Global vs. Local Banking:
A Double Adverse Selection Problem[*]

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Abstract

This paper provides a new theory of credit allocation in financial systems with both global and local banks, and tests it using cross-country loan-level data. I first point out that the traditional theory in banking and corporate finance of firm-bank sorting based on hard versus soft information does not explain the sorting patterns between firms and global versus local banks. In light of this puzzle, I propose a new perspective: global banks have a comparative advantage in extracting *global* information, and local banks have a comparative advantage in extracting *local* information. I formalize this view in a model in which firms have returns dependent on global and local risk factors, and each bank type can observe only one component of the firms' returns. This double information asymmetry creates a segmented credit market with a double adverse selection problem: in equilibrium, each bank lends to the worst type of firms in terms of the unobserved risk factors. Moreover, I show that the adverse selection problem has important macroeconomic implications. When one of the bank types faces a funding shock, the adverse selection affects credit allocation at both the extensive and intensive margins, generating spillover and amplification effects through adverse interest rates. I formally test the model using detailed firm-bank micro data and empirical strategies that tightly map to the model set-up. I find firm-bank sorting patterns, and effects of US and Euro area monetary policy shocks on credit allocation, that support the model predictions. This evidence reveals a novel *adverse selection channel* of international monetary policy transmission.

1　Introduction

One of the most striking developments in credit markets across the world over the past two decades has been the increase in global banking credit—loans given by global banks to firms abroad.[1] Global banking credit has more than tripled since the mid-1990s, reaching almost \$15 trillion and accounting for around 20% of total domestic private credit on average for a developed or major emerging market economy (Figure 1). This implies that there has been both a transformation of the competitive structure of credit markets and an expansion of financing sources for corporations: in a typical financial system today, firms can get credit not only from local banks but also from global banks.

Global banking credit also has important macroeconomic and policy implications. The global financial crisis has revealed that fluctuation in this credit serves as a key channel through which monetary policy and liquidity conditions get transmitted abroad (see, e.g., Cetorelli and Goldberg 2012a, Schnabl (2012), Rey 2016, Bräuning and Ivashina 2017). This, in turn, has prompted debate on optimal bank regulation and macroprudential policies in the presence of globalized credit markets (see e.g., Stein 2014, Fischer 2015, Rajan 2015, and Bernanke 2017).

Despite extensive debates on measures to minimize the risks entailed by global banking credit, it remains an open question how credit is allocated in financial systems with both global and local banks in the first place. Why do some firms get loans from global banks instead of local banks? Is existing theory in banking and corporate finance sufficient for explaining patterns of firm-bank sorting in globalized financial systems? How do global banks propagate monetary policy and liquidity shocks across borders?

In this paper, I study these questions theoretically and empirically. I point out that the traditional theory in banking and corporate finance of firm-bank sorting based on hard versus soft information does not explain the sorting patterns between firms and global versus local banks. Instead, I show that bank specialization in *global* versus *local* information constitutes a key mechanism driving firm-bank sorting in financial systems with both global and local banks. Global banks specialize in information on global risk factors, and local banks specialize in information on local risk factors. This micro-foundation reveals a problem of double adverse selection in credit allocation in globalized financial systems, and has important macroeconomic implications. In particular, the double adverse selection constitutes a novel *adverse selection channel* of international transmission.

I start the analysis by testing whether the sorting pattern between firms and global versus

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[1] Global banking credit, as described here, can be summarized as cross-border loans. Global banks are defined as banks that make cross-border loans and thereby have sizable foreign positions on their balance sheets.

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Figure 1: **Global Banking Credit to Private Sector**

(a) Total Global Banking Credit, All Countries

(b) Share in Total Private Credit, by Country
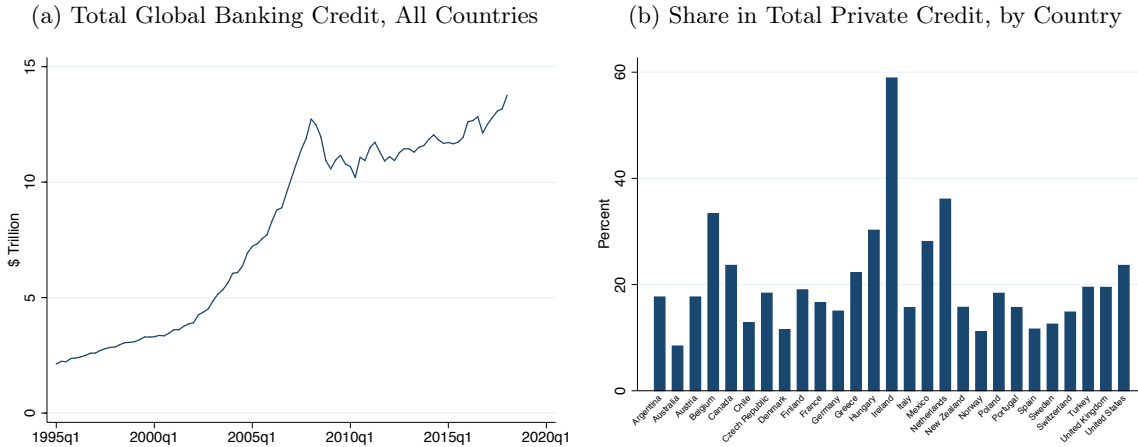
Notes. Panel (a) plots a time-series of total cross-border credit to the non-bank private sector across all BIS reporting countries. Source: BIS Locational Banking Statistics. Panel (b) plots the share of cross-border credit in total private credit, averaged over 2005-2016, for a cross-section of developed and major emerging market economies. Source: BIS Locational Banking Statistics and IMF International Financial Statistics.

local banks follows the prediction from traditional banking and corporate finance theory. The traditional theory posits that banks and firms sort based on hard and soft information[2]: large banks are more likely to lend to firms with more readily available hard information, which tend to be large and established firms, while small banks are more likely to establish relationships with firms with more soft information, which tend to be small and young firms. Mapping this theory to the context of firm-bank sorting in globalized financial systems, one would conjecture that global banks are more likely to lend to firms with more hard information, since global banks tend to be larger than local banks. However, using a cross-country firm-bank loan-level dataset, I find that the traditional theory does *not* predict the sorting patterns between firms and global versus local banks: both global and local banks lend to firms across the entire asset size and age distribution. This points to a puzzle in the mechanism driving global banking credit: why do firms of similar size and age borrow from different types of banks?[3]

In light of this puzzle, I raise a new perspective. I argue that global and local banks differ in their specialization in global and local information: global banks have a comparative

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[2] A well-established strand of literature in finance has used the distinction between hard and soft information to explain lending relationships between banks and firms. Section 2 provides an overview of the traditional theory.

[3] Another mechanism we may conjecture driving the sorting may be bank specialization in loans of particular currency denominations. I provide evidence in Section 2 showing that, in fact, global and local banks lend in both local and non-local currencies.

advantage in extracting information on global risk factors, and local banks have a comparative advantage in extracting information on local risk factors. Each bank type's comparative informational advantage plays a key role in determining firm-bank sorting in financial systems with both bank types. This idea is motivated by the observation that global banks are uniquely positioned to extract information on global factors through global market making activities and research efforts within the banking organizations.[4] At the same time, local banks are more conveniently positioned to extract information on local factors through local lending relationships (Petersen and Rajan 1994, Berger et al. 2005).

To formalize the new perspective and provide guidance for empirical testing, I first develop a model with global and local banks in which each bank type's comparative informational advantage serves as the key ingredient. From this one key ingredient, the model generates a sharp prediction about the equilibrium credit allocation in a two-bank-type economy: firms with higher expected return based on global factors relative to local factors are more likely to borrow from global banks, and vice versa for firms with returns more dependent on local factors. Using cross-country firm-bank loan-level data and empirical strategies that closely map to the model, I find empirical evidence that is consistent with the prediction.

To make this result more concrete, consider two firms: Oil States International, an American multinational corporation that provides services to oil and gas companies, and Zale Corporation, an American jewelry retailer that has a large presence in malls around the US. While both firms are public firms, headquartered in Texas, and of similar size (with total assets around $1.3 billion in 2017), Oil States International's return is more dependent on global risk factors, since, as a multinational firm in the petroleum industry, it is highly exposed to global demand and supply shocks. On the other hand, Zale Corporation's return is more exposed on local risk factors, since its main sources of sales revenue are local customers. The model predicts that on average, Oil States International is more likely to borrow from global banks, while Zale Corporation is more likely to borrow from local banks. The data confirms this prediction: banks that lend to Oil States International are mostly global banks, including Bank of Nova Scotia, Credit Suisse, and Royal Bank of Canada, while mostly local banks such as Bank of Boston, First Republic Bank Dallas, and Rhode Island Hospital Trust National Bank lend to Zale Corporation.

This result of firm-bank sorting based on banks' comparative informational advantage and firms' relative exposure to global and local risk reveals a problem of double adverse selection: both global and local banks are adversely selected against through firm selection, since firms select into borrowing from the bank which observes the more favorable component

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[4] For instance, global banks heavily recruit PhD economists to work in their macro research departments. See past and current job listings from global banks such as Citi, JP Morgan, and Goldman Sachs on the American Economic Association's Job Openings for Economists site: https://www.aeaweb.org/joe/listings.

of their returns. I further demonstrate that this adverse selection problem has important macroeconomic implications. Given a funding shock to one of the banks, the adverse selection affects credit allocation at both the extensive and intensive margins, generating spillover and amplification effects through adverse interest rates. That is, a decrease in the funding cost of one of the bank types induces firm switching, attracting higher-return firms to contract with it (amplification effects) and leaving the other bank type with a riskier pool of firm (spillover effects). This constitutes a new channel through which monetary policy and liquidity shocks from abroad can be transmitted to firms. I test these predictions by analyzing how US and Euro area monetary policy shocks affect credit allocation in the Euro area, using tick-by-tick data on Federal Funds futures and Euribor futures to identify monetary policy shocks. The empirical results support the predictions.

This adverse selection channel of international transmission is not only new to the existing views on channels of international transmission through bank credit, but also clarifies the forces underlying the "international risk-taking channel" of monetary policy transmission.[5] It reveals that the empirical results which the existing literature (e.g., Morais et al. 2018) points to as evidence for risk-taking behavior by global banks could be confounded with a force generated by the adverse selection problem, substitution between global banking credit and local banking credit.

The main features of the model are as follows. I consider an economy comprised of global and local banks, and firms that have returns dependent on global and local risk factors. There is perfect competition within each bank type. Each faces a problem of asymmetric information: global banks have the technology to extract information on global factors but not local factors, and vice versa for local banks. This double information asymmetry is common knowledge and thereby incorporated in the loan contracts offered by the banks. Consequently, each bank prices loans based on the component of firm return it observes, as well as its expectation of the component of return it does not observe for the subset of firms that selects the respective bank. Each bank type holds Nash-type conjectures about the other bank type's loan pricing and plays best response strategies. Firms, in turn, select the best loan contract. Given the setup, I characterize the equilibrium in the economy and then conduct comparative analysis to study how the equilibrium changes in response to changes in bank funding cost.

