

Specialization in Bank Lending: Evidence from Exporting Firms*

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November 27, 2021

Abstract

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

*We thank Luana Zaccaria for outstanding research assistance. We thank Luis Garicano, Asim Khwaja, Nicola Gennaioli, Rebecca Zarutskie, Johan Hombert, Gregor Matvos, and participants at Bank de France, Cambridge University, CEMFI, ERWIT, Financial Intermediation Research Society Conference, LBS Finance Symposium, LSE, NBER CF, NY Fed, Paris Trade Group, ICD Annual Conference in Financial Economics, SED, Stanford University, Stanford University GSB, University of British Columbia Sauder School of Business, UC Berkeley, UC Berkeley Haas School of Business, UC San Diego, and University of Zurich seminars, workshops, and conferences for useful comments. All errors are our own. Please send correspondence to Daniel Paravisini (d.paravisini@lse.ac.uk), Veronica Rappoport (v.e.rappoport@lse.ac.uk), and Philipp Schnabl (schnabl@stern.nyu.edu).

1 Introduction

A longstanding view in financial economics is that competition in bank credit markets is curtailed by the informational monopoly obtained from interacting repeatedly with opaque borrowers.¹ Relationship lending confers an information advantage relative to other lenders that is firm-specific and developed over time. Absent this firm-specific advantage, it is often presumed that bank credit markets are fairly competitive.

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

We first develop an intuitive *relative debt concentration* measure of bank specialization, in the spirit of revealed comparative advantage indexes from international trade (Balassa, 1965), and use it to evaluate whether bank lending portfolios in the data are consistent with a credit market characterized by bank specialization. Then we examine how firms' choice of lender is related to this measure of specialization. Specifically, we test whether firm output in a market comoves disproportionately with funding from the bank specialized in that market, both along the intensive and extensive margins. Finally, we assess the economic importance of specialization, evaluating how it shapes the choice of lender when firms face demand shocks and how it affects the impact of credit supply shocks on the real economy. Throughout, we distinguish which observed patterns can be attributed

¹For 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 \(2000\)](#).

to market-specific specialization, as opposed to being driven by firm-specific information gathered through relationship lending.

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

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

In line with the example, we measure bank specialization in a country based on its export-value weighted portfolio share of lending to exporters to the country, relative to the portfolio shares of other banks to the same country. We show that this 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 financing exports to specific countries). Relative portfolio shares provide an intuitive measure of specialization, which is feasible with available granular data and has multiple desirable features that we discuss in detail below. For example, by comparing bank portfolio shares to the same destination, the measure is not biased by bank or

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

export market size.

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

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

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

with a specialized bank, the firm is 1.2 percentage points more likely to begin exporting to the bank's country of specialization, relative to a country in which the bank is not specialized in. This magnitude is also economically significant, as the probability of exporting to a new destination is 0.69% per year unconditionally.

These findings are significant because they represent the first direct evidence that banks possess market-specific advantages in lending. These are distinct from the firm-specific advantage that emerges because of private information collected as part of an ongoing lending interaction.³ The potential market power conferred by bank specialization has a broader reach, as it applies to all firms operating (or that intend to operate) in a market. We use bank mergers to document further that the observed patterns are unlikely to be driven by relationship lending. The advantage conferred by relationship lending diminishes with bank size.⁴ In contrast, there is no reason to expect the advantage from market-specific bank specialization to be lost as banks expand. We show that the advantage conferred by bank specialization before a merger carries over to the combined entity after the merger. These results indicate that market-specific bank specialization is scalable and not hindered by organizational constraints.

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

³On 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 \(1997\)](#).

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

to a country, it substantially tilts its demand for credit towards the bank that is specialized in that country.

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

These results have significant implications for the interpretation of a broad academic literature that studies the transmission and amplification of shocks through the banking sector. The now-standard approach for the empirical identification of bank credit supply shocks, pioneered in [Khwaja and Mian \(2008\)](#), controls for changes in firm credit demand using firm-time fixed effects. As discussed in [Khwaja and Mian \(2008\)](#), the empirical identification may fail if firms' loan demand is bank-specific. Our setting represents a concrete example of where this is the case. The point estimates imply that if an exporter faces a decline in the demand for its products in a certain country, the firm will reduce its demand for credit by 50% more from the bank specialized in that country than from non-specialized banks. The firm fixed-effects approach would incorrectly attribute this tilt in borrowing to a credit supply change by the specialized bank. We show that the magnitude of the bias can be evaluated by augmenting the standard firm-time fixed effects specification with measures of bank export specialization. Using the same capital flow reversals episode in 2008 described above, we find that demand shocks explain more than half of the same-firm tilts in credit across banks than bank funding shocks. The results imply that ignoring market-specific bank specialization can lead to severe biases in credit supply estimation with the commonly used firm-time fixed effects approach.

Our paper relates to two main strands in the literature. The first strand is the work on the industrial organization of bank credit markets and its consequences for the real economy. Market-specific bank specialization provides a rationale for why firms have multiple banking relationships and why banks form syndicates: multiple bank relationships and syndicates arise naturally when banks are differentially equipped 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 does not have expertise.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 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 iden-

⁵Leading 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. [Antras and Foley \(2015\)](#), [Niepmann and Schmidt-Eisenlohr \(2017\)](#), and [Ahn and Sarmiento \(2019\)](#) emphasize the importance of specialized financing in international trade.

⁷This 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](#)).

tify 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 our measure of bank specialization. Section 4 discusses the empirical methodology to identify a bank's lending advantage and presents results. Section 5 evaluates the economic importance of bank specialization in the presence of demand and supply shocks. Section 6 examines potential sources of bank lending advantage. Section 7 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 (Superintendencia 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 AFP, 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: Descriptive Statistics

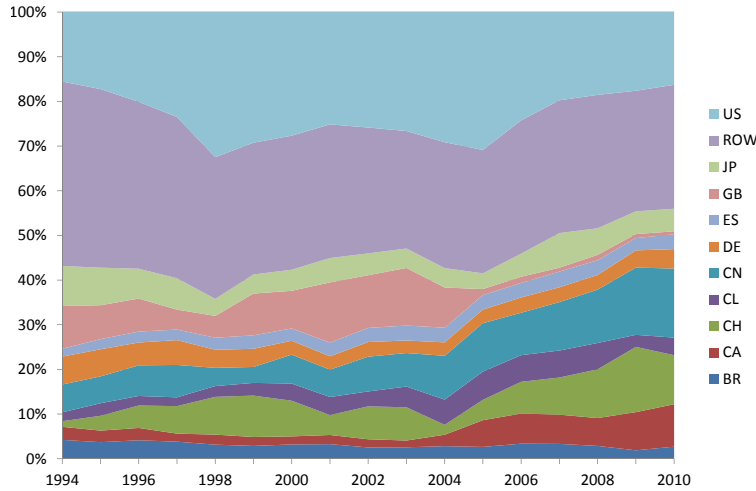
	Mean (1)	S.D (2)	Min (3)	Median (4)	Max (5)
Panel 1: the unit of observation is firm-bank-country-time (N = 378,766)					
Outstanding Debt (US\$ '000)	2,044	6,804	0	260	235,081
Exports (US\$ '000)	2,148	19,821	0	87	1,470,300
Panel 2: the unit of observation is firm-time (N = 45,762)					
Total Debt (US\$ '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: Outstanding Debt has the same value across all destinations within the same firm-bank-time and Exports has the same value across all banks for the same firm-country-time. There are 14,267 firms in the dataset.

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 special-

Figure 1: Export Composition by Destination



Note: Export shares according to export values

ization 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

⁸The 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.

⁹We do not observe data on loan covenants. It is our understanding that loan covenants have limited economic significance in our setting because they are difficult and costly to enforce in the Peruvian judicial system.

3 Specialization: Framework, Measurement, and Descriptive Statistics

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

3.1 Specialization Measure

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

Regarding the first challenge, a bank will be larger in overall lending if it charges lower interest rates or if it is more efficient irrespective of the activity. To cancel out these bank-

wide factors affecting all activities, our starting point is to compare the lending of bank b towards activity c to all firms $i = 1, \dots, I$ (i.e., $\sum_i L_{ib}^c$), relative to the lending of bank b towards all activities ($\sum_i L_{ib}$). That is, we start by using the portfolio share of lending of bank b towards activity c :

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

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

$$RCA_b^c = \frac{\tilde{S}_b^c}{\tilde{S}^c},$$

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

Regarding the third challenge, one cannot construct the ideal index RCA_b^c from available data. The reason is that activity- c specific credit (L_{ib}^c) is unobservable. The typical credit registry data will contain information on the credit from bank b to firm i (L_{ib}) but will not distinguish what fraction of that credit is used to fund exports by firm i to country c (X_i^c).¹⁰ Therefore, as a second step, we proxy RCA_b^c with an empirically observable counterpart.

