ibt}^c, defined in (7), over the entire sample period. Columns 2 and 3 show the results of an augmented version of specification 5 (demeaned). $CountryOwnership_b^c$ is a dummy equal to 1 if the destination country of the export flow coincides with the country of ownership of the bank. Similarly $CountrySubsidiary_b^c$ is equal to 1 if the bank has a subsidiary in the destination country of the export flow. The variables distance (in (log) km) and common language (dummy variable) refer to the connection between the bank's country of ownership and the export destination. Standard errors are two-way clustered at the bank and firm levels. ***p$<$ 0.01, **p $<$ 0.05, and *p $<$ 0.1.

Table 10: Bank Specialization, Bank Branches, and Product Mix

Dep. Variable	$\ln(L_{ibt})$		
	(1)	(2)	(3)
$S^c_{ibt} \times \ln(X^c_{it})$	0.020***	0.019***	
	(0.006)	(0.006)	
$\ln(X^c_{it})$	0.027***	0.009	
	(0.006)	(0.013)	
S^c_{ibt}	0.003	0.003	0.031
	(0.035)	(0.035)	(0.023)
$BranchDistrict_{ib}$		-0.000	
		(0.054)	
$N\ BranchDistrict_{ib}$		-0.007	
		(0.006)	
$BranchDistrict_{ib} \times \ln(X^c_{it})$		0.013	
		(0.015)	
$N\ BranchDistrict_{ib} \times \ln(X^c_{it})$		0.000	
		(0.001)	
$S^c_{ibt} \times \ln(X^{pc}_{it})$			0.014**
			(0.007)
$S^p_{ibt} \times \ln(X^{pc}_{it})$			-0.007
			(0.024)
$\ln(X^{pc}_{it})$			0.019***
			(0.005)
S^p_{ibt}			0.205***
			(0.054)
Firm-year FE	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Country-Bank FE	Yes	Yes	Yes
Observations	228,911	228,911	402,332
$R^2 adj$	0.33	0.33	0.29

Note: Results of specification 5 (demeaned). In columns 1 and 2 the period is 2001-2010, for which branch locations are available. $BranchDistrict_{ib}$ is a dummy equal to 1 if the firm is located in a district where the bank has a branch. $N\ BranchDistrict_{ib}$ is number of branches of the bank in the firm's district. In column 3, exports are disaggregated at the product-destination level, X^{pc}_{it}. There are 33 product categories corresponding to HS 2-digits with at least 0.25% of Peruvian exports in the pool sample. S^p_{ibt} is computed parallel to (7):

$$S^p_{ibt} \equiv \frac{\sum_{i \neq k}^{I} L_{bkt} X^p_{kt}}{\sum_{p=1}^{P} \sum_{i \neq k}^{I} L_{bkt} X^p_{kt}}.$$

Standard errors are two-way clustered at the bank and firm levels. ***p< 0.01, **p < 0.05, and *p < 0.1.

Online Appendix

A.1 Data simulation of a discrete choice model

In this appendix we simulate data to illustrate how a simple version of the discrete choice model of firms, borrowing from banks with different lending advantages, translates into a distribution of loan-weighted export shares used to measure specialization in Subsection 3.2. We purposely simplify the framework to make it symmetric. Thus, any heterogeneity across banks in the simulated data comes from firms' bank choice.

The firm-i's choice of bank for export market c is given by equation (1):

$$b = \arg\max \left\{ \ln \left(\frac{\gamma_b^c}{r_b} \right) \mu \epsilon_{ib}^c \right\}$$

where ϵ_{ib}^c is a random variable drawn from Gumbel(1,1) distribution.

In this simulation, markets are perfectly competitive, each firm exports \$1 to only one country (a firm is an activity) and an equal number of firms exports to each destination (therefore, all countries have the same market size). Banks are symmetric; that is, $r_b = r$ for all b, the lending advantage takes two values only, $\gamma_c^b = \{\gamma_H, \gamma_L\}$, with $\gamma_H > \gamma_L$, and we assume that banks are specialized in a single country. That is, for each bank b, there is only one country c for which $\gamma_b^c = \gamma_H$. We set the parameter γ_H and γ_L so that $\log(\gamma_H/r) = 1$ and $\log(\gamma_L/r) = 0$. Without loss of generality, we normalize r to one.

The simulations presented here are generated with 100,000 firms, nine banks, $b = b1...b9$, and nine export markets, $c = c1...c9$ of equal size. Bank $b1$ has lending advantage in $c1$; bank $b2$ has lending advantage in $c2$, and so on.