The model generates three sharp predictions. First, in equilibrium, firm-bank sorting and credit allocation feature a problem of double adverse selection. Both types of banks are adversely selected against through firm selection, since firms with higher expected return

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[5] The international risk-taking channel of monetary policy transmission is based on the view that low monetary policy rates and QE in developed economies could induce banks to lend to riskier firms abroad (Bruno and Shin 2015a, Coimbra and Rey 2017, and Morais et al. 2018).

based on global factors relative to local factors are more likely to borrow from global banks, and vice versa for firms with higher expected return based on local factors. The intuition is straightforward. Given the information asymmetry, banks can only assign interest rates contingent on the component of firms' risk exposure that they observe (global or local), but not on the unobserved component, for which their rates must be uniform. Since firms select the bank that offers that best loan contract, they select into borrowing from the bank which observes the more favorable component of their return, resulting in adverse selection against banks. Moreover, banks, knowing firms' selection process, assign interest rates based on the expected risk of the firms which will approach them: they directly observe one component of risk, but assume the expected value of the other. As a result, relative to the first-best outcome, firms that are riskier in their unobserved exposure component face more favorable interest rates, and firms with relatively balanced global and local risk exposure face more adverse interest rates.

Second, shocks to bank funding cost affect credit allocation at the extensive margin. Specifically, suppose global banks face a decrease in funding cost due to expansionary monetary policy in the home country of the global banks. The model predicts that firms with relatively balanced global and local risk exposure components are more likely to switch into contracting with global banks. The result is driven by adverse selection: since the firms with relatively balanced global and local risk exposure are more adversely selected against, they are more likely to switch lenders given any changes in the credit market. These marginal firms that switch away from local banks into global banks are less risky than the infra-marginal firms that continue to borrow from either the local banks or the global banks.

Third, shocks to bank funding cost affect credit allocation at the intensive (interest rate) margin, and generate spillover and amplification effects. Continuing with the scenario of a lowering of global banks' funding cost due to expansionary monetary policy, the model predicts that i) the interest rates of the infra-marginal firms that remain with the local banks are expected to increase (i.e., a spillover effect), and ii) the interest rates of the infra-marginal firms that remain with the global banks are expected to decrease by more than the direct effect caused by the funding cost change (i.e., an amplification effect). The spillover effect on the infra-marginal firms that continue to borrow from local banks is solely driven by an exacerbation of the adverse selection problem. Since the marginal firms that switch away from local banks are less risky than these infra-marginal firms, local banks are left with a riskier pool of firms, which induce the banks to increase interest rates, despite no changes to their funding cost. On the other hand, the impact of the funding cost change is positively amplified for infra-marginal firms that continue to borrow from global banks because the marginal firms that switch into global banks are less risky than these infra-marginal firms, which alleviate

the adverse selection problem for the global banks.

The model shows that adverse selection resulting from competitive interactions between banks with differing specialization in global versus local information forms a novel channel of international monetary policy transmission. Next, I formally test the three model predictions, using data on global syndicated corporate loans from Dealscan, matched with international firm-level databases including Amadeus, Orbis, Compustat, and Compustat Global. I further categorize the lead bank on each loan into global banks and local banks. The resulting sample includes 115,166 loans, borrowed by 12,979 firms across 24 countries, over the period 2004-2017. This cross-country firm-bank loan-level dataset is uniquely appropriate for this study because it captures a significant portion of cross-border lending that other loan datasets such as credit registry data would not capture.

To test the model prediction on firm-bank sorting, I implement an empirical strategy that tightly maps to the model set-up to construct measures for each firm's global and local risk exposure. I first compute a total exposure measure for each firm that can be interpreted as exposure to both demand and productivity risk, from which I estimate the firm's global and local risk exposure using principal component analysis. The results based on the new measures show a stark pattern of firm-bank sorting: as predicted by the model, global banks lend more to firms with higher exposure to global risk relative to local risk, and vice versa for local banks. I further show that, once I control for bank specialization in global and local information using the new measures, the firm-bank sorting patterns predicted by the traditional banking theory are recovered.

To test the model predictions of how funding shocks to banks affect credit allocation, I take the Euro area as an empirical laboratory and analyze how US and Euro area monetary policy, through US and Euro area banks, respectively, affect credit allocation across firms in the Euro area. To identify exogenous shocks to US and Euro area monetary policy, I use high-frequency data on Federal Funds futures and Euribor futures. I find that an expansionary shock to US monetary policy induces firms in the Euro area with relatively balanced global and local risk components to switch their borrowing from Euro area banks to US banks, conditional on Euro area monetary policy. The analogue applies to an expansionary shock to Euro area monetary policy.

Furthermore, I find that, conditional on Euro area (US) monetary policy and given expansionary US (Euro area) monetary policy, the interest rates of the infra-marginal firms that continue to borrow from Euro area (US) banks increases, reflecting a spillover effect. Specifically, a 25-basis-point expansionary US (Euro area) monetary policy shock increases the interest rate spread for the infra-marginal firms that continue to borrow from Euro area (US) banks by 22-27 (25-32) basis points. At the same time, the interest rate spreads of the

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infra-marginal firms that continue to borrow from US (Euro area) banks decreases, reflecting an amplification effect. A 25-basis-point expansionary shock to the US (Euro area) monetary policy decreases the interest rate spread for the infra-marginal firms that continue to borrow from US (Euro area) banks by 25-32 (34-40) basis points. The results are consistent with the model prediction on the effects of bank funding shocks on credit allocation at both the extensive and intensive margins, revealing an adverse selection channel of monetary policy transmission.

Related Literature   The primary contribution of this paper—formalizing and providing empirical evidence of a novel micro-foundation for credit allocation in globalized banking systems—adds to two broad strands of literature in finance, macroeconomics, and international finance: banking, and the macroeconomic implications of banking.

First, the new perspective I propose builds on the traditional information view of banking from classic papers by Campbel and Kracaw (1980), Diamond (1984), Ramakrishnan et al. (1984), and Boyd and Prescott (1986). They argue that the special role of banks derives from their ability to collect and process information. Through this lens, a subsequent strand of literature in banking and corporate finance, including Petersen and Rajan (1994), Stein (2002), Berger et al. (2005), and Liberti and Petersen (2018), argues that different banks specialize in hard versus soft information, and lend to different types of firms as a result. I provide evidence showing hard versus soft information is insufficient for explaining firm-bank sorting in globalized banking systems, and propose an alternative dimension of bank specialization.[6]

In the context of global banking specifically, this paper is related to the strand of banking literature that studies the effects of foreign bank entry on credit access. The framework developed in this paper builds on the work by Dell'Ariccia and Marquez (2004), Sengupta (2007), Detragiache et al. (2008), and Gormley (2014), which emphasize the importance of (imperfect) information in shaping competition and credit allocation in economies with both local banks and foreign banks. The focus of that line of studies is foreign bank entry into low-income countries, where overall information asymmetries may be large. Local banks are considered to have an informational advantage over the foreign banks, which, as a result, are able to target only the largest or the least informationally opaque firms. In contrast, the focus of this paper is cross-border lending by global banks in developed economies, where the majority of global banking activities occurs. What sets this paper apart is the new perspective on how banks' comparative advantage in different types of information, or global and local

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[6] Section 2 describes the traditional theory and the relevant empirical tests in detail.

information specifically, can affect credit allocation.[7] While the existing models predict that the smaller, more informationally opaque firms are more likely to borrow from local banks[8], the framework in this paper predicts that some large and informationally transparent firms are still likely to borrow from local banks, as long as their returns are more dependent on local risk factors.

Detragiache et al. (2008), Beck and Peria (2010) and Gormley (2014) also explore the impact of foreign banking on overall credit access, relating it to debates on the benefits and costs of financial openness. They argue that foreign banking entry undermines overall access to credit since it worsens the credit pool left to local banks, gives rise to adverse selection, and thereby lowers overall financial development. While my model also points to the possibility of a decline in aggregate credit due to adverse selection, I show that access to global banking credit actually leads to a more efficient credit allocation in the financial system. This is in line with papers which argue that the benefits of financial openness outweigh the costs, such as Levine (1996), Claessens et al. (2001), Edison et al. (2002), Claessens (2006), and Beck et al. (2007).

Second, this paper also contributes to the literature on the macroeconomic implications of banking. The global financial crisis put the spotlight on the importance of financial intermediaries for macroeconomic stability and monetary policy transmission.[9] In particular, global banks have emerged as a key channel for international transmission of liquidity conditions and monetary policy, sparking both theoretical and empirical research. On the theoretical front, several recent papers have introduced models with global banks for studying international transmission, including Dedola et al. (2013), De Blas and Russ (2013), Niepmann (2015), Bruno and Shin (2015b), and Aoki et al. (2016). While these models solely focus on emergence and implications of one type of bank,[10] this paper argues that the competitive interaction between global and local banks plays an important role for international transmission. On the empirical front, a growing literature uses bank-level and loan-level data to trace out the channels through which global banking affects domestic bank lending, includ-

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[7] The key ingredient incorporated in my model to formalize the idea of banks' differing specialization in global versus local information, double asymmetric information, and the ensuing result of double adverse selection, is new to the line of research in contract theory on adverse selection in credit markets, starting with the classic papers such as Stiglitz and Weiss (1981) and De Meza and Webb (1987).

[8] Papers including Berger et al. (2001), Clarke et al. (2005), Mian (2006), and Gormley (2010) provide empirical evidence in support of this prediction, though the empirical settings studied in these papers are all low-income economies.

[9] In the domestic macro literature, an emerging set of papers have introduced macroeconomic models with financial frictions in the form of balance sheet constraints on financial intermediaries to study aggregate economic activities, including Gertler and Kiyotaki (2010) and Gertler and Karadi (2011).

[10] In the framework in Bruno and Shin (2015b), there are both global and local banks. But local banks simply act as a conduit that intermediates funds from global banks to firms, which essentially make only one type of bank active in the economy.

ing Cetorelli and Goldberg (2012b), Popov and Udell (2012), Schnabl (2012), De Haas and Lelyveld (2014), Ivashina et al. (2015), and Baskaya et al. (2017). This paper contributes to this line of work by pointing out a new channel of international transmission through global banks—adverse selection.

Furthermore, the adverse selection channel of international transmission raised in this paper is new to the literature on international transmission of monetary policy. Recent papers by Rey (2016) and Miranda-Agrippino and Rey (2018) provide evidence of large spillovers of US monetary policy on credit creation around the world, suggesting global banks as the main source for transmission. Existing work has pointed to currency mismatches on global banks' balance sheets (Ongena et al. 2017, Bräuning and Ivashina 2017, Bräuning and Ivashina 2018) and internal capital markets within global banks (Cetorelli and Goldberg 2012a) as channels of international monetary policy transmission. In addition, low international monetary policy rates and expansive quantitative easing in large developed economies over the past decade have prompted debates on the extent of a bank risk-taking channel of monetary policy transmission, as explained in Borio and Zhu (2012), Bruno and Shin (2015a), and Coimbra and Rey (2017). Morais et al. (2018), using firm-bank loan data, show that low monetary policy rates and QE in developed economies led global banks to increase credit supply to firms in Mexico, especially firms with higher-than-average ex-ante loan rates. They consider that evidence of bank risk-taking. Contrary to their explanation, I show that the force driving increased credit supply to riskier firms could be substitution between global banking credit and local banking credit, raising adverse selection as a new channel of international transmission of monetary policy.

The rest of this paper is structured as follows. Section 2 reviews the traditional theory and presents a new puzzle on firm-bank sorting in globalized credit markets. Section 3 presents the model. Section 4 applies the model to analyze the effects and implications of changes to bank funding cost on credit allocation. Section 5 outlines the model predictions and describes the data used for empirical testing. Section 6 presents the empirical strategy used to test the prediction on firm-bank sorting and discusses the results. Section 7 presents the empirical strategy used to test the predictions on credit allocation given bank funding shocks and discusses the results. Section 8 concludes. Proofs are relegated to APPENDIX A.