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

$$S_b^c \equiv \frac{\sum_{i=1}^I L_{ib} X_i^c}{\sum_{k=1}^C \sum_{i=1}^I L_{ib} X_i^k} \quad (1)$$

¹⁰There are some financial instruments associated with specific export markets, for example letters of credit. We discuss in Section 6 the limitations of using such instruments for identifying the pattern of lending advantage across countries.

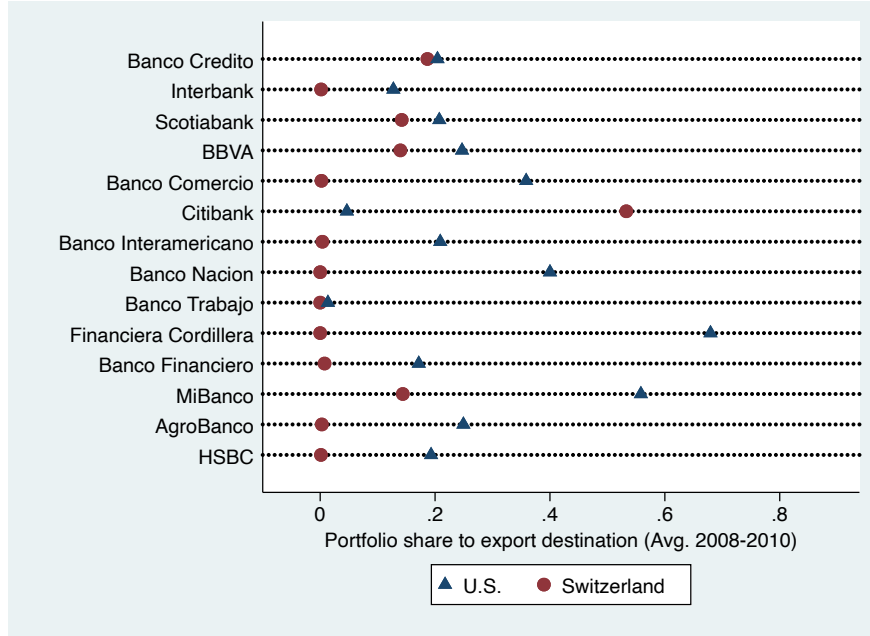
which represents bank- b borrowers' exports to country c , weighted by their debt in bank- b , as a share of bank- b borrowers' total debt-weighted exports. In the theory framework of the next subsection we demonstrate that S_b^c is a good proxy for a bank's c -specific lending advantage under mild assumptions.

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

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

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

Figure 2: Specialization Measure: Example



Note: Average (2008-2010) portfolio share S_{bt}^c by bank for two countries. Portfolio shares calculated according to the definition in equation (1).

amongst all banks, indicating a large degree of specialization and lending advantage.

This illustration highlights that the cardinal value of S_b^c does not, *per se*, capture specialization. Citibank's portfolio share in Switzerland does not tell us whether Citibank has a revealed comparative advantage unless we know the position of its portfolio share relative to the distribution of S_b^c for all banks in the same country. Thus, in all the analysis that follows we use indicators for the quartile of the country- c distribution a bank belongs to as a single and simple measure of its relative specialization.

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

3.2 Theoretical Framework of Specialized Bank Lending

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. Since the source of advantages is unobserved by the econometrician, we model specialization in reduced form. We use the model to derive observable implications of the existence of market-specific bank lending advantage (whatever their source) on bank lending portfolios and the equilibrium relationship between credit from specialized banks and the economic activity in the sector in which they specialize.

3.2.1 Setup

We characterize the firms' demand of credit across banks with a nested logit model with deterministic second stage. Each bank b is characterized by an interest rate r_b and a vector of absolute lending advantage for each economic activity $c = 1, \dots, C$ (e.g., export destination country), $\gamma_b = [\gamma_b^1, \dots, \gamma_b^C]$, with $\gamma_b^c > 0$ for all c, b . We assume this vector γ_b to be independently distributed across banks. The interpretation of the lending advantage parameter, γ_b^c , is broad. For example, it could represent a bank service attached to credit issuances.

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

To focus on the choice of credit, we assume that credit is the single factor of production used to produce the commodity exported to country c . Specifically, we assume a linear

production function: $q_i^c = \gamma_b^c L_{ib}^c \exp\{\mu \epsilon_{ib}^c\}$, where ϵ_{ib}^c is an idiosyncratic factor unobserved to the econometrician.

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

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

This firm-activity specific bank follows a *bang-bang* solution. For each activity c , the firm i chooses a single bank depending on the interest rate r_b , the absolute advantage γ_b^c , and its idiosyncratic motive ϵ_{ib}^c . For the chosen bank b , the activity-specific demand of credit is $L_{ib}^c = [\frac{1}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}] q_i^c$; we can rewrite the optimal loan amount in terms of marginal cost such that $L_{ib}^c = \frac{MC_i^c}{r_b} q_i^c$ where $MC_i^c = \frac{r_b}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}$. For any other bank $b' \neq b$: $L_{ib'}^c = 0$.

The discrete-choice micro-foundation highlights two features of the framework. First, firms may have multiple banking relationships because they may choose different banks to fund different activities. Thus, our analysis provides a rationale for multiple banking relationships as a consequence of the multi-activity nature of the firm and the activity-specific advantage of banks.¹¹ 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.¹²

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

¹¹In 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.

¹²This 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](#)).

$$L_{ib} = \sum_c L_{ib}^c = \frac{1}{r_b} \sum_c \mathbb{I}_{ib}^c \cdot MC_i^c \cdot q_i^c, \quad (2)$$

where L_{ib}^c is the loan amount for activity c taken from bank b , q_i^c is total output associated with productive activity c , and \mathbb{I}_{ib}^c is an indicator function equal to one if bank b is optimal for activity c and zero otherwise.

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

$$Pr_b^c = \frac{\exp \{ \ln(\gamma_b^c) - \ln(r_b) \} / \mu}{\sum_{b'} \exp \{ \ln(\gamma_{b'}^c) - \ln(r_{b'}) \} / \mu} = \frac{\left(\frac{\gamma_b^c}{r_b} \right)^{1/\mu}}{\sum_{b'} \left(\frac{\gamma_{b'}^c}{r_{b'}} \right)^{1/\mu}}. \quad (3)$$

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

In our setting, activities correspond to export destination markets, so we substitute $MC_i^c \cdot q_i^c$ in equation 2 for exports of firm i to c (i.e., $X_i^c = p_i^c q_i^c$). This approximation is exact under perfect competition or constant markup (marginal cost is proportional to price, $MC_i^c \propto p_i^c$), a good description of Peruvian exports, mostly commodities. Then, in expectation, a firm i that exports X_i^c to each country $c = 1, \dots, C$ would have the following overall standing credit with bank b :

$$E[L_{ib}] = \frac{1}{r_b} \sum_c Pr_b^c X_i^c. \quad (4)$$

A direct implication of equation 4 is that the elasticity of demand for bank- b loans with respect to the value of goods exported to country c , vis-a-vis other destinations k , is increasing in the relative lending advantage, embedded in the probability Pr_b^c . We use this result to test the existence of lending advantages in the next section.

3.2.2 Specialization Measure

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

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

where $\tilde{S}^c \equiv \frac{\sum_{i=1}^I L_i^c}{\sum_{k=1}^C \sum_{i=1}^I L_i^k}$ recovers the importance of the activity in the overall banking sector and $\nu_b \equiv \frac{\sum_k Pr_b^k \sum_k X^k}{\sum_k Pr_b^k X^k}$ is a bank-wide constant equal to one in expectation, given our assumption of independence between the distribution of the γ parameters and exports across countries.¹³ Comparing RCA_b^c across-banks and within-destination, this index successfully captures our theoretical object of interest, $\tilde{\gamma}_b^c$, the relative advantage of bank b in activity c .

Since the ideal index RCA_b^c cannot be constructed from available data, we proposed the observable empirical proxy S_b^c (equation 1), which represents bank- b borrowers' exports to country c , weighted by their debt in bank- b , as a share of bank- b borrowers' total debt-weighted exports. Under mild assumptions, S_b^c is a good proxy for a bank's c -specific lending advantage $\tilde{\gamma}_b^c$, in the sense that the covariance between the two variables across-banks within-activity is positive.