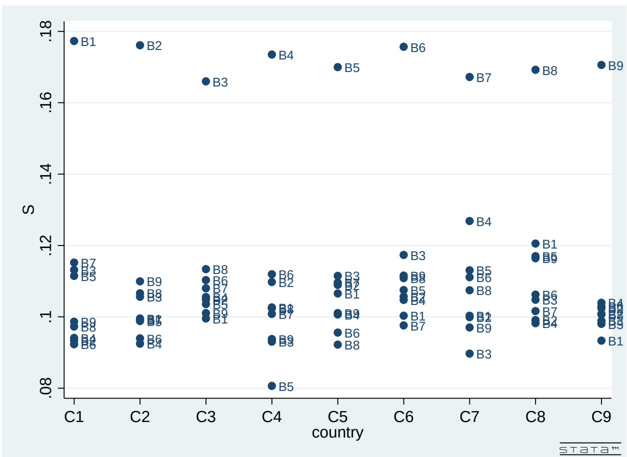
With firm choices simulated this way, we construct the shares of export-weighted lending for each country-bank pair, as defined in equation 3, Subsection 3.2. To illustrate the role of idiosyncratic noise versus bank lending advantage in the identification of specialization, we show two simulations, Figure A.1 sets $\mu = 2$ and Figure A.2, $\mu = 20$.

With $\mu = 2$ and ϵ_{ib}^c follows Gumbel(1,1), the random component is still relevant: $\mu\ \epsilon_{ib}^c$ has median 2.73, while the lending advantage parameter $\ln(\gamma_H/r_b) = 1$. Still, firms choose banks on the basis of their lending advantage. The distribution of bank-country lending shares has clear outliers and all bank are specialized, according to our definition (Figures A.1a and A.1b) .

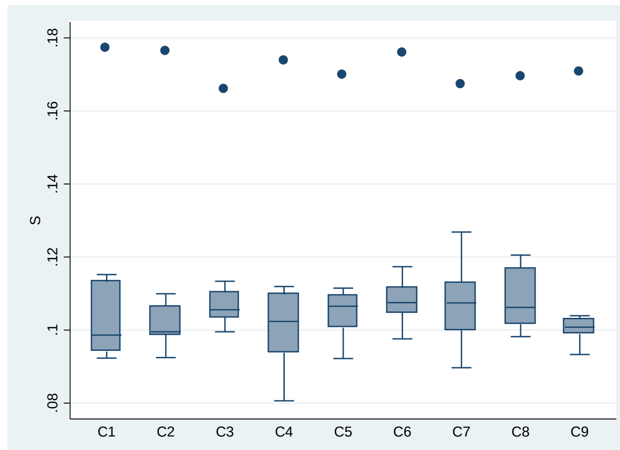
When $\mu = 20$ (Figures A.1c and A.1d), on the other hand, the firms' idiosyncratic non-observable motives (i.e., the random component) for choosing the lending bank are too powerful relative to the advantage parameter. Definition 1 in Subsection 3.2 would identify only one specialized bank (bank $b9$ specialized in country $c9$). In this case, the bank lending advantage is not a relevant factor behind firms' choice.

Figure A.1: Simulation

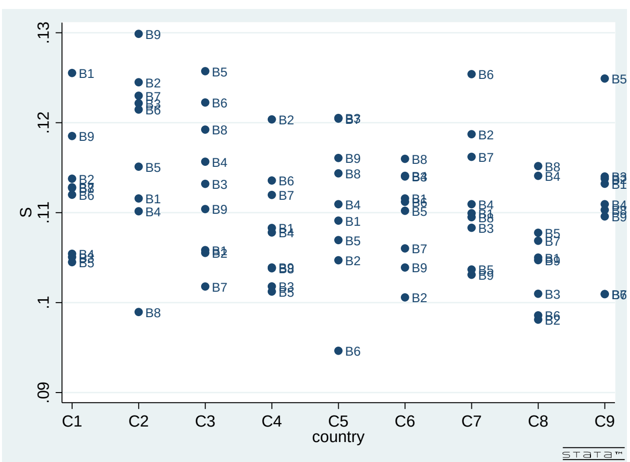
(a) Distribution with $\mu = 2$



(b) Specialization wth $\mu = 2$



(c) Distribution $\mu = 20$



(d) Specialization $\mu = 20$