2 Traditional Theory and New Perspective

In this section, I review the traditional theory on firm-bank sorting and test whether it predicts the patterns of firm-bank sorting in globalized credit markets.

Classic banking theory argues that banks exist because of their unique ability to collect and

process information. Built on this view, a long strand of literature in banking and corporate finance has used the distinction between hard and soft information to explain how banks and firms establish relationships (see, e.g., Petersen and Rajan 1994, Stein 2002, Petersen and Rajan 2002, and Liberti and Petersen 2018). Hard information is information that is quantifiable, independent of its collection process, and easy to transmit in impersonal ways. Soft information is information that is not easily quantifiable, dependent on its collection process, and requires context-specific knowledge to fully understand. Theory based on this view conjectures that large banks are more likely to lend to firms with more readily available hard information, while small banks are more likely to establish relationships with firms with more soft information.

As a first step to understand patterns of firm-bank sorting in globalized credit markets, I test whether the sorting patterns between firms and global versus local banks bear out the prediction of the traditional banking theory. Since global banks tend to be larger, I test whether global banks are more likely to lend to firms with more hard information, and local banks are more likely to lend to firms with more soft information, using a firm-bank loan-level dataset that spans across 24 countries and covers the period 2004-2017.[11] For measures of hard and soft information, I follow the empirical papers in this line of work (e.g., Berger et al. 2005 and Mian 2006), which often use firm asset size and firm age to proxy for hard information.

I sort firms into quartiles based on the distribution of firm asset size and firm age in each year in each country, and then calculate the proportion of loans given by global banks and local banks in each quartile. Figure 2 plots the distribution of lending from global and local banks over the entire sample. The plot shows that both global banks and local banks lend to firms of *all* sizes and ages, revealing that the traditional theory does not predict the pattern of firm-bank sorting in financial systems with both global and local banks.

I further test whether the differences between global and local banks illustrated in Figure 2 are indeed insignificant in a statistical sense. For each given variable measuring hard information, I test whether the value-weighted mean of that variable for global banks is different from that for local banks. Table 1 presents these means and their differences. The results confirm the takeaways from the graphical analysis: the differences in value-weighted means are statistically *insignificant* between global and local banks for firm asset size and firm age.

Another conjecture about the mechanism driving the sorting between firms and global versus local banks may be bank specialization in loans of particular currency denominations. This is particularly motivated by recent papers by Maggiori et al. (2018) and Gopinath and Stein (2018) that highlight the prevalence of Dollar use, and to a lesser extent, Euro use,

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[11] See Section 5 of the paper for a detailed discussion of the data and data-cleaning procedure.

Figure 2: **Firm-Bank Sorting, by Firm Size and Age Quartile**
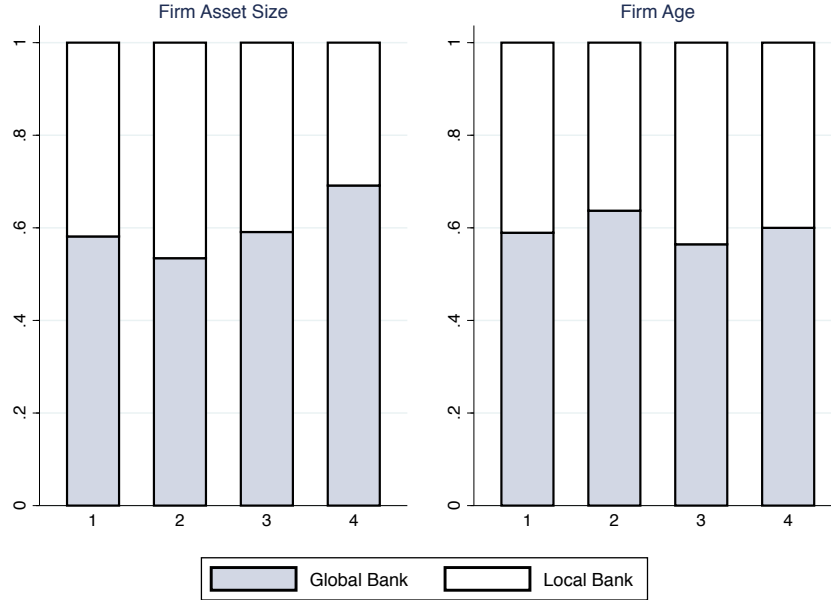
Notes. The plot shows sorting patterns between firms and global versus local banks, with firms sorted into quartiles by asset size and age. Data sample consists of syndicated loans between firms global and local banks and firms across 24 countries from 2004-2017. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

Table 1: **Firm-Bank Sorting, by Firm Size and Age Quartile: Statistical Test**

	(1)	(2)
	Size	Age
(1) Mean: Global Bank	3.196***	2.759***
	(0.0299)	(0.0208)
(2) Mean: Local Bank	3.099***	2.726***
	(0.0674)	(0.0367)
(3) Difference	0.0969	0.0330
	(0.0716)	(0.0426)
Observations	115,166	114,323

Notes. The dependent variable in each regression (Y) is one of the hard information variables, firm size (column 1) or firm age (column 2), coded 1-4 based on the quartile number to which each respective firm belong. Note the firms are sorted every year by country. Row 1 and row 2 show the means for each variable for global banks and local banks, respectively, by running a value-weighted regression of Y on a constant. For differences in means of the two types of banks, the whole data is used in the regression and a dummy for global banks is added (row 3). Standard errors reported in parentheses are clustered at the bank-level. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

in international financial markets. Given these considerations, I test whether global banks specialize in lending in non-local currencies, while local banks specialize in lending in local currency. As shown in Figure 3, in fact, global and local banks make loans in both local and non-local currencies. This empirical observation holds even when the US or both the US and Euro area countries are excluded from the sample.

Figure 3: **Loan Currency Denominations by Global and Local Banks**
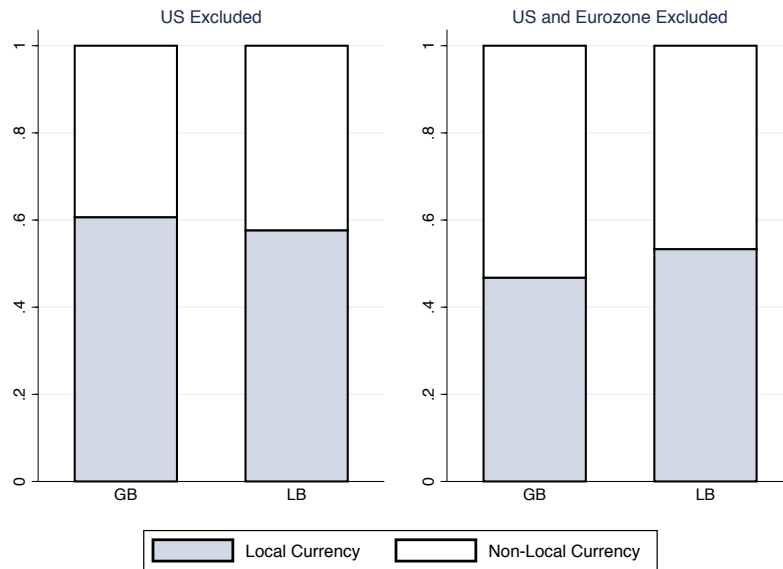
Notes. The plot shows the share of loans in local currency versus non-local currency given by global and local banks. The left panel is based on loans from all countries in the sample except the US. The right panel is based on loans from all countries in the sample except the US and Euro area countries. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

The empirical evidence shows that the traditional banking theory of bank specialization in hard or soft information, as well as the view of bank specialization in particular currency denominations, is insufficient to explain observed sorting patterns between firms and global versus local banks. This points to a puzzle in the mechanism driving firm-bank sorting in globalized credit markets. In light of the puzzle, I propose a new perspective. I argue that global and local banks' differing specialization in global and local information constitutes a key mechanism for firm-bank sorting and credit allocation in financial systems with both types of banks. Global banks have a comparative advantage in extracting information on global risk, and local banks have a comparative advantage in extracting information on local risk.

This new perspective builds on the classic information view of banking. Furthermore, it incorporates global banks' unique position to acquire "global" information through global

market-making activities and research efforts they invest in for analyzing global economic and market trends. Next, I proceed to formalize the new perspective by developing a model with global and local banks in which each bank type's comparative informational advantage serves as the key ingredient.

3 A Model with Global and Local Banking

In this section I develop a model to study firm-bank sorting and credit allocation in an economy with two types of banks—global banks and local banks—and firms heterogenous in their exposure to global and local risks. Each type of bank can perfectly observe only one component of firms' risk exposure, giving rise to double information asymmetry. I show that firm-bank sorting and credit allocation in equilibrium reveal a problem of double adverse selection.

3.1 Set-up

Consider an economy with two periods ($t = 0, 1$), a single good, and two classes of agents: firms and banks. All agents are risk neutral and cannot end with a negative amount of cash due to limited liability.

Firms. There is a continuum of heterogenous firms that have access to a fixed-size project requiring an investment of one. Each firm i's production technology is characterized by the following production function:

$$z_i = z_i^G + z_i^L + u_i \tag{1}$$

where z_i^G denotes firm i's component of return due to global risk, z_i^L denotes firm i's component of return due to local risk, and u_i denotes firm i's idiosyncratic risk. Each component is independently and uniformly distributed, with $z_i^G \sim U(0,1)$, $z_i^L \sim U(0,1)$, and $u_i \sim U(0,1)$. More specifically, z_i^G can be considered to encompass two components, $z_i^G = \beta_i^G z^G$, where β_i^G denotes firm i's exposure to global risk and z^G denotes global risk. Similarly, z_i^L can be considered to encompass two components, $z_i^L = \beta_i^L z^L$, where β_i^L denotes firm i's exposure to local risk and z^L denotes local risk.[12]

Firms have full information on their returns due to global and local risk at the time of investment (period 0), while idiosyncratic risks are not realized until after investment (period 1). Firms have no private wealth; to implement the project, they need to raise one unit of external funds from a bank j through a loan contract.

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[12] These considerations become more applicable when mapping the model to empirics, which I describe more in detail in Section 6.

Banks. There are two types of banks, *global banks* (G) and *local banks* (L), denoted as $j \in \{G, L\}$. They can enter the financial market and compete on projects by offering standard debt contracts. There is perfect competition within each bank type in the financial market.

The key feature that differentiates global banks from local banks is their information acquisition technology on global and local information: global banks have the technology to evaluate firms' return due to global risk (z_i^G) but are not able to extract information on firms' return due to local risk (z_i^L), while local banks are able to evaluate firms' return due to local risk but are not able to extract information on firms' return due to global risk. This gives rise to an environment with double information asymmetry. The nature of the double information asymmetry problem and the distributions of the firms' return due to global risk and local risk are common knowledge across banks and firms.

Given the information structure, the loan rate offered by the two types of banks can be made contingent on the component of firm return observable to each respective bank type. Each type-contingent interest rate applies uniformly for all firms of the given observable component regardless of their unobserved return component. More specifically, global banks can offer type-contingent gross interest rate $R^G(z_i^G)$ for firms with return component z_i^G, and that rate applies for all firms with a given z_i^G regardless of z_i^L. Similarly, local banks can offer type-contingent interest rate $R^L(z_i^L)$ for firms with return component z_i^L, and that rate applies for all firms with a given z_i^L regardless of z_i^G.