For example, if lending advantages across activities are not correlated, and neither are export across destinations, then this *observable* index is positively correlated with $\tilde{\gamma}_b^c$, our

¹³This independence assumption is not crucial. The constant ν_b accounts for the correlation between the bank's pattern of lending advantage and cross-country market size. Intuitively, the bank's overall lending is larger if it has a relative advantage in lending towards larger export markets.

unobservable object of interest, for any destination c (formally, $\text{cov}(X_i^k; X_i^c) = \text{cov}(\gamma_b^k; \gamma_b^c) = 0$ for $k \neq c$):

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

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

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

3.3 Bank Specialization Descriptive Statistics

In our data, firms $i = 1, \dots, I$ are Peruvian exporters, $c = 1, \dots, C$ are the destination country of exports, X_{it}^c are exports by firm i to destination country c in year t , and L_{ibt} is the outstanding debt of exporting firm i with bank b in year t . We compute the portfolio shares that constitute the basis for our specialization measure, S_b^c , associated with each export market using the outstanding debt of Peruvian firms in the 33 banks operating in Peru between 1994 and 2010, as well as the firm-level export data by shipment to the 22 largest destination markets.¹⁴

Table 2 presents descriptive statistics of S_{bt}^c by country. Large export destination countries have large average shares (e.g, the average U.S. share is 21% and the average Switzerland share is 2.7%). Within-country shares are very heterogeneous: for the mean country, the standard deviation of the shares across banks is 1.77 times the country's average share. The within-country share distribution across banks is also right-skewed for every country, and the mean country's share skewness is 5.3.

¹⁴The bank panel is unbalanced because of entry, exit and M&A activity (we discuss M&A activity in more detail in subsection 4.4).

Table 2: Country Portfolio Share, Descriptive Statistics

Country	Code	S_{bt}^c			
		Mean (1)	S.D. (2)	Median (3)	Skewness (4)
Belgium	BE	0.023	0.027	0.018	3.4
Bulgaria	BG	0.0032	0.0062	0.00075	3
Bolivia	BO	0.022	0.049	0.01	7.7
Brazil	BR	0.025	0.03	0.014	2.3
Canada	CA	0.033	0.046	0.023	5.1
Switzerland	CH	0.027	0.088	0.0014	5.2
Chile	CL	0.083	0.16	0.039	4.2
China	CN	0.15	0.13	0.12	1.1
Colombia	CO	0.035	0.069	0.025	9.7
Germany	DE	0.055	0.059	0.047	3
Ecuador	EC	0.029	0.079	0.013	8.2
Spain	ES	0.031	0.066	0.019	11
France	FR	0.014	0.026	0.0069	5.5
Great Britain	GB	0.035	0.043	0.021	3
Italy	IT	0.019	0.027	0.013	7.7
Japan	JP	0.061	0.065	0.059	5.7
South Korea	KR	0.017	0.025	0.0094	3.9
Mexico	MX	0.03	0.088	0.013	8.2
Netherlands	NL	0.023	0.034	0.013	3.6
Panama	PA	0.024	0.072	0.003	5.4
Trinidad and Tobago	TT	0.0014	0.0041	0.000063	5.8
Taiwan	TW	0.021	0.023	0.018	2.4
USA	US	0.21	0.18	0.17	1.7
Venezuela	VE	0.028	0.038	0.017	3.5
Overall		0.042	0.087	0.015	5.3

Note: Portfolio shares calculated according to the definition in equation 1 using the outstanding debt of Peruvian firms for 33 banks operating in Peru between 1994 and 2010, as well as firm-level export data by shipment to the 22 largest destination markets.

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

Table 3 presents the transition probability matrix of $D(S_b^c \in Q_q)$ calculated over all pairs of consecutive years between 1994 and 2010 for the full country and bank sample. The transition probabilities on the upper-left and bottom-right corners of the matrix are above 60%, indicating that banks with a large (small) portfolio share in a country relative to other banks are likely to retain a large (small) share over time. More generally, the heavy weight on the diagonal of the transition probability matrix indicates that portfolio shares are very persistent over time. The persistent lending portfolio tilts towards certain countries is consistent with a bank credit market for exporters that is segmented by export destination country.

To summarize, we consider a bank to be specialized in a export destination market if it exhibits a portfolio share that is persistently in the top quartile of the share distribution across all banks for that destination market. All banks in our data specialize in at least one country. We interpret bank portfolio specialization as a revealed comparative advantage in lending to exporters to a given destination market. In the next section we develop an empirical approach to test whether banks indeed have a lending advantage towards destinations in which they exhibit large and persistent portfolio shares.¹⁵

¹⁵Our 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.

Table 3: Portfolio Share Quartile Transition Probability Matrix

To portfolio share quartile:	1st	2nd	3rd	4th	Sum
From portfolio share quartile:					
1st	0.64	0.17	0.10	0.10	1.00
2nd	0.13	0.48	0.28	0.11	1.00
3rd	0.06	0.24	0.46	0.24	1.00
4th	0.06	0.11	0.23	0.60	1.00

Note: table shows the probability that a bank’s portfolio share in a given country transitions from quartile q (rows) to quartile r (columns) between consecutive years. Portfolio shares, quartiles, and transition probabilities calculated using the outstanding debt of Peruvian firms for 33 banks operating in Peru between 1994 and 2010, and firm-level export data by shipment to the 22 largest destination markets.

4 Identifying Advantage in Lending

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

We empirically distinguish this market-specific lending advantage from firm-specific information gathered through relationship lending. We test whether specialization predicts decisions at the extensive margin of where to export and from whom to borrow. Specifically, we test whether the probability that a firm starts a new banking relationship increases for specialized banks, when the firm starts exporting to the market of specialization. By construction, this extensive margin comovement cannot be explained by relationship lending. Finally, we use bank mergers and test whether the advantage conferred by bank specialization before a merger carries over to the combined entity after the merger. The advantage conferred by relationship lending is expected to diminish with

bank size. In contrast, there is no reason to expect the advantage from market-specific bank specialization to be lost as banks expand.

4.1 Baseline Empirical Strategy

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

$$L_{ibt} = L(L_{bt}^S, L_{it}^D, \mathcal{L}_{ibt}). \quad (5)$$

Bank-firm outstanding credit is an equilibrium outcome at time t , determined by the overall supply of credit by the bank, L_{bt}^S , which varies with bank-level variables such as overall liquidity, balance-sheet position, etc.; the firm's overall demand for credit L_{it}^D , which varies with firm-level productivity, demand for its products, investment opportunities, etc.; and, finally, a firm-bank specific component, \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_{bt}^S (common in expectation across all firms) and all firm-specific credit demand shocks L_{it}^D (common in expectation across all banks) by saturating the empirical model with a full set of bank-time and firm-time dummies, α''_{bt} and α'_{it} .¹⁶ Thus, for each country-bank-firm-year, we estimate:

$$\ln L_{ibt} = \alpha_{ib}^c + \alpha'_{it} + \alpha''_{bt} + \beta_1 \ln X_{it}^c + \beta_2 S_{ibt}^c + \beta_3 S_{ibt}^c \times \ln X_{it}^c + \epsilon_{ibt}^c, \quad (6)$$

where L_{ibt} is the observed amount of debt of firm i from bank b at time t , X_{it}^c are exports from firm i to country c , and S_{ibt}^c is a measure of bank specialization in country c . Under

¹⁶This 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 null hypothesis that funding across banks is perfectly substitutable we have $\beta_3 = 0$, meaning that firm exports to a country are not systematically correlated with borrowing from banks specialized in that country.

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

$$\ln L_{ibt} = \alpha_{ib}^c + \alpha'_{it} + \alpha''_{bt} + \beta_1 \ln X_{it}^c + \sum_{q=2}^4 \beta_{2q} D(S_{ibt}^c \in Q_q) + \sum_{q=2}^4 \beta_{3q} D(S_{ibt}^c \in Q_q) \times \ln X_{it}^c + \epsilon_{ibt}^c. \quad (7)$$

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

Our measure of specialization, S_{ibt}^c , is based on a rolling period of three years up to the year of the loan.¹⁷ 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:

$$S_{(-i)b\tau}^c \equiv \frac{\sum_{k \neq i}^I L_{bk\tau} X_{k\tau}^c}{\sum_{c=1}^C \sum_{k \neq i}^I L_{bk\tau} X_{k\tau}^c}, \quad (8)$$

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

$$S_{ibt}^c = \frac{1}{3} \sum_{\tau=t-2}^t S_{(-i)b\tau}^c, \quad (9)$$

¹⁷As an alternative, we also constructed estimates based on two-year and four-year rolling windows. The results are qualitatively and quantitatively unchanged.