It follows that the interest rates offered by each type of bank can be generated by interest rate functions that map the observable return components to type-contingent interest rates from the respective bank type: global banks offer contracts based on the interest rate function $\mathcal{R}^G : z_i^G \mapsto R^G(z_i^G)$, and local banks offer contracts based on the interest rate function $\mathcal{R}^L : z_i^L \mapsto R^L(z_i^L)$. For both types of banks, each bank's objective is to maximize expected profit across firms of each observable type: global banks maximize expected profit across firms of each given z_i^G, and local banks maximize expected profit across firms of each given z_i^L.

Global banks and local banks face gross funding rate r^G and r^L, respectively, for the funds they intermediate.[13]

Firm-Bank Sorting. This environment in which each type of bank can perfectly observe only one component of the firms' return, while firms have full information on both return components, gives rise to a sorting process between banks and firms. The timing of the model is presented in Figure 4.

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[13] Since the funding market is not of central importance to this paper, it is not explicitly modeled for analytical convenience. The funding rates r^G and r^L could reflect funding conditions in the interbank market, the deposit market, or other risk premiums. While funding is fully elastic here, the model predictions do not change if r^G and r^L are considered to be decreasing in loan amounts.

Figure 4: **Model Timeline**
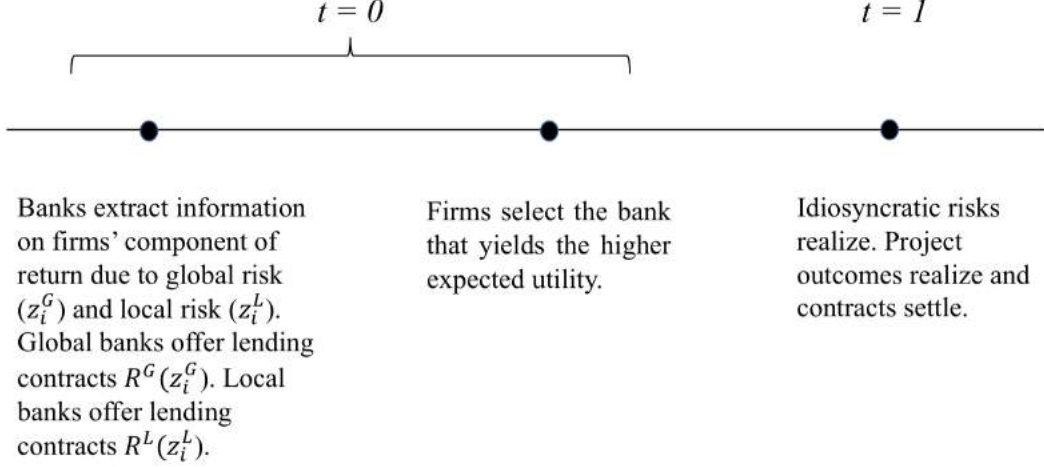
Let E_i denote the expectation of firm i conditional on its information set. Between global banks and local banks, each firm i selects the contract offered by bank $j \in \{G, L\}$ that yields the higher expected utility $E_i\big[\max(z_i - R^j(z_i^j), 0)\big]$.[14] Firm selection results in a partition of the set of all firms into two subsets, as each firm i with return component (z_i^G, z_i^L) selects to borrow from either a global bank or a local bank given the interest rate functions of the two bank types. One subset, denoted as S^G, chooses to sign a lending contract with a global bank, and the other subset, denoted as S^L, chooses to sign a lending contract with a local bank:

$$S^G = \left\{ (z_i^G, z_i^L) : E_i\big[\max(z_i - \mathcal{R}^G(z_i^G), 0)\big] \geq E_i\big[\max(z_i - \mathcal{R}^L(z_i^L), 0)\big] \right\}; \qquad (2\text{a})$$

$$S^L = \left\{ (z_i^G, z_i^L) : E_i\big[\max(z_i - \mathcal{R}^L(z_i^L), 0)\big] > E_i\big[\max(z_i - \mathcal{R}^G(z_i^G), 0)\big] \right\}. \qquad (2\text{b})$$

The following assumptions about firm selection hold throughout the paper.

Assumption 1. *Suppose $\mathcal{R}^G(z_i^G) > z_i^G + z_i^L + 1$ or $\mathcal{R}^L(z_i^L) > z_i^G + z_i^L + 1$. Then $(z_i^G, z_i^L) \in S^G$ if $\mathcal{R}^G(z_i^G) \leq \mathcal{R}^L(z_i^L)$; and $(z_i^G, z_i^L) \in S^L$ otherwise.*

Assumption 1 states that in the region of the parameter space when the firm's expected utility is zero when it borrows from either a global bank or a local bank, it chooses the bank that

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[14] Note that the expectation here is taken with respect to idiosyncratic shocks only.

offers the lower interest rate. This assumption ensures that there is no ambiguity in firm selection across all regions of the parameters.

Remark 1. *Based on Equations (2a) and (2b) and Assumption 1, each firm i selects into borrowing from a global bank if and only if $\mathcal{R}^G(z_i^G) \leq \mathcal{R}^L(z_i^L)$, and each firm i selects into borrowing from a local bank if and only if $\mathcal{R}^G(z_i^G) > \mathcal{R}^L(z_i^L)$. In sum, each firm chooses the bank that offers the lowest rate.*

The selection of firms directly affects global and local banks' expected profits. Let E_G denote the expectation of a global bank conditional on its information set and E_L denote the expectation of a local bank conditional on its information set. The expected profits for a global bank (G) for firms of a given z_i^G and a local bank (L) for firms of a given z_i^L are given by

$$\text{G:} \quad E_G[\pi_G(z_i^G)] = \int_{G_1} \min\left(z_i^G + z_i^L + u_i, \mathcal{R}^G(z_i^G)\right) dF_{G_1}(z_i^L, u_i) - r^G,$$

$$\text{where} \quad G_1(z_i^G) = \left\{ (z_i^L, u_i) \mid z_i^L \colon (z_i^G, z_i^L) \in S^G, \ 0 \leq u_i \leq 1 \right\};$$

(3a)

$$\text{L:} \quad E_L[\pi_L(z_i^L)] = \int_{L_1} \min\left(z_i^G + z_i^L + u_i, \mathcal{R}^L(z_i^L)\right) dF_{L_1}(z_i^G, u_i) - r^L,$$

$$\text{where} \quad L_1(z_i^L) = \left\{ (z_i^G, u_i) \mid z_i^G \colon (z_i^G, z_i^L) \in S^L, \ 0 \leq u_i \leq 1 \right\}.$$

(3b)

The first term on the right hand side of Equations (3a) and (3b) is the expected gross return across loan contracts to firms of a given z_i^G and z_i^L for a global bank and a local bank, respectively. In the global bank's expected profit function, $G_1(z_i^G)$ summarizes the set of firms which select global banks given z_i^G. This includes firms with idiosyncratic risk u_i from any part of the u_i distribution, and z_i^L such that they are in the subset of firms that choose the global bank's contract. Similarly in the local bank's expected profit function, $L_1(z_i^L)$ summarizes the set of firms which select global banks given z_i^G. This includes firms with idiosyncratic risk u_i from any part of the u_i distribution, and z_i^G such that they are in the subset of firms that choose the local bank's contract. The integrand in both equations shows the relationship between bank profit and firm profit in a standard debt contract: for each firm, when its realized return is less than the contractual interest rate, it defaults and gives up any realized project returns to the lending bank; otherwise, the firm is able to repay the loan at the contractual rate and keep the difference between the project return and rate as profit. $F_{G_1}(.)$ and $F_{L_1}(.)$ denotes the cumulative distribution function of the relevant variable conditional on G_1 and L_1, respectively. The last terms in Equations (3a) and (3b) are the funding cost for the global bank and local bank, respectively.

3.2 Strategies and Equilibrium Definition

As shown in Equations (3a) and (3b), each type of bank's choice of the interest rate function affects the expected profit of the other type of bank since it influences the subset of firms that selects loan contracts from one versus the other. I consider the competitive interplay between a global bank and a local bank a non-cooperative game.

In the game, the global bank's strategy set U^G consists of the set of possible interest rate functions $\mathcal{R}^G$, and the local bank's strategy set U^L consists of the set of possible interest rate functions $\mathcal{R}^L$. The payoff function for the global bank is the expected profit function $E_G[\pi_G(\mathcal{R}^G, \mathcal{R}^L)]$ across all firms, and that for the local bank is the expected profit function $E_L[\pi_L(\mathcal{R}^G, \mathcal{R}^L)]$.[15] A given strategy $\mathcal{R}^G$ is a best response to the strategy $\mathcal{R}^L$ if $E_G[\pi_G(\mathcal{R}^G, \mathcal{R}^L)] \geq E_G[\pi_G(\mathcal{R}^{G'}, \mathcal{R}^L)] \; \forall \; \mathcal{R}^{G'} \in U^G$, and vice versa for $\mathcal{R}^L$.

In a competitive equilibrium in this credit market, both global and local banks play best responses to each other's strategies. Each operating bank earns an expected profit of zero given perfect competition and free entry, and the selection of firms is consistent with the banks' equilibrium strategies.

Formally, the definition of the competitive equilibrium is as follows:

Definition 1. *For a given set of parameters on r^G, r^L, and the distributions of z_i^G, z_i^L, and u_i, a competitive equilibrium with free entry in the credit market is a strategy profile $\{\mathcal{R}^G, \mathcal{R}^L\}$ and sets S^G and S^L such that:*

1. *(No Unilateral Deviation):*
   $E_G[\pi_G(\mathcal{R}^G, \mathcal{R}^L)] \geq E_G[\pi_G(\mathcal{R}^{G'}, \mathcal{R}^L)] \;\; \forall \; \mathcal{R}^{G'} \in U^G;$
   $E_L[\pi_L(\mathcal{R}^G, \mathcal{R}^L)] \geq E_L[\pi_G(\mathcal{R}^G, \mathcal{R}^{L'})] \;\; \forall \; \mathcal{R}^{L'} \in U^L;$

2. *(Zero Profit Condition, Global Bank):*
   $\int_{G_1} \min\left(z_i^G + z_i^L + u_i, \mathcal{R}^G(z_i^G) \right) dF_{G_1}(z_i^L, u_i) = r^G;$

3. *(Zero Profit Condition, Local Bank):*
   $\int_{L_1} \min\left(z_i^G + z_i^L + u_i, \mathcal{R}^L(z_i^L) \right) dF_{L_1}(z_i^G, u_i) = r^L;$

4. *(Firm Selection):*
   $S^j = \left\{ (z_i^G, z_i^L) : E_i\big\{ \max[z_i - \mathcal{R}^j(z_i^j), 0] \big\} \geq E_i\big\{ \max[z_i - \mathcal{R}^k(z_i^k), 0], j \neq k \in \{G, L\} \big\} \right\}.$

Part 1 of Definition 1 requires that no unilateral deviation in strategy by any bank is profitable for that bank. Parts 2 and 3 impose zero profit among global banks and local

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[15] Banks also strictly prefer making a loan with zero expected profit to not making a loan.

banks, respectively. Part 4 defines the set of firms that choose to subscribe to the loan contract with either of the two types of banks in an incentive-compatible fashion. All banks that enter the market hold correct expectations about both the other type of bank's pricing choices and the pool of firms that will accept the contract. As a consequence, the allocations of credit across firms are consistent with the banks' equilibrium strategies.

Before turning to characterizing the equilibrium in the credit market of two bank types under double information asymmetry, I describe two useful benchmarks.