Note that although outstanding debt is a firm-bank-year value, L_{ibt} , there are 22 relationships like the one in 7 for each firm-bank-year—one for each country c in our analysis sample. To estimate the parameters of 7, 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_{ib}^c , accounts for all unobserved heterogeneity in the firm-bank-country lending relationship, such as the distance between bank headquarters and the destination country.

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

4.2 Baseline Results

Column 1 of Table 4 presents results for the the baseline specification with quartiles (equation 7) . We find that lending is more sensitive to changes in exports for more specialized banks. The effect is increasing in specialization and largest for highly specialized banks in the top quartile of the country-specific distribution. Column 2 shows that the effect is robust to estimating a linear specification (equation 6). These results show that when a firm expands its exports to a country, it increases its borrowing disproportionately from banks that specialize in the same country.

We note that our estimation includes firm-time and bank-time fixed effects. This means that this correlation holds within a firm: if a firm’s export composition shifts from country A to country B, its borrowing composition shifts from a bank specialized in country A to a bank specialized in country B.¹⁸ The bank-time fixed effects imply that this cor-

¹⁸This coefficient captures the correlation between the firm-bank specific component of debt and the

Table 4: Lending Advantage and Specialization

Dep. Variable	$\ln(L_{ibt})$	
	(1)	(2)
$\ln(X_{it}^c)$	-0.013*	-0.003**
	(0.007)	(0.002)
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_2)$	0.010	
	(0.009)	
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_3)$	0.016	
	(0.010)	
$\ln(X_{it}^c) \times (S_{ibt}^c \in Q_4)$	0.026**	
	(0.012)	
$\ln(X_{it}^c) \times S_{ibt}^c$		0.053**
		(0.025)
Observations	327,727	327,727
R^2 adj	0.569	0.569

Note: All specifications include bank-country, firm-year and bank-year fixed effects. Standard errors are clustered at the bank and firm levels. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

relation is not driven by generic shocks to credit supply that affect all firms in the same manner.

To interpret the role bank specialization, we compare the estimates for specialized (top quartile) and non-specialized (bottom quartile omitted) lenders from Column 1. For the same change in exports to a given country, the firm shifts lending from non-specialized (elasticity -0.013) towards a bank highly specialized in that destination (elasticity $+0.013 = -0.013 + 0.026$). These results reject the hypothesis that debt is perfectly substitutable across banks and confirm that banks have advantages in lending to the countries in which they specialize. The results also validate that our measure of specialization captures lending advantages.

firm's average exports to the countries in which bank b does not specialize (bottom quartile of the distribution). Note that there is independent bank-firm variation in exports—variation that is not captured by the firm-time dummies—because banks differ in their pattern of specialization across countries, so not all banks are in the top quartile for the same countries.

4.3 New Banking Relationships and Export Entry

The basic premise behind the firm-specific advantages gained through relationship lending is the following: banks gather private information through repeated interactions with a firm, which implies an advantage vis-à-vis other uninformed banks. If the observed patterns of specialization in export markets and their associated advantages are firm-specific, then our specialization measure should not predict firm behavior at the extensive margin. We begin by testing whether the probability that a firm starts borrowing from a bank increases after the firm starts exporting to the country of specialization. We estimate the following linear probability model (parallel to specification 7):

$$\begin{aligned} (L_{ibt} > 0 | L_{ibt-1} = 0) &= \alpha_{ib}^c + \alpha'_{it} + \alpha''_{bt} + \beta_1 (X_{it-1}^c > 0 | X_{it-2}^c = 0) + \sum_{q=2}^4 \beta_{2q} D(S_{bt}^c \in Q_q) \\ &+ \sum_{q=2}^4 \beta_{3q} D(S_{bt}^c \in Q_q) \times (X_{it-1}^c > 0 | X_{it-2}^c = 0) + \epsilon_{ibt}, \end{aligned} \quad (10)$$

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, $(X_{it-1}^c > 0 | X_{it-2}^c = 0)$ is a dummy equal to 1 if firm i exports to country c in year $t - 1$, but not in year $t - 2$. In this case, the specialization measure, S_{bt}^c , is not specific to firm i .

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

$$\begin{aligned} (X_{ibt} > 0 | X_{ibt-1} = 0) &= \alpha_{ib}^c + \alpha'_{it} + \alpha''_{bt} + \beta_1 (L_{it-1}^c > 0 | L_{it-2}^c = 0) + \sum_{q=2}^4 \beta_{2q} D(S_{bt}^c \in Q_q) \\ &+ \sum_{q=2}^4 \beta_{3q} D(S_{bt}^c \in Q_q) \times (L_{it-1}^c > 0 | L_{it-2}^c = 0) + \epsilon_{ibt}. \end{aligned} \quad (11)$$

Our coefficient of interest in specifications 10 and 11 is β_{3q} for increasing quartiles q of the specialization measures (bottom quartile Q_1 is omitted in both regressions).

Table 5 presents the OLS estimates of the entry margin specifications in 10 and 11.¹⁹ The coefficient estimates in column 1 indicate that exporting to a new destination decreases the probability of starting a banking relationship with a non-specialized bank (bottom quartile omitted) by 1.07 percentage points, and increases with the degree of specialization. The probability of starting a new banking relationship increases by 0.82 p.p. ($1.89 - 1.07$) the year after first exporting, for banks in the top quartile of specialization in the new destination market. This is an economically large effect given that the unconditional probability that an exporter starts a new relationship with a bank at any point in time is 0.74%. Then, this probability doubles for banks specialized in a given country the year after first exporting to this new destination.

The probability of exporting to a new country decreases by 0.55 percentage points the year after a firm starts borrowing from a bank not specialized in that destination (column 2). On the other extreme, this probability increases by 0.6 p.p. ($1.15 - 0.55$) for countries in which the bank specializes. To assess the economic importance of this effect, we compare the magnitude of the coefficient with the unconditional probability that an exporting firm with positive credit adds a new destination in any given year (0.69%). It follows that the likelihood of exporting to a new destination doubles after a firm starts borrowing from a specialized bank.

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

¹⁹The sample for this estimation is the combination of all possible bank-firm relationships—meaning all the bank-firm pairs that do not have a positive outstanding balance in any given year (the large sample size and the low probability of a new relationship).

Table 5: Specialization and New Banking Relationships

Dep. Variable	$(L_{ibt} > 0 L_{ibt-1} = 0)$ (x100) (1)	$(X_{it}^c > 0 X_{it-1}^c = 0)$ (x100) (2)
$(X_{it-1}^c > 0 X_{it-2}^c = 0)$	-1.07*** (0.02)	
$(X_{it-1}^c > 0 X_{it-2}^c = 0) \times (S_{ibt}^c \in Q_2)$	1.15*** (0.03)	
$(X_{it-1}^c > 0 X_{it-2}^c = 0) \times (S_{ibt}^c \in Q_3)$	1.25*** (0.03)	
$(X_{it-1}^c > 0 X_{it-2}^c = 0) \times (S_{ibt}^c \in Q_4)$	1.89*** (0.03)	
$(L_{ibt-1} > 0 L_{ibt-2} = 0)$		-0.55*** (0.03)
$(L_{ibt-1} > 0 L_{ibt-2} = 0) \times (S_{ibt}^c \in Q_2)$		0.13*** (0.03)
$(L_{ibt-1} > 0 L_{ibt-2} = 0) \times (S_{ibt}^c \in Q_3)$		0.82*** (0.03)
$(L_{ibt-1} > 0 L_{ibt-2} = 0) \times (S_{ibt}^c \in Q_4)$		1.15*** (0.03)
Observations	158,463,338	158,713,474
R^2 adj	0.267	0.248

Note: All specifications include bank-country, bank-year and firm-year fixed effects, and the interaction terms $(S_{ibt}^c \in Q_q), q = 2, \dots, 4$, not shown. Standard errors are two-way clustered at the bank and firm levels. ***p < 0.01, **p < 0.05, and *p < 0.1.

4.4 Transmission of Lending Advantage into Merged Banks

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

We modify the data and specification [7](#) to perform event studies around the years in which bank mergers take place. Eight-year interval subsamples around the time of the merger—four years before and four years after the event—are drawn from the original data and stacked to perform a single estimation. We use as a measure of bank specialization the variable S_{ib}^c , defined in [equation 1](#) and computed the year before the merger. We combine the merging entities into a single one before the merger, and, conservatively, we use the maximum of the two banks as a measure of their combined specialization (e.g., if, before the merger, bank-1 and bank-2 were in the top and 3rd quartile of specialization in country A respectively, then the combined entity is considered to be in the top-quartile before the merger, irrespectively of the relative size of the two banks).

We first replicate our baseline estimation in [equation 7](#) without the merger interaction term to corroborate that the point estimates are robust to the change in sample and specification ([Table 6](#), column 1). The coefficient on the term $D(S_{ib}^c \in Q_4) \times \ln(X_{it}^c)$ is positive and significant, larger in magnitude than that in our baseline result in [Table 4](#) (0.051 vs. 0.026 in the baseline regression). Also, the correlation between exports and credit for non-specialized size is negative and significant, larger in magnitude than in the baseline results (−0.023 vs. −0.013).

In column 2, these regressions are augmented with the interaction of $Merger_{bt}$, a

Table 6: Persistence of Specialization after a Merger

Dep. Variable	$\ln(L_{ibt})$	
	(1)	(2)
$\ln(X_{it}^c)$	-0.023*	-0.022
	(0.013)	(0.013)
$Merger_{bt}$		0.325
		(0.238)
$\ln(X_{it}^c) \times Merger_{bt}$		-0.024
		(0.024)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_2)$	0.013	0.012
	(0.013)	(0.013)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_3)$	0.031*	0.032*
	(0.016)	(0.016)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_4)$	0.051**	0.051**
	(0.025)	(0.024)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_2) \times Merger_{bt}$		0.014
		(0.016)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_3) \times Merger_{bt}$		0.012
		(0.016)
$\ln(X_{it}^c) \times (S_{ibPreMerger}^c \in Q_4) \times Merger_{bt}$		0.021
		(0.015)
Observations	539,885	539,885
R-squared	0.5677	0.5677

Note: Both specifications include bank-merger-year, firm-merger-year and country-bank-merger fixed effects, and the interaction terms $(S_{ibPreMerger}^c \in Q_q)$ and, for column 2, $(S_{ibPreMerger}^c \in Q_q) \times Merger_{bt}$ for $q = 2, \dots, 4$, not shown. Standard errors are two-way clustered at the bank and firm levels. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

dummy equal to 1 during the four years after the event for the merging entity. We also augment the bank-time, firm-time, and bank-country sets of dummies with an event dummy interaction (e.g., there is a separate bank-time dummy for every merger event). The coefficient on the triple interaction with the merger indicator, $D(S_{ib}^c \in Q_q) \times \ln(X_{it}^c) \times Merger_{bt}$, measures whether the link between the specialization and lending is affected by the merger. The point estimate in column 2 is positive but not statistically significant. That is, the merged entity inherits the specialization of the original banks.

These results imply that banks retain their capabilities in their markets of specialization even as they are acquired or merged into larger institutions. Thus, the source of the

lending advantage analyzed here is distinct from that derived from firm-specific information (as emphasized in [Stein, 2002](#)), and it is not hindered by organizational constraints.

5 Economic Relevance

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

5.1 Elasticity of Credit Demand to Exports

To obtain the elasticity of credit to changes in the demand for exports we use again specification 7, 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

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

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

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

Table 7, column 1, shows evidence of the existence of a first stage. It shows the estimated coefficients from a regression of exports on GDP growth and real exchange rate in the destination country. The coefficients on both variables are positive and significant, and the F-statistic exceeds 20.

Table 7: Lending Advantage and Specialization

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

Note: The specification includes firm-year, bank-year and bank-country fixed effects, and all interaction terms (not shown). Standard errors are clustered at the bank and firm levels. ***p < 0.01, **p < 0.05, and *p < 0.1.

data for French firms.

Table 7, column 2 shows the instrumental variables (IV) estimation of specification 7, using GDP growth and real exchange rate in the destination country as instruments for export demand. Since the exports variable is interacted with three portfolio share quartile dummies, we also interact the two instruments with the quartile dummies for a total of eight instruments.²² The IV estimates indicate that the elasticity of credit to an export demand shock is positive for all levels of specialization. Even for non-specialized banks, this elasticity is 0.227 (bottom quartile omitted). However, the credit elasticity from banks in the top two quartiles of specialization is 50% larger. This result is important because it implies that the lending advantages have a first order impact on firms' marginal credit demand decisions. The result also implies that the same export market shock will have a very heterogeneous impact across banks with different markets of specialization.

We note that the point estimates of the credit elasticities are an order of magnitude larger than the baseline OLS estimates discussed in the previous subsection. The IV approach isolates the variation in exports and credit due to market-specific export demand shocks. In contrast, the baseline OLS estimates in Table 4 capture covariances between exports to a country and borrowing from specialized banks that may be driven by export-demand shocks, firm shocks (e.g., productivity, credit, etc.) and product shocks (e.g, changes in world prices, cost). The comparison of the two estimates indicates that a small fraction of the total variation in exports is driven by aggregate demand shocks in the country of destination.

5.2 Elasticity of Exports to Credit Supply

The results so far indicate that banks have lending advantages across different markets and that firms demand credit disproportionately from specialized banks to expand output in their market of specialization. These results, however, do not answer the question of whether differences in bank lending advantages are large or whether they have important implications for output. The reason is that even small differences in lending advantages

²²Estimates of the four first stages are omitted for brevity and available from the authors.

may lead to large swings in demand across banks if banks are close substitutes as capital suppliers. To shed light on this issue we turn to exploring how a firm's output in a market responds to changes in the supply of credit from specialized and non-specialized banks.

We now evaluate how shocks to the credit supply of specialized banks affect firm output in the market of specialization (relative to other markets). To isolate bank-specific credit supply shocks, we use the empirical setting in [Paravisini et al. \(2015\)](#) (hereafter, PRSW): bank-level heterogeneity in the exposure to the 2008/09 financial crisis as an instrument for changes in credit supply. In 2008, international portfolio capital inflows to Peru decreased sharply, and, as a result, funding to banks with a high share of international liabilities dropped substantially. To account for variation in the demand for exports PRSW use country of destination-product-time dummies. We augment their analysis to assess whether a bank credit supply shock has a larger impact on exports to the bank's country of specialization:

$$\ln X_{ipt}^c = \alpha_{ibp}^c + \alpha_{pt}^c + \beta_1 \ln L_{ibt} + \sum_{q=2}^4 \beta_{2q} D(S_{ibt}^c \in Q_q) + \sum_{q=2}^4 \beta_{3q} D(S_{ibt}^c \in Q_q) \times \ln L_{ibt} + \epsilon_{ibpt}^c \quad (12)$$

where X_{ipt}^c is the (volume) of exports of product p by firm i to country c during the intervals $t = \{Pre, Post\}$, Pre and $Post$ periods correspond to the 12 months before and after July 2008. L_{ibt} is firm- i 's credit from bank- b in the period t . We instrument the change in credit supply in $t = Post$ with $Exposed_b \times Post_t$, where $Exposed_b$ is a dummy equal to 1 if the bank has a share of foreign debt above 10% in 2006, and $Post_t$ is a dummy equal to 1 during the 12 months after July 2008.²³ In the next subsection we show that this instrumental approach is still valid in the context of specialized banks. The coefficient β_{3q} in specification 12 captures the elasticity differential of exports towards countries the bank specializes (quartile q) relative to destinations in which the banks does not (bottom quartile omitted).

The regression includes firm-product-bank-country fixed effects, α_{ipb}^c , which control

²³The 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.

for all (time-invariant) unobserved heterogeneity across firms and banks in exporting that product to that destination. It also includes a full set of country-product-time dummies, α_{pt}^c , 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_{ipt}^c , the right-hand side of specification 12 varies also at the bank level. To estimate the parameters in specification 12, 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_{ipt}^c is constant across banks for a given product-country-firm-time combination.