First Best. In an environment where both types of banks observe full information on each firm's return due to global and local risk, the only margin that differentiates the loan rate charged by global banks versus local banks is the funding cost faced by each bank type. As a result, only the bank type with lower funding cost (r) exists in the credit market in equilibrium, and its interest rate function is strictly decreasing in $(z_i^G + z_i^L)$. Panel (a) of Figure 5 shows an illustration of the first-best equilibrium in an economy with full information. The diagonal line $\underline{z}_{FB}^L + \underline{z}_{FB}^G + 1/2 = r$ denotes a threshold.[16] The firms in the region below this threshold are not able to receive loans, as their expected profits are too low for the bank to break even in expectation.

Closed Economy. In an environment where there exist only local banks that observe information on each firm's return due to local risk, the interest rate function $\mathcal{R}^L(z_i^L)$ is strictly decreasing in z_i^L and uniform across the entire distribution of z_i^G. Panel (b) of Figure 5 shows an illustration of the equilibrium in this economy. Firms with z_i^L below $\underline{z}_{CE}^L = r^L - 1$ (firms in Regions a and c) are not able to receive loans. Relative to the first-best allocation without information asymmetries, the equilibrium in a closed economy overfunds firms whose return due to local risk is high relative to return due to global risk (firms in Region b) and underfunds firms whose return due to local risk is low relative to return due to global risk (firms in Region c).

3.3 Equilibrium Characterization

In the following I characterize the equilibrium in a credit market of two bank types under double information asymmetry. I start by establishing the properties of the bank interest rate functions in equilibrium.

Subject to the zero profit conditions from Parts 2 and 3 of Definition 1, Equation (3a) determines the global banks' type-contingent interest rate function $\mathcal{R}^G$ given firm selection as specified in Equation (2a), and Equation (3b) determines the local banks' type-contingent interest rate function $\mathcal{R}^L$ given firm selection as specified in Equation (2b). Since firm selection depends on interest rates from both types of banks in equilibrium, Equations (3a) and (3b)

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[16] Note $E[u_i] = 1/2$.

Figure 5: **Benchmark Equilibrium: First-Best and Closed Economy**

(a) First-Best (b) Closed Economy
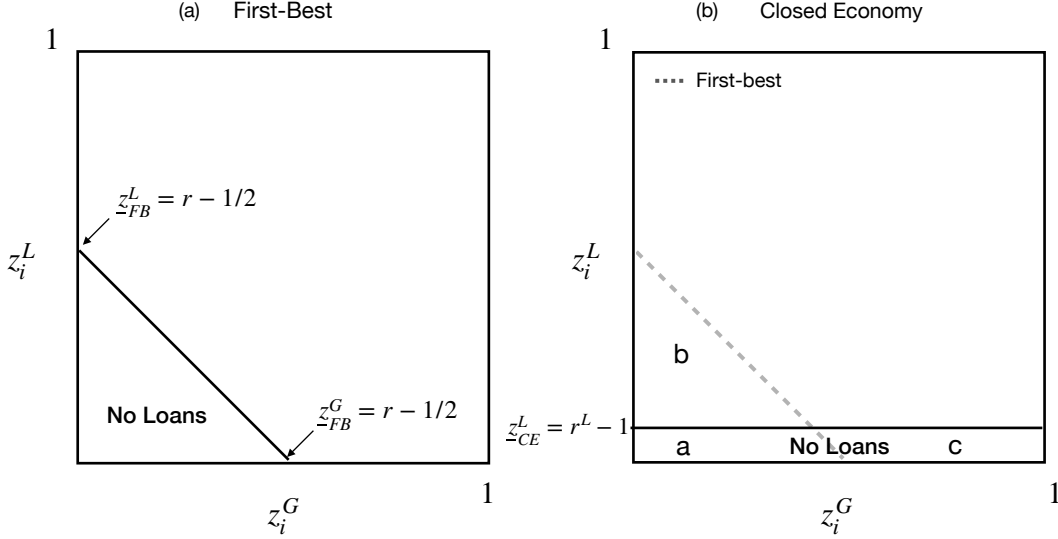
Notes. Panel (a) illustrates the first-best equilibrium in an economy with full information. Panel (b) illustrates the equilibrium credit allocation in a closed economy in which there are only local banks.

given Equations (2a) and (2b) simultaneously determine the type-contingent interest rate functions $\mathcal{R}^G$ and $\mathcal{R}^L$ in equilibrium.

Let $E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G, z_i^G]$ denote the global banks' expectation of the average z_i^L for the set of firms with (z_i^G, z_i^L) in S^G conditional on z_i^G, and $E_L[z_i^G \mid (z_i^G, z_i^L) \in S^L, z_i^L]$ denote the local banks' expectation of the average z_i^G for the set of firms with (z_i^G, z_i^L) in S^L, conditional on z_i^L. Proposition 1 characterizes $\mathcal{R}^G$ and $\mathcal{R}^L$.

Proposition 1. *(Type-Contingent Interest Rate Functions)*

1. *$\mathcal{R}^G$ is strictly decreasing in z_i^G for $z_i^G \in [\underline{z}^G, 1]$, where $\underline{z}^G \equiv r^G - E_G[z_i^L \mid (\underline{z}^G, z_i^L) \in S^G, z_i^G] - 1/2$.*

2. *$\mathcal{R}^L$ is strictly decreasing in z_i^L for $z_i^L \in [\underline{z}^L, 1]$,, where $\underline{z}^L \equiv r^L - E_L[z_i^G \mid (z_i^G, \underline{z}^L) \in S^L, z_i^L] - 1/2$.*

Part 1 of Proposition 1 establishes that the global banks' interest rate function is strictly monotone for $z_i^G \in [\underline{z}^G, 1]$. The lower bound $\underline{z}^G$ pins down a cut-off point on z_i^G below which the expected profits of the pertinent firms are too low for the global banks to break even in expectation. In other words, $\underline{z}^G$ defines the lowest z_i^G firm to which the global banks lend. The lower bound $\underline{z}^G$ is increasing in global bank's funding cost (r^G), decreasing in the average z_i^L of the set of firms that are expected to select the global bank, and decreasing in the expected idiosyncratic shocks for firms. The explanation for local banks' interest rate

function $\mathcal{R}^L$ established in Part 2 of Proposition 1 is entirely analogous. Panel (a) of Figure 6 illustrates the interest rate functions in a graph with z_i^L on the x-axis. Since global banks cannot observe z_i^L, $\mathcal{R}^G$ is uniform across z_i^L. $\mathcal{R}^L$ is strictly decreasing in z_i^L, as established in Proposition 1.

Using strict monotonicity, I next establish that the competitive interplay between global and local banks generates a unique form of horizontal segmentation in equilibrium, in which there exists a set of marginal firms that are indifferent between taking loans from global banks and local banks. Formally,

Proposition 2. *(Threshold Functions) Let* $RG = \{\mathcal{R}^G(z_i^G) \mid z_i^G \in [\underline{z}^G, 1]\}$ *and* $RL = \{\mathcal{R}^L(z_i^L) \mid z_i^L \in [\underline{z}^L, 1]\}$. *In the region* $RG \cap RL$, *there exist threshold functions* $\bar{z}^L(z_i^G)$ *and* $\bar{z}^G(z_i^L)$ *such that:*

1. $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(\bar{z}^L(z_i^G))$.

   $\mathcal{R}^L(z_i^L) = \mathcal{R}^G(\bar{z}^G(z_i^L))$.

2. $S^G = \{(z_i^G, z_i^L) : z_i^L \leq \bar{z}^L(z_i^G)\}$, *and* $S^L = \{(z_i^G, z_i^L) : z_i^L > \bar{z}^L(z_i^G)\}$.

   $S^L = \{(z_i^G, z_i^L) : z_i^G < \bar{z}^G(z_i^L)\}$, *and* $S^G = \{(z_i^G, z_i^L) : z_i^G \geq \bar{z}^G(z_i^L)\}$.

Part 1 of Proposition 2 establishes that, for every firm with z_i^G (resp. z_i^L), there exists a threshold on z_i^L (resp. z_i^G), denoted as $\bar{z}^L(z_i^G)$ (resp. $\bar{z}^G(z_i^L)$), at which both the global bank and local bank offer the same interest rate. Panel (b) of Figure 6 illustrates the threshold: for a given z_i^G, there exists a threshold $\bar{z}^L(z_i^G)$ at which the interest rate functions of the two banks intersect, $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(\bar{z}^L(z_i^G))$.

Part 2 of Proposition 2 follows from the monotonic property of the type-contingent interest rate. Given $\mathcal{R}^G(z_i^G)$ and $\mathcal{R}^L(z_i^L)$ are strictly decreasing in z_i^G and z_i^L, respectively, firms (z_i^G, z_i^L) with $z_i^L < \bar{z}^L(z_i^G)$ face a lower rate from global banks and therefore select global banks (i.e, the firms are in S^G). Firms with $z_i^L > \bar{z}^L(z_i^G)$ face a lower rate from local banks and thereby select local banks (i.e, they are in S^L). This idea is shown in Panel (b) of Figure 6. An analogous explanation applies to firms with $z_i^G < \bar{z}^G(z_i^L)$ and $z_i^G > \bar{z}^G(z_i^L)$.

Parts 1 and 2 of Proposition 2 establish the existence of thresholds that segment the credit market into two parts, with global banks as the lender in one, and local banks as the lender in the other. In equilibrium, the threshold values $\bar{z}^L(z_i^G)$ and $\bar{z}^G(z_i^L)$ are determined by the interaction between the interest rate schedules of the global and local banks, where $\bar{z}^L(z_i^G) = (\mathcal{R}^L)^{-1}(\mathcal{R}^G(z_i^G))$ and $\bar{z}^G(z_i^L) = (\mathcal{R}^G)^{-1}(\mathcal{R}^L(z_i^L))$.