Table 8: Credit Supply Shock and Specialization

Dep. Variable	$\ln(L_{ibt})$	$\ln(X_{ipt}^c)$				
		FS (1)	OLS (2)	IV (3)	OLS (4)	IV (5)
$Exposed_b \times Post_t$	-0.195** (0.083)					
$\ln(L_{ibt})$		0.025** (0.010)	0.195*** (0.046)	0.011 (0.012)	0.035 (0.070)	
$\ln(L_{ibt}) \times (S_{ibt}^c \in Q_2)$				-0.009 (0.015)	-0.596 (0.542)	
$\ln(L_{ibt}) \times (S_{ibt}^c \in Q_3)$				0.031** (0.015)	-0.063 (0.231)	
$\ln(L_{ibt}) \times (S_{ibt}^c \in Q_4)$				-0.016 (0.010)	0.446** (0.173)	
Observations	33,214	51,024	51,024	51,024	51,024	
R^2 adj	0.197	0.438		0.609		

Note: All specifications include product-country-year and bank-firm-product-country FE (HS 4-digits). The specifications in (4) and (5) include the interaction terms $(S_{ibt}^c \in Q_q)$, not shown. Standard errors are clustered at the bank and product-destination level. ***p < 0.01, **p < 0.05, and *p < 0.1.

Table 8, column 1, shows evidence of the existence of a first stage for the IV estimation. The coefficient of a regression of bank credit on the bank exposure instrument is negative and statistically significant (F-statistic exceeds 10), implying that banks with more expo-

²⁴Products 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.

sure to foreign liabilities reduced lending more after the crisis.

Table 8, columns 2 through 5, present the OLS and IV estimates of specification 12, where the endogenous variable, credit by bank b to firm i , is instrumented with bank exposure, $Exposed_b \times Post_t$. Columns 4 and 5 augment the regression with interactions of credit with the bank specialization quartile dummies, and the instrument set is augmented to include bank exposure interacted with the specialization quartile dummies.²⁵

The IV estimate of the overall elasticity of exports to the credit supply shock is shown in column 3. On average, a 10% reduction in credit supply results in a 1.9% drop in the volume of exports. Column 5 shows how this elasticity varies depending on whether the destination country corresponds to the bank's set of specialization countries. These results suggest that the entire effect of the credit supply shock on export is in destination markets where the bank specializes in. The point estimates imply that a 10% reduction in a bank's credit supply leads to a 4.5% decline in exports towards countries in which the bank specializes (top quartile), while it does not affect exports towards destinations in which the bank does not. The difference between the top and bottom quartiles is statistically significant at the 5%-level. This shows that the effect on credit supply during a financial crisis is non-linear, with the effect being concentrated among specialized banks.²⁶

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

²⁵Estimates of the four first stages are omitted for brevity.

²⁶As in the previous subsection, the elasticity estimates are significantly larger than the OLS estimates, indicating that a small fraction of the total variation in bank credit during the 2008 financial crisis was driven by credit supply.

5.3 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.²⁷ The main idea behind this approach is that using firm fixed effects controls for the endogenous matching of banks and firms (Khwaja and Mian, 2008). This assumption does not hold in general when banks are specialized, but it may still hold under restricted circumstances: if the source of the credit supply shock is uncorrelated with anything affecting specialized demand. We provide a formal derivation of this result in the internet appendix.

We can illustrate in our setting how regressions saturated with firm fixed effects and augmented with specialization measures can be used to evaluate this approach to identification. 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 firm-bank-year credit data we estimate the following specification:

$$\ln(L_{ibt}) = \alpha_{ib} + \alpha_{it} + \beta \cdot Exposed_b \times Post_t + \nu_{ibt}, \quad (13)$$

where the definition of the variables and time periods coincide with those in specification 12. 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.

²⁷For 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).

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 9, column 1 (this is an exact replication of the within-firm estimates in PRSW). The point estimate suggests that the supply of credit by exposed banks dropped by 16.8%, relative to not-exposed banks, after the capital flow reversals. However, firm-time dummies may not fully absorb credit demand variation in the presence of bank specialization.

Table 9: Identification of Credit Supply Shocks

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

Note: Results of 15 in within-firm differences (*Post* vs. *Pre*). All specifications include firm fixed effects. Standard errors clustered at the bank level. ***p < 0.01, **p < 0.05, and *p < 0.1.

We augment specification 15 with the variable $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q)) \times Post_t$, for $q = 2, \dots, 4$ (bottom quartile Q_1 omitted). The dummy $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q))$ 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 countries in which bank- b is in the q -th quartile of the specialization, $C(S_{ib}^c \in Q_q)$ —i.e., countries for which S_{ib}^c defined in equation 9 is in the q -th quartile of the country-specific distribution in the *Pre* period. The coefficient on this additional term measures the change in the equilibrium amount of credit to firms that export to the country in which bank b has some level of specialization, relative to the change in

credit to firms that do not (bottom quartile). The estimated coefficients of the augmented specification are shown in Table 9, column 2. The estimated coefficient on the additional term is largest (in absolute terms) for the top quartile, -0.158 . This result has most likely has a demand interpretation: the global demand for Peruvian exports declined during 2008, and firms reduced their demand for credit from banks specializing in their exporting activities. The magnitude of the coefficient indicates that the demand for export-related credit dropped by 16% during the sample period. Thus, the variable $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_4))$ recovers bank-specific credit demand shocks that *are not* accounted for by the firm-time dummies in specification 15.²⁸

Adding $(C(X_i^c > 0) \cap C(S_{ib}^c \in Q_q))$ to specification 15 does not have a statistically significant impact on the magnitude of the coefficient on $Exposed_b$. This implies that, in the context of the PRSW application, the foreign funding shock affecting Peruvian banks was virtually uncorrelated with confounding effects related to the banks' export market of expertise. This is a necessary condition for disentangling credit supply from credit demand.

The signs and magnitudes of the estimated supply and demand effects are informative of the potential bias that may result if the two sources of variation simultaneously affect the bank and its market of expertise. Both estimates have the same sign, indicating that, in this setting, confounding demand and supply would lead to an overestimation of the credit supply shock. The magnitude of the potential bias is large. Interpreting the entire within-firm variation in credit as supply-driven would lead to overestimating the size of the supply shock by a factor of 2 in the case of banks in the top quartile of specialization—i.e, $(0.158 + 0.158)/0.158$.²⁹

The large bias may be specific to our application in the context of the 2008 financial

²⁸An 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.

²⁹We focus on comparing the coefficients rather than the marginal R^2 because most variation in bank specialization is controlled for by fixed effects.

crisis, when large and heterogenous export demand shocks occurred concurrently with the variation in bank credit supply. The result highlights how the assumptions behind the saturated regression approach to identifying credit supply are less likely to hold when the approach is applied during periods when sector-specific demand is also fluctuating.

The role of market-specific bank specialization is also important when interpreting the statistical decomposition of credit variation into bank-specific and firm-specific factors using fixed effects (see, for example, [Amiti and Weinstein \(2018\)](#)). When banks specialize in certain markets or activities, then bank fixed effects do not correspond to supply. The reason is that a pure sector-specific demand shock will not affect the demand for credit proportionally across all banks. Instead, as our results above demonstrate, it will affect the demand for credit disproportionately from the bank specialized in the sector where the demand shock occurred and may be captured by the bank fixed effects.³⁰ Mapping bank fixed effects to credit supply shocks requires adjusting for market-specific bank specialization.

6 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 guarantees, 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

³⁰When banks are relationship lenders, firm fixed effects do not correspond to demand either. A pure credit supply shock will not affect bank credit proportionally across all firms, but differentially depending on the magnitude of the bank's informational advantage. In this case the supply heterogeneity across firms may be captured by the firm fixed effects.

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 3.1. 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 and, in doing so, narrow down potential mechanisms. We first evaluate the correlation between our measure of bank specialization in a country and the variables that capture the geographical advantages conferred by the ownership country and subsidiary network. Table 10, 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;³¹ 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 .³² For this cross-sectional analysis, we use the measure of specialization in equation 1, S_{bt}^c , averaged during the entire life of the bank.³³ We find that, indeed, there is a connection between the bank's country of ownership and the bank's set of specialization countries. Banks are more likely to specialize in the country of their headquarters. We

³¹We 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).

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

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

Table 10: Specialization and Global Banks

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

Note: Specification in (1) includes bank, country and year fixed effects. In (2) and (3), firm-year, bank-year and country-bank fixed effects, and the interactions terms ($S_{ibt}^c \in Q_q$), not shown. Standard errors are two-way clustered at the bank and firm levels. ***p < 0.01, **p < 0.05, and *p < 0.1.

find no correlation between our measure of country-specialization and the language in headquarters nor the location of subsidiaries.