The following corollary characterizes the threshold functions, describing how they change given changes in z_i^G, z_i^L, and the interest rate functions. Let $\tilde{z}^G$ be a cut-off that pins down an upper bound on z_i^G, above which firms with z_i^L from any part of the z_i^L distribution are

Figure 6: **Illustration of Interest Rate Functions and Threshold Functions**
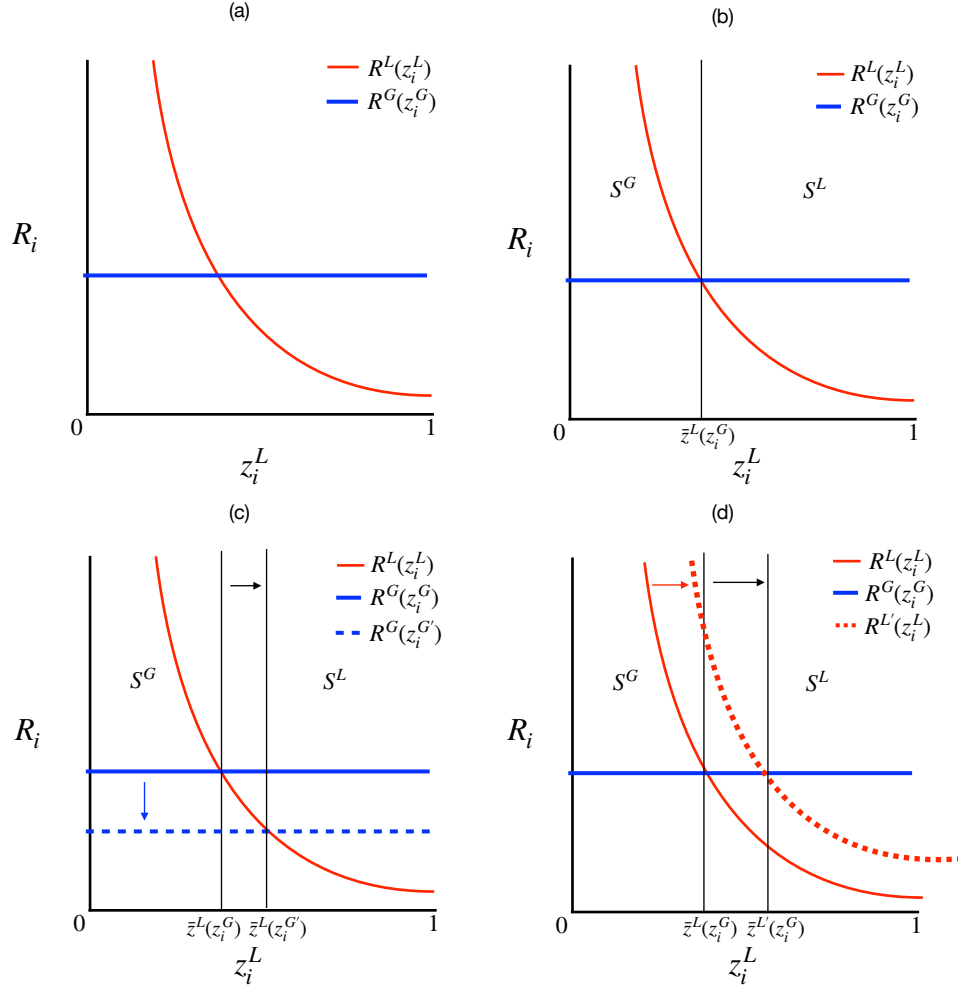
Notes. Panel (a) illustrates Proposition 1, showing the monotonically decreasing property of the interest rate functions, given information asymmetry. Panel (b) illustrates Part 1 and 2 of Proposition 2, showing, for a given z_i^G, there exists a threshold $\bar{z}^L(z_i^G)$ at which $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(\bar{z}^L(z_i^G))$. Firms below the threshold borrow from global banks; firms above which borrow from local banks. Panel (c) illustrates Part 3 of Proposition 2, showing an increase in z_i^G lowers $\mathcal{R}^G(z_i^G)$ and increases $\bar{z}^L(z_i^G)$, holding all else constant. Panel (d) illustrates Part 4 of Proposition 2, showing an increase in $\mathcal{R}^L(z_i^L)$ increases $\bar{z}^L(z_i^G)$, holding all else constant.

expected to select the global bank (i.e., $\bar{z}^L(z_i^G) = 1$ for all $z_i^G \geq \tilde{z}^G$), and the analogue applies to $\tilde{z}^L$.

Corollary 1. *(Threshold Functions Characterization) Let $\tilde{z}^G = min\{z_i^G : \bar{z}^L(z_i^G) = 1\}$ and $\tilde{z}^L = min\{z_i^L : \bar{z}^G(z_i^L) = 1\}$.*

   1. *$\bar{z}^L(z_i^G)$ is increasing in z_i^G for $z_i^G \in [\underline{z}^G, min(\tilde{z}^G, 1)]$.*

      $\bar{z}^G(z_i^L)$ is increasing in z_i^L for $z_i^L \in [\underline{z}^L, min(\tilde{z}^L, 1)]$.

   2. *$\bar{z}^G(z_i^L)$ is decreasing in $\mathcal{R}^L(z_i^L)$ and $\bar{z}^L(\bar{z}^G(z_i^L))$ is increasing in $\mathcal{R}^L(z_i^L)$, for $z_i^G \in [\underline{z}^G, min(\tilde{z}^G, 1)]$ and $z_i^L \in [\underline{z}^L, min(\tilde{z}^L, 1)]$.*

      $\bar{z}^L(z_i^G)$ is decreasing in $\mathcal{R}^G(z_i^G)$ and $\bar{z}^G(\bar{z}^L(z_i^G))$ is increasing in $\mathcal{R}^G(z_i^G)$, for $z_i^G \in [\underline{z}^G, min(\tilde{z}^G, 1)]$ and $z_i^L \in [\underline{z}^L, min(\tilde{z}^L, 1)]$.

The intuition for Part 1 of Corollary 1 is straightforward. Suppose there is an increase in z_i^G from z_i^G to $z_i^{G'}$, or in other words, the global component of firm i's return strengthens. Global banks' expected profit increases, and perfect competition drives down $\mathcal{R}^G(z_i^G)$. At the margin, this attracts firms with higher z_i^L to contract with global banks. Thus, the threshold on z_i^L increases, $\bar{z}^L(z_i^{G'}) > \bar{z}^L(z_i^G)$. This relationship is illustrated in Panel (c) of Figure 6.

The intuition for Part 2 of Corollary 1 (shown in Panel (d) of Figure 6) is as follows. Suppose the local banks' interest rate function changes such that $\mathcal{R}^L(z_i^L)$ increases for some $z_i^L \in [\underline{z}^L, min(\tilde{z}^L, 1)]$. A higher interest rate induces a set of marginal firms to switch from contracting with local banks to global banks, holding constant z_i^G and $\mathcal{R}^G(z_i^G)$. In particular, the local component (z_i^L) of the switching firms is greater than that of the firms in global banks' original portfolio, which implies an increase of the threshold $\bar{z}^L(z_i^G)$. At the same time, the global component (z_i^G) of the switching firms is higher than that of the firms that remain with local banks, which implies a decrease of the threshold $\bar{z}^G(\bar{z}^L(z_i^G))$.

Based on the results from Proposition 1 and 2 and Corollary 1, I next characterize the competitive interaction between the two interest rate functions offered by the two types of banks.

Proposition 3. *(Interaction of Rate Functions in Equilibrium) Given z_i^G, for any increase in $\mathcal{R}^L(z_i^L)$ such that $\bar{z}^L(z_i^G)$ increases, $\mathcal{R}^G(z_i^G)$ declines. Given z_i^L, for any increase in $\mathcal{R}^G(z_i^G)$ such that $\bar{z}^G(z_i^L)$ increases, $\mathcal{R}^L(z_i^L)$ declines.*

Proposition 3 points out that each bank's type contingent interest rate function is determined by two inputs: the observed risk component of each firm's return and the threshold value of the unobserved risk component. For a given z_i^G, if there is a change in the local banks' interest rate function $\mathcal{R}^L$ such that the threshold $\bar{z}^L(z_i^G)$ increases, a set of marginal firms

with z_i^L greater than all the z_i^L's in global banks' original portfolio switches into borrowing from global banks. As a result, the global banks offer a lower $\mathcal{R}^G(z_i^G)$ for the firms with the given z_i^G. The interaction between the interest rates functions of global and local banks point to a stable equilibrium in which the two banks interact as strategic substitutes.

Propositions 1–3 lead to a full characterization of the equilibrium solution on $\mathcal{R}^G$ and $\mathcal{R}^L$. The solutions for the equilibrium interest rates $\mathcal{R}^G(z_i^G)$ and $\mathcal{R}^L(z_i^L)$, and thresholds $\bar{z}_i^L = \bar{z}^L(z_i^G)$ and $\bar{z}_i^G = \bar{z}^G(z_i^L)$, for $z_i^G \in [\underline{z}^G, 1]$ and $z_i^L \in [\underline{z}^L, 1]$ are described in detail in APPENDIX A, I.A.

Figure 7: **Firm-Bank Sorting Firm Space**
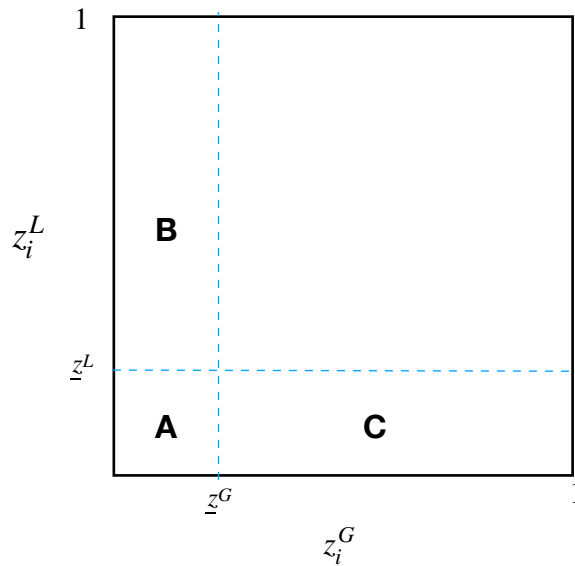
Notes. The plot summarizes all the firms in the economy. The bounds $\underline{z}^G$ and $\underline{z}^L$ define the cut-offs below which global banks and local banks, respectively, would not make loans. Firms in Region A are not offered loans. Firms in Region B can only receive loans from local banks. Firms in Region C can only receive loans from global banks.

3.4 Firm-Bank Sorting Under Double Asymmetric Information

I proceed to study the equilibrium firm-bank sorting in this economy.

Symmetric Equilibrium. To build intuition, I first study firm-banking sorting in the case where global and local banks face the same funding cost, $r^G = r^L = r$. This can be motivated by the idea that both types of banks have access to funds from a global interbank market that provides an elastic supply of funds at the risk-free interest rate r. This case allows me to focus solely on the implications of the double information asymmetry on firm-bank sorting.

Given the assumption $r^G = r^L = r$, the expected profit functions of the global and local banks become completely symmetric. With perfect competition and free entry, the equilibrium thresholds also become symmetric.

Lemma 1. *(Thresholds: Symmetric Case) If $r^G = r^L$, then $\bar{z}^L(z_i^G) = z_i^G$ and $\bar{z}^G(z_i^L) = z_i^L$.*

Given Lemma 1, sorting between firms and global versus local banks immediately follows.

Corollary 2. *(Firm-Bank Sorting: Symmetric Case) Let $r^G = r^L$. A firm selects a global bank if and only if $z_i^G \geq z_i^L$. A firm selects a local bank if and only if $z_i^L > z_i^G$.*

Panel (a) of Figure 8 provides a simple illustration of firm-bank sorting for the symmetric case. Global and local banks compete for loans borrowed by firms with $z_i^G \in [\underline{z}^G, 1]$ and $z_i^L \in [\underline{z}^L, 1]$. In equilibrium, the thresholds form a 45 degree line that segments the credit market. Firms in Region L, which have $z_i^L > z_i^G$, select into local banks, and firms in Region G, which have $z_i^G \geq z_i^L$, select into global banks.

Corollary 2 reveals that the information asymmetry problem faced by global and local banks creates a segmented credit market affected by double adverse selection. Both types of banks are adversely selected against, as firms select into borrowing from the bank which observes the more favorable component of their risk exposure. Specifically, firms with a weaker local component (z_i^L) relative to their global component (z_i^G) select into a global bank — the bank that cannot observe the weaker component.