We then explore whether the bank's country of ownership is a sufficient statistic of the market-specific lending advantages found in our baseline regressions in Table 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 equation 7 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 10, columns 2 and 3. None of the interaction terms are statistically significant, and their inclusion in the regression does not change the magnitude or the significance of the interaction of exports and specialization.³⁴

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

7 Conclusions

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

The findings in this paper have important implications for the industrial organization

³⁴Our 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.

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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Internet Appendix

Model extension

The exposition in subsection 3.2 focuses on the firm's optimal choice of bank per activity, which is our object of interest. It purposely simplifies the problem of the firm to cost minimization for any given level of output, in each activity c . This problem could be understood as a step within a more complete profit maximization, where output level and total variable cost are endogenous optimal outcomes.

Consider the case of CES demand structure, with activity-wide demand shifter Q^c (i.e., Q^c recovers market size, competition prices, and other market-wide variables exogenous to the firm) and elasticity of substitution $\sigma > 1$ (an application mentioned in the body of the paper). Firm i faces the following demand function for activity c :

$$q_i^c = Q^c (p_i^c)^{-\sigma}.$$

As in the body of the paper, the production function incorporates the bank-activity lending advantage and the firm idiosyncratic factor: $q_i^c = \gamma_b^c L_{ib}^c \exp\{\mu \epsilon_{ib}^c\}$, provided that bank b is chosen to fund activity c .

The firm chooses the level of output q_i^c and the bank b that maximizes profits for activity c . Replacing with the demand and production functions, the problem can be rewritten as:

$$\max_{q,b} (Q^c)^{\frac{1}{\sigma}} (q_i^c)^{\frac{\sigma-1}{\sigma}} - \frac{r_b}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\} q_i^c.$$

The first and second terms correspond to revenues and total cost, respectively.

This problem can be solved in two steps. $MC_i^c = \frac{r_b}{\gamma_b^c} \exp\{-\mu \epsilon_{ib}^c\}$ is the marginal cost of production, given the yet-to-be-chosen bank b . Then, the profit maximization problem can be expressed as:

$$\max_q (Q^c)^{\frac{1}{\sigma}} (q_i^c)^{\frac{\sigma-1}{\sigma}} - MC_i^c q_i^c.$$

The optimal output and price are:

$$\begin{aligned} q_i^c &= Q^c \left[\frac{\sigma}{\sigma-1} MC_i^c \right]^{-\sigma} \\ p_i^c &= \frac{\sigma}{\sigma-1} MC_i^c. \end{aligned}$$

In the body of the paper, we pair activities with export destinations. Then, total cost of credit $r_b L_{ib}^c$ is proportional to exports towards c :

$$r_b L_{ib}^c = MC_i^c q_i^c = \frac{\sigma-1}{\sigma} p_i^c q_i^c = \frac{\sigma-1}{\sigma} X_i^c,$$

and lending towards activity c , provided b is the chosen bank to fund this activity, is simply:

$$L_{ib}^c = \frac{\sigma-1}{\sigma} \frac{X_i^c}{r_b},$$

Optimal profits depend negatively of the marginal cost of production MC_i^c :

$$\Pi_i^c = \left(\frac{\sigma-1}{\sigma} \right)^{\sigma-1} Q^c (MC_i^c)^{-\sigma+1}.$$

Then, the maximization is complete with firm's choice of bank for each activity c , which is the step explained in the body of the paper:

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

Proxy for comparative lending advantage using observable data

We do not observe L_{ib}^c but only $L_{ib} = \sum_{k=1}^C L_{ib}^k$. Then, as explained in subsection 3.2, we use $\sum_i L_{ib} X_i^c$, as a proxy for $\sum_i L_{ib}^c$, to recover our object of interest, $\tilde{\gamma}_b^c$, i.e., the pattern of banks' comparative advantage by export destination.

We define S_b^c as follows:

$$S_b^c = \frac{\sum_i^I L_{ib} X_i^c}{\sum_k^C \sum_i^I L_{ib} X_i^k}.$$

Notice that, from equation 2 in the body of the paper,

$$\sum_{i=1}^I L_{ib} X_i^c = \sum_{i=1}^I \left(\sum_{k=1}^C L_{ib}^k \right) X_i^c = \sum_{i=1}^I \left(\frac{1}{r_b} \sum_k^C \mathbb{I}_{ib}^k X_i^k \right) X_i^c,$$

where \mathbb{I}_b^k is an indicator function that signals whether bank b is chosen by firm i to fund activity k . Since the idiosyncratic motive $\{\epsilon_{ib}^c\}$ is assumed to be i.i.d across firms, we get (for a large number of firms):

$$\begin{aligned} \sum_{i=1}^I L_{ib} X_i^c &= \frac{1}{r_b} \sum_{k'=1}^C Pr_b^{k'} \sum_{i=1}^I (X_i^{k'} X_i^c) \\ \sum_{k=1}^C \sum_{i=1}^I L_{ib} X_i^k &= \frac{1}{r_b} \sum_{k'=1}^C Pr_b^{k'} \sum_{k=1}^C \sum_{i=1}^I (X_i^{k'} X_i^k). \end{aligned}$$

Then, we can express the observable object S_b^c in terms of the parameters of interest in our model, $\{\tilde{\gamma}_b^k\}$:

$$S_b^c = v \sum_{k=1}^C \left\{ \tilde{\gamma}_b^k \sum_{i=1}^I (X_i^k X_i^c) \right\} \quad \tilde{\gamma}_b^k \equiv \frac{Pr_b^k}{\sum_{k'=1}^C Pr_b^{k'}},$$

where, using the assumption of independence of $\{\tilde{\gamma}_b^c\}$ and $\sum_{k=1}^C \tilde{\gamma}_b^k = 1$, we get that (for a large number of banks) $v > 0$ is constant across all banks:

$$v^{-1} = \sum_{k=1}^C \left\{ \tilde{\gamma}_b^k \sum_{k'=1}^C \sum_{i=1}^I (X_i^k X_i^{k'}) \right\} = \sum_{k=1}^C \sum_{k'=1}^C \sum_{i=1}^I (X_i^k X_i^{k'}).$$

We now show the conditions under which S_b^c is a good proxy for our object of interest $\tilde{\gamma}_b^c$, for any given destination c . In particular, the conditions on the correlation between destinations in the distribution of firm exports and the correlation between destination in the bank lending advantages, so that the covariance between these two objects is positive

for any country c (i.e., $\text{cov}_c(\tilde{\gamma}_b^c, S_b^c) > 0$):

$$\begin{aligned}
\text{cov}_c(\tilde{\gamma}_b^c; S_b^c) &= B^{-1} \sum_{b=1}^B \{\tilde{\gamma}_b^c \cdot S_b^c\} - \left\{ B^{-1} \sum_{b=1}^B \tilde{\gamma}_b^c \right\} \cdot \left\{ B^{-1} \sum_{b=1}^B S_b^c \right\} \\
&= v B^{-1} \sum_{b=1}^B \left\{ [\tilde{\gamma}_b^c - \bar{\gamma}^c] \cdot \sum_{k=1}^C \left[\tilde{\gamma}_b^k \sum_{i=1}^I (X_i^c X_i^k) \right] \right\} \\
&= v \cdot \left\{ B^{-1} \sum_{b=1}^B \sum_{k=1}^C [\tilde{\gamma}_b^c - \bar{\gamma}^c] \tilde{\gamma}_b^k \right\} \cdot \left\{ \sum_{k=1}^C \sum_{i=1}^I (X_i^c X_i^k) \right\},
\end{aligned} \tag{14}$$

where we use the overline for averages, i.e., $\bar{\gamma}^c \equiv B^{-1} \sum_b \tilde{\gamma}_b^c$. Moreover, we refer to export aggregates as $\sum_i X_i^c \equiv X^c$ and the covariance between export destinations as σ_{ck} , so that $\sum_i (X_i^c X_i^k) = X^c X^k + \sigma_{ck}$. Correspondingly, and $\text{cov}_b(\tilde{\gamma}_b^c; \tilde{\gamma}_b^k) = \rho_{ck}$ for $c \neq k$. Then:

$$\text{cov}_c(\tilde{\gamma}_b^c; S_b^c) = v \sum_{k=1}^C \{ (X^c X^k + \sigma_{ck}) \cdot \rho_{ck} \}.$$

If the covariances between destinations in exports and lending advantages are zero (i.e., $\sigma_{ck} = \rho_{ck} = 0$ for all $c \neq k$), then the expression above is simplified to (the case considered in the body of the paper):

$$\text{cov}_c(\tilde{\gamma}_b^c; S_b^c) = v \sum_{i=1}^I (X_i^c)^2 B^{-1} \sum_{b=1}^B (\tilde{\gamma}_b^c - \bar{\gamma}^c)^2 > 0.$$

More generally, a sufficient condition for this covariance to be positive is $\frac{d\rho_{ck}}{d\sigma_{ck}} \geq 0$. This condition has an intuitive interpretation. Some export markets share common attributes (for example, EU countries have common administrative rules), which may result in positive correlation in the expertise of both firms and banks towards those markets. This condition states that some of those shared attributes are common for banks and firms, so that the correlation between destinations in the pattern of banks' lending advantage, σ_{ck} , and in the pattern of firms' export, ρ_{ck} , satisfy $d\rho_{ck}/d\sigma_{ck} > 0$.