Furthermore, firms are borrowing at higher interest rates relative to the first-best outcomes. This is because banks, given the information asymmetry problem, can only assign interest rates contingent on the component of firms' risk exposure that they observe, but not on the unobserved component, for which their rates must be uniform, as shown by the iso-interest rate curves in Panel (b) of Figure 8. Knowing the firm selection process, they assign interest rates based on the expected risk of the firms which will approach them. This gives rise to heterogeneity among firms in the degree to which they are charged higher interest rates relative to the first-best outcomes. The firms that are riskier in their unobserved exposure component face more favorable interest rates, and firms with relatively balanced global and local risk exposure (i.e., closer to the thresholds) face more adverse interest rates. Specifically, consider firms a and b in Panel (a) of Figure 8. In this economy, both firms select into borrowing from a global bank in equilibrium, and are offered the same interest rate $\mathcal{R}^G(z_i^G)$ since their z_i^G component is the same. However, the z_i^L component of firm a is much stronger than that of b, which means that firm a faces a worse outcome relative to the first-best outcome.

Asymmetric Equilibrium. Next I solve the model numerically to study firm-bank sorting in the general case when there is variation between the funding costs of global and local banks

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Figure 8: **Firm-Bank Sorting and Interest Rates Under Symmetric Equilibrium**
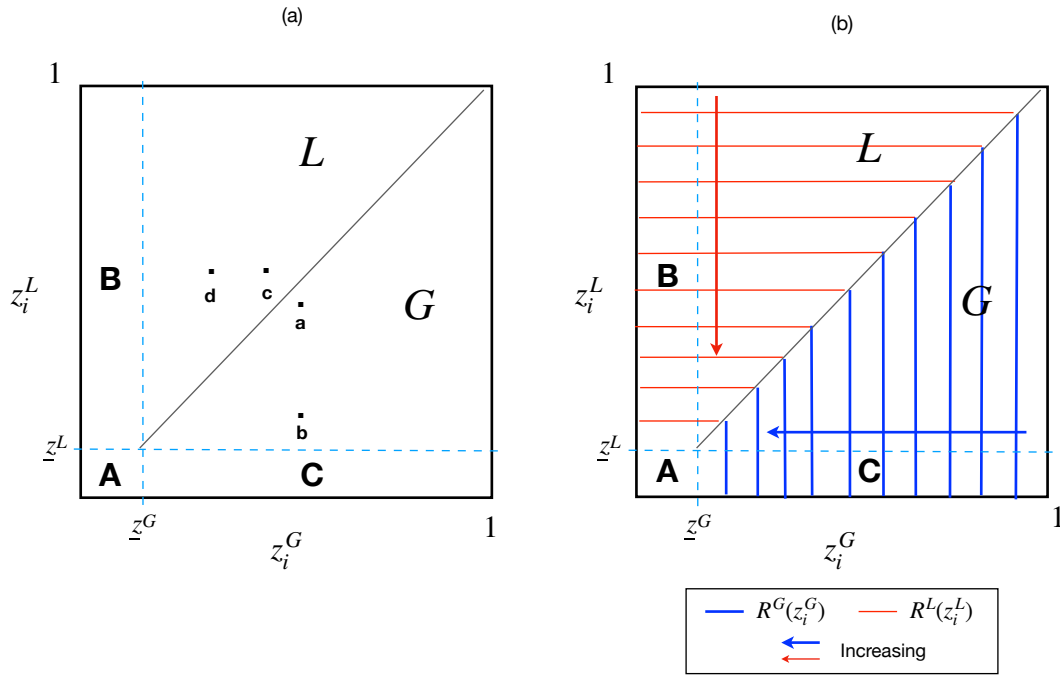
Notes. Panel (a) shows the equilibrium firm-bank sorting when $r^G = r^L$. Panel (b) shows iso-interest rate curves by global banks and local banks. For both plots, Region A depicts the region where no loans are given. Region B depicts the region where only local bank loans are given and no global banks would give loans. Region C depicts the region where only global bank loans are given and no local banks would give loans. Region L depicts the region where both global and local bank compete for loans, and loans are given by local banks in equilibrium. Region G depicts the region where both global and local bank compete for loans, and loans are given by global banks in equilibrium.

Figure 9: **Firm-Bank Sorting under Asymmetric Equilibrium**
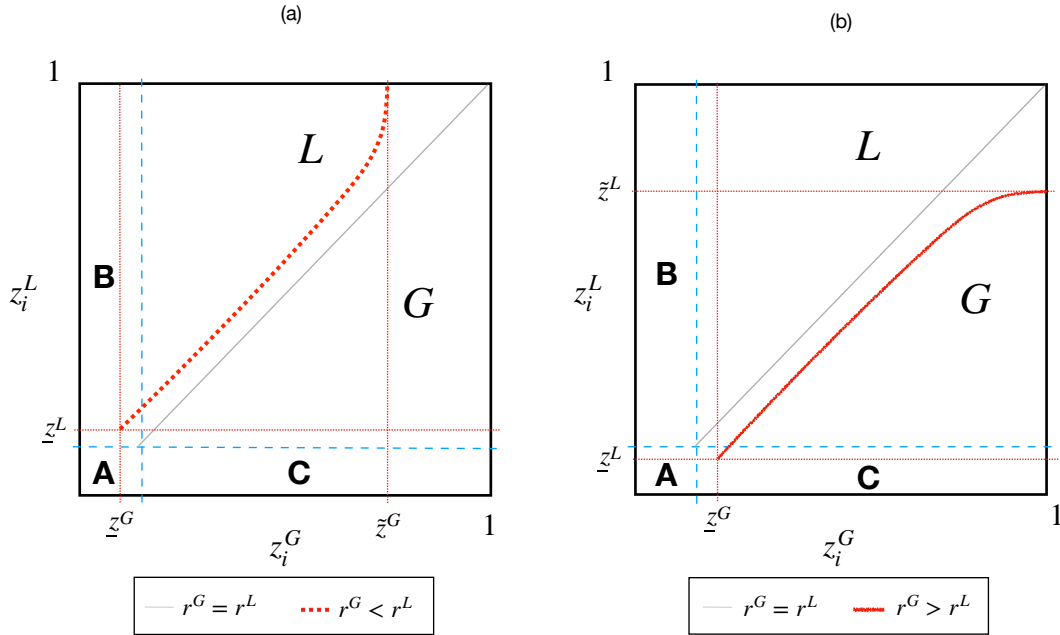
Notes. Panel (a) illustrates the firm-bank sorting when $r^G < r^L$, where $r^G = 1.00$ and $r^L = 1.01$. Panel (b) illustrates the firm-bank sorting when $r^G > r^L$, where $r^L = 1.00$ and $r^G = 1.01$. For both plots, Region A depicts the region where no loans are given. Region B depicts the region where only local bank loans are given and no global banks would give loans. Region C depicts the region where only global bank loans are given and no local banks would give loans. Region L depicts the region where both global and local banks compete for loans, and loans are given by local banks in equilibrium. Region G depicts the region where both global and local banks compete for loans, and loans are given by global banks in equilibrium.

$(r^G \neq r^L)$.

Panel (a) of Figure 9 provides an illustration of the equilibrium when $r^G < r^L$, where $r^G = 1.00$ and $r^L = 1.01$. Compared to the symmetric case, global banks are able to capture a greater share of the loan market given their funding advantage. In particular, they are able to attract all the firms with $z_i^G > \tilde{z}^G$, and they provide loans to firms with lower z_i^G components than before, since the cut-off $\underline{z}^G$ is increasing in r^G (Equation (A.3)).

Panel (b) of Figure 9 illustrates the equilibrium when $r^G > r^L$, where $r^L = 1.00$ and $r^G = 1.01$. The results are analogous.

Closed Economy vs. Financial Integration. An interesting counterfactual to consider is how this financially integrated economy compares with the benchmark closed economy, in terms of firm-bank sorting, aggregate credit, and efficiency. In a closed economy where there are only local banks, firms with $z_i^L < r^L - 1$ are considered too risky to get loans (illustrated in Panel (b) of Figure 5). With financial integration, most of those firms, specifically firms with $z_i^G > \underline{z}^G$, would be able to get loans from global banks (firms in Region n in Panel (a) of Figure 10). Furthermore, a set of firms with stronger global components (z_i^G) relative to their local components (z_i^L) would switch into borrowing from global banks (firms in Region G in Panel (a) of Figure 10), since they would receive lower interest rates from global banks, as shown in Panel (b) of the figure. Those firms would all benefit from financial integration.

However, the switching of firms leaves local banks with a riskier pool of firms, inducing an increase in interest rate for the infra-marginal firms that remain with local banks (firms in Region L in Panel (a) of Figure 10), as shown in Panel (b) of the Figure. This means that financial integration can give rise to an adverse selection problem. Moreover, this adverse selection problem would force a set of firms to exit the credit market (firms in Region e in Panel (a) of Figure 10). This result suggests that financial integration can induce a decline in aggregate credit due to adverse selection, which is in line with the arguments raised in Detragiache et al. (2008) and Gormley (2014).

Despite the potential decline in aggregate credit, it is important to point out that credit allocation in a fully integrated financial system is more efficient relative to a closed economy. I define efficiency in terms of how closely credit allocation corresponds to that in the benchmark full-information economy. As shown in Panels (c) and (d) in Figure 10, in a full information economy, firms in Regions a and b would not get loans, and firms in regions c and d would get loans. In both a closed economy and a financially integrated economy, firms in Region b are overfunded, while firms in Region c are underfunded. Nevertheless, for all reasonable parameters values, Regions b and c in a financially integrated economy are smaller than the corresponding regions in a closed economy. Quantitatively, let efficiency be defined as

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Figure 10: **Effects of Financial Integration**

(a) Firm-Bank Sorting

(b) Rate Change

(c) Efficiency: Closed Economy

(d) Efficiency: Financial Integration
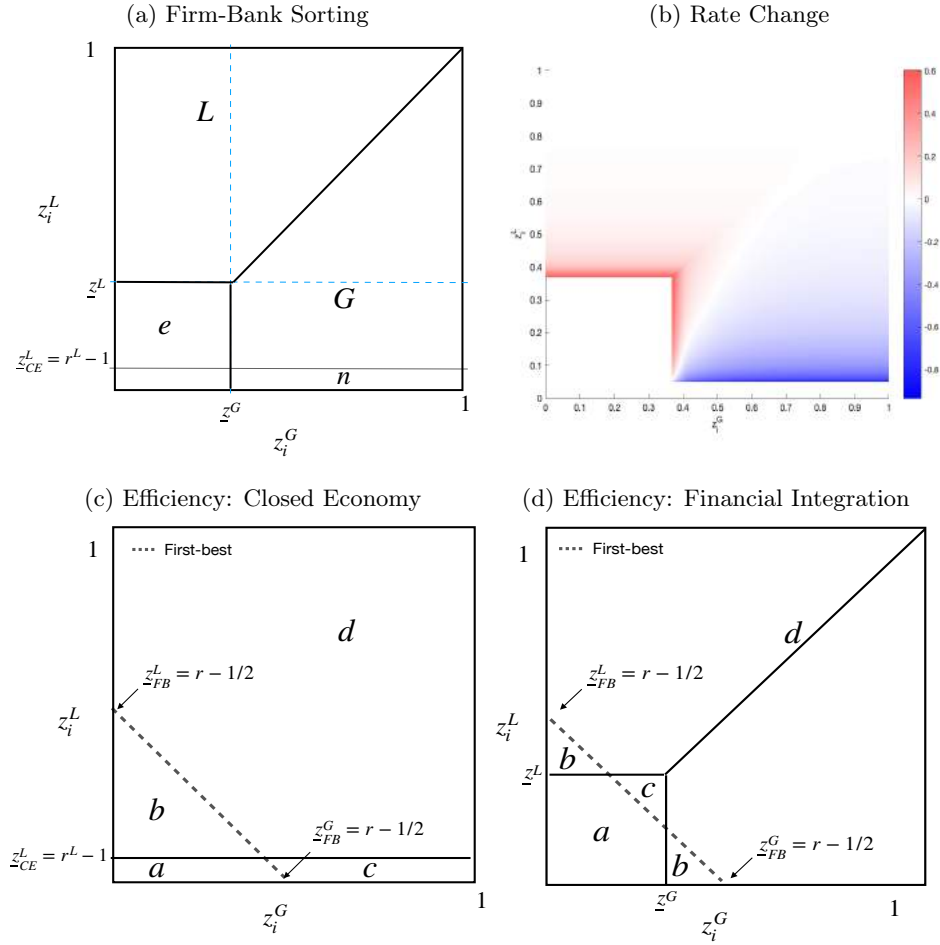
Notes. Panel (a) characterizes the equilibrium characterization after financial integration. Relative to a closed economy, upon financial integration, firms in Region e are no longer able to get loans, and firms in Region n are able to get loans. Panel (b) shows the interest rate change as measured by $\Delta R_i = R_i^{\mathrm{FI}} - R_i^{\mathrm{CE}}$ upon financial integration. The plot is based on simulations using parameter values $r^G = 1.05$ and $r^L = 1.05$. Panel (c) and (d) compares the firm space in a closed economy and a financially integrated economy, respectively, to that in the benchmark full-information economy. According to the first-best outcome, firms in Regions a and b would not get loans, and firms in Regions c and d would get loans.