Under those conditions, country- c specific ranking of $\{S_b^c\}_{b \in B}$ is a good instrument for

the unobservable ranking of $\{\tilde{\gamma}_b^c\}_{b \in B}$ across banks, for any destination c .

Empirical Identification of Credit Supply Shocks

We present a simple model based on Khwaja and Mian (AER, 2008; henceforth “KM”) to explain why firm-time fixed effects cannot fully account for changes in firm credit demand when banks are specialized. We start with the model described in KM and derive the identification assumption in their setting. Next, we consider an extension of the KM model in which banks specialize and discuss how it affects the identification assumption.

KM assumes that each bank makes a single loan. We follow KM’s notation and denote the loan made by bank i to firm j at time t as L_{ij}^t . Banks can finance the loan with deposits or bonds. The following balance sheet identity holds:

$$L_{ij}^t = D_i^t + B_i^t,$$

where D_i^t is deposit financing and B_i^t is bond financing.

KM assumes that deposit funding is insured and available up to an exogenous amount denoted by \bar{D}_i^t . Because of deposit insurance, banks strictly prefer deposit financing over bond financing. To make the problem interesting, KM assumes that deposit funding is scarce such that $L_{ij}^t > \bar{D}_i^t$. It follows that banks need to issue bonds to finance the loan.

KM assumes that bond financing has a *marginal* cost of $\alpha_B B_i^t$. It is straightforward to see that the marginal cost of bond financing is increasing in the amount of bond financing, B_i^t . This can be interpreted as a reduced form way of capturing informational frictions in bank financing (e.g., Stein, 1998).

KM assumes that the marginal return to a loan is given by $\bar{r} - \alpha_L \times L_{ij}^t$. It is straightforward to see the marginal return on loan L_{ij}^t is decreasing in loan size.

KM assumes that there are shocks to the supply of deposit funding. The supply shock is modeled as a shock to the total availability of deposit funding. Total deposit funding is given by $D_i^{\bar{t}+1} = \bar{D}_i^t + \bar{\delta}_t + \delta_{it}$ where $\bar{\delta}_t$ is an aggregate deposit shock and δ_{it} is an

idiosyncratic shock to bank i at time t .

KM assumes that there are shocks to the demand for credit. The demand shock is modeled as a shock to the return on lending. It can be interpreted as a productivity shock. The return to lending is given by $\bar{r} - \alpha_r \times L_{ij}^t + \bar{\eta}_t + \eta_{jt}$ where $\bar{\eta}_t$ is the aggregate demand shock and η_{jt} is an idiosyncratic shock to firm j at time t .

KM solves this model for a two-period setup. KM drops subscript t when examining the two period setup. They use the FOC conditions for each period combined with the balance sheet identity to solve for loan growth, denoted as ΔL_{ij} , in terms of the exogenous demand and supply shocks and the cost parameters:

$$\Delta L_{ij} = \frac{\alpha_B}{\alpha_L + \alpha_B} (\bar{\delta} + \delta_i) + \frac{1}{\alpha_L + \alpha_B} (\bar{\eta} + \eta_j).$$

This equation can be rewritten in terms of exposure to an aggregate shock and idiosyncratic shocks:

$$\Delta L_{ij} = \frac{1}{\alpha_L + \alpha_B} (\bar{\eta} + \alpha_B \bar{\delta}) + \frac{1}{\alpha_L + \alpha_B} \eta_j + \frac{\alpha_B}{\alpha_L + \alpha_B} \delta_i. \quad (15)$$

KM suggests estimating this equation using the following OLS regression:

$$\Delta L_{ij} = \beta_0 + \beta_1 D_i + \gamma_j + \varepsilon_{ij},$$

where $D_i = \delta_i$ captures a bank-specific deposit shock.

Assume that the econometrician cannot observe $\gamma_j = \frac{1}{\alpha_L + \alpha_B} \eta_j$. It follows that the combined error term is $\gamma_j + \varepsilon_{ij}$. The OLS coefficient $\hat{\beta}_1$ identifies the lending channel if $Cov(D_i, \gamma_j + \varepsilon_{ij}) = 0$.

KM argues that it is unlikely that the condition $Cov(D_i, \gamma_j + \varepsilon_{ij}) = 0$ holds in most empirical settings. They argue that γ_j is likely to be positively correlated with D_i . The reason is that firms experiencing a negative shock (low realization of firm-level shock η_j) are likely to be matched to banks that experience a negative deposit shock (low realization

of bank funding shock δ_i). As discussed in KM, this implies that the coefficient $\hat{\beta}_1$ would be biased upwards.

To address this issue, KM propose to include firm fixed effects FE_j in the OLS regression. The firm fixed effects control for firm-level shocks γ_j . Conditional on firm fixed effects, it is sufficient to assume that $Cov(D_i, \varepsilon_{ji}) = 0$. This is a weaker identification assumption. Under this assumption the OLS coefficient $\hat{\beta}_1$ identifies the lending channel. This is approach taken in KM.

KM points out this assumption could be violated. Specifically, they point out that this assumption does not hold if firm's loan demand is bank-specific and correlated with shocks to bank liquidity. Next, we discuss how bank specialization can create loan demand that is bank-specific and correlated with shocks to bank liquidity.

Let us add bank specialization to this framework. Suppose firms engage in activities $k \in \{1, \dots, K\}$. Given that KM assumes that each bank only makes one loan, each bank is specialized in one activity k . We assume that each firm engages in two different activities.

Assume that the marginal return to lending depends on the activity such that the firm are subject to activity-specific demand shocks, η_{jt}^k . In our setting, this is isomorphic to having a bank-specific loan demand shock. Intuitively, this can be interpreted as a positive net present value derived from services provided by specialized banks.³⁵ It follows that the marginal return to loan L_{ij}^t is given by $\bar{r} - \alpha_r \times L_{ij}^t + \bar{\eta}_t + \eta_{jt}^k$ where k denotes the specialization of bank i .

Solving for the two-period setup, this yields the following equilibrium condition:

$$\Delta L_{ikt} = \frac{1}{\alpha_L + \alpha_B} (\bar{\eta} + \alpha_B \bar{\delta}) + \frac{1}{\alpha_L + \alpha_B} \eta_j^k + \frac{\alpha_B}{\alpha_L + \alpha_B} \delta_i. \quad (16)$$

Note that the only difference between the equilibrium condition (15) and (16) is that we replaced η_j with η_j^k .

³⁵For example, a borrower expects a higher return when exporting to Argentina if the borrower takes out a loan from a bank that specializes in Argentina.

Now suppose we estimate the following OLS regression:

$$\Delta L_{ij} = \beta_0 + \beta_1 D_i + \gamma_j^k + \varepsilon_{ij},$$

where $D_i = \delta_i t$ represents a bank-specific deposit shock. Assume the econometrician cannot observe $\gamma_j^k = \frac{1}{\alpha_L + \alpha_B} \eta_{jt}^k$. It follows that the combined error term is $\gamma_j^k + \varepsilon_{ij}$. The OLS coefficient $\hat{\beta}_1$ identifies the lending channel if $Cov(D_i, \gamma_j^k + \varepsilon_{ij}) = 0$. As discussed above, this assumption is unlikely to hold in many empirical settings.

Now consider adding a firm fixed effect FE_j in the OLS regression. The firm fixed effect does not control for firm-level shocks because the shock varies across activities within the same firm. Hence, contrary to the KM setup, the condition $Cov(D_i, \varepsilon_{ji}) = 0$ is *not* sufficient for identification of the lending channel. This is the sense in which firm fixed effects do not solve the identification problem in the presence of bank specialization.

To summarize, if loan-demand is bank-specific then adding firm fixed effects (as in KM) does not solve the identification problem.