the share of total credit in the economy relative to the benchmark full-information economy ($Efficiency = 1 - (b + c)/(a + b + c + d)$) based on the illustrations Panels (c) and (d) in Figure 10). Given parameter values $r^G = 1.05$ and $r^L = 1.05$, the closed economy is 85% efficient, while a financially integrated economy is 95% efficient.

4 Comparative Analysis and Implications

In this section, I explore the macroeconomic implications of the model. I study how the equilibrium credit allocation responds to changes in banks' funding cost (e.g., a change in monetary policy of the home country of one of the banks) at both the extensive (firm selection) and intensive (interest rate) margins. In addition, I apply the model to clarify the forces underlying the international risk-taking channel of monetary policy, and examine the impact of changes to banks' funding conditions on the riskiness of the banks' portfolios.

The following corollary summarizes the effects of a shock to banks' funding cost on the thresholds and the equilibrium interest rates.

Corollary 3. *(Funding Shock) Holding all else constant,*

1. *$\bar{z}^L(z_i^G)$ is decreasing in r^G and increasing in r^L; $\bar{z}^G(z_i^L)$ is decreasing in r^L and increasing in r^G.*

2. *$\mathcal{R}^G(z_i^G)$ is increasing in r^G and decreasing in r^L; $\mathcal{R}^L(z_i^L)$ is increasing in r^L and decreasing in r^G.*

To expand on its intuition and implications, I describe the results from Corollary 3 in the context of a decrease in global banks' funding cost, e.g., a decrease in funding rate due to expansionary monetary policy in the home country of the global banks. The effects of a lower funding cost, r^G, are also illustrated in Figure 11, which is based on simulation results with parameter values $r^G = 1.015$, $r^{G'} = 1.005$, and $r^L = 1.040$, where $r^{G'}$ denotes the new gross funding rate for global banks.

Extensive Margin Effects. A decrease in global banks' funding costs lowers the equilibrium interest rates offered by global banks for all firms. Based on Part 4 of Proposition 2, $\bar{z}^L(z_i^G)$ increases, and $\bar{z}^G(z_i^L)$ decreases, which implies that a set of marginal firms switch from local banks to global banks. The changes in the thresholds are illustrated in Panel (a) of Figure 11. It is interesting to point out that the marginal firms that switch into global banks are less risky than the infra-marginal firms that continue to borrow from either the local banks or the global banks. Moreover, the funding cost change affects $\underline{z}_i^G$ and $\underline{z}_i^L$, the

cut-offs on z_i^G and z_i^L below which global and local banks, respectively, would not make loans. A set of risky firms that initially were not able to get loans from either bank can now get loans from global banks (firms in Region G_2'), while a set of firms that initially were getting loans from local banks are no longer able to borrow from either class of bank (firms in Region G_3').
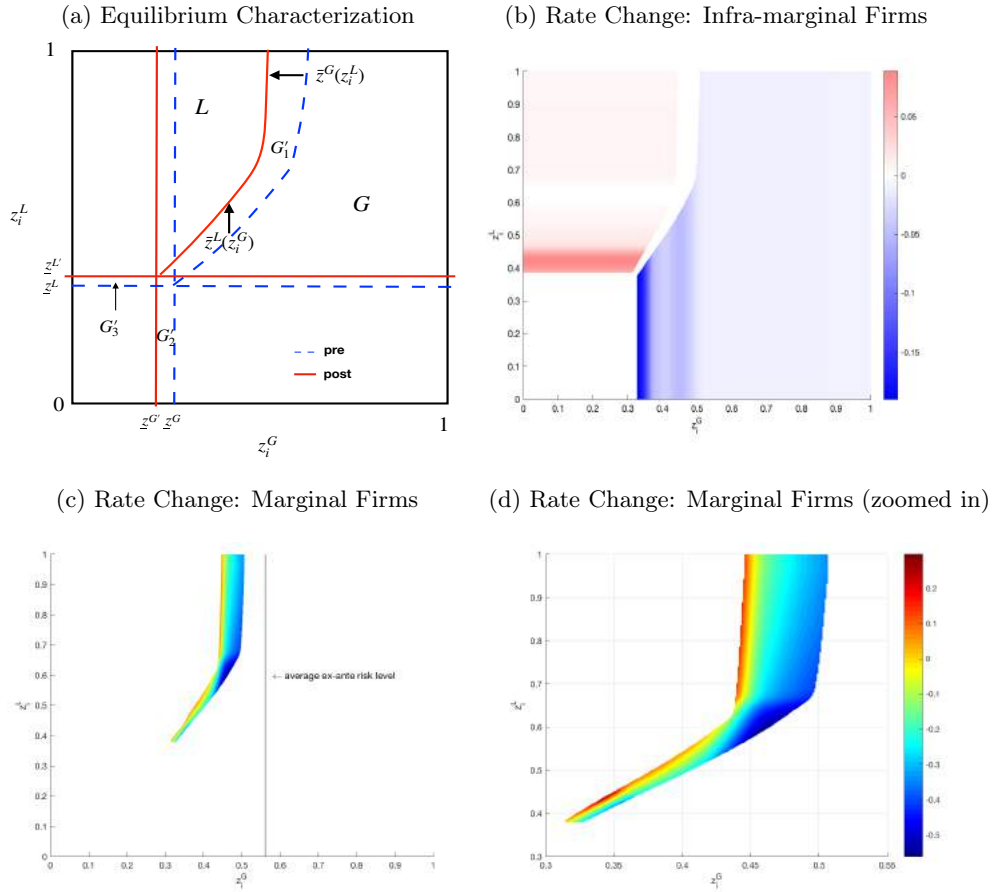
This result shows that a shock to bank funding cost affects credit allocation at the extensive margin. Specifically, the model predicts that firms near the thresholds, which are firms with relatively balanced global and local risk exposure components, are more likely to switch into contracting with global banks. The result is driven by adverse selection: since the firms with relatively balanced global and local risk exposure are more adversely selected against, they are more likely to switch lenders given any changes in the credit market.

Intensive Margin Effects. Changes in bank funding cost also affect credit allocation at the intensive margin. Given a decline in r^G, for each value of z_i^L, the z_i^G components of the marginal firms that switch away from local banks are higher than those of all the infra-marginal firms that remain with the local banks. Since the local banks are left with a riskier pool of firms, they charge higher interest rates, despite no changes to their funding cost. This points to a spillover effect, one that is solely driven by an exacerbation of the adverse selection problem. Simulation results show that, given a 100 basis point decrease in r^G (specifically a decrease from $r^G = 1.015$ to $r^{G'} = 1.005$), the interest rates that local banks offer to the infra-marginal firms that continue to borrow from them increase by 126 basis points on average, as shown in the red region in Panel (b) of Figure 11.

From the global banks' perspective, the z_i^L components of the marginal firms that switch into them are higher than those of all the infra-marginal firms that were getting loans from them in the initial equilibrium, conditional on z_i^G. Since the pool of firms that borrows from global banks is less risky given the funding cost shock, they lower $\mathcal{R}^G(z_i^G)$. In other words, the interest rates of the infra-marginal firms that remain with the global banks are expected to decrease by an amount more than that caused by the decrease in global banks' funding cost, reflecting an amplification effect. The impact of the funding shock is positively amplified for those infra-marginal firms because firm switching alleviates the initial adverse selection problem for the global banks. Simulation results show that a decrease of 100 basis points in r^G translates to a decrease of 180 basis points for an average infra-marginal firm that borrows from global banks, as shown in the blue region in Panel (b) of Figure 11.

Panels (c) and (d) of Figure 11 illustrate the change in interest rate for the marginal firms that switch banks given the funding cost shock (firms in Region G_1' in panel (a) of the Figure). The effects are heterogenous across the firms: while interest rates decrease for the switching

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Figure 11: **Effects of a Positive r^G Shock (r^G lowers)**

(a) Equilibrium Characterization

(b) Rate Change: Infra-marginal Firms

(c) Rate Change: Marginal Firms

(d) Rate Change: Marginal Firms (zoomed in)

Notes. Simulations based on parameter values $r^G = 1.015$, $r^{G'} = 1.005$, and $r^L = 1.040$. Panel (a) Illustrates the equilibrium characterization before and after a decrease in r^G. Panel (b) shows $\Delta R_i = R_i^{\text{post}} - R_i^{\text{pre}}$ for the infra-marginal firms. Panel (c) shows $\Delta R_i = (R_i^{\text{post}} - R_i^{\text{pre}})/(R_i^{\text{pre}} - 1)$ for the marginal firms. Panel (d) shows a zoomed-in version of part (c) of this figure.

firms that are closer to initial threshold; rates increase for firms closer to new threshold. Nevertheless, those firms would have been worse off if there were frictions to switching that left them with the local banks.

Altogether, this analysis of the effects of a funding cost shock on credit allocation reveals an adverse selection channel of international transmission of funding conditions. It results from the key ingredient in the model: competitive interactions between banks with differing specialization in global versus local information. One of factors that can affect banks' funding cost is monetary policy rate changes. When this happens, the model points to a novel adverse selection channel of international monetary policy transmission through bank lending, one that is distinct from the channels discussed in the existing literature, including currency mismatches on global banks' balance sheets (Bräuning and Ivashina 2017, Ongena et al. 2017, Bräuning and Ivashina 2018) and internal capital markets within global banks (Cetorelli and Goldberg 2012a).

International Monetary Policy Transmission. One channel of international monetary policy transmission that has received much attention in recent years is the risk-taking channel. Papers, including Bruno and Shin (2015a) and Coimbra and Rey (2017), argue that low international monetary policy rates and QE could induce global banks to reach for yield and take on excess risk. In particular, Morais et al. (2018), using loan-level data, show that low monetary policy rates and QE in developed economies led global banks in Mexico to increase credit supply to firms charged higher-than-average ex-ante interest rates (riskier firms). They consider this result as evidence for risk-taking behavior by global banks.

To better understand the forces underlying their result, I implement the empirical exercise in Morais et al. (2018) in my model using numerical simulation and examine whether bank risk-taking is indeed the main driving force. Following their procedure, I first categorize each firm in the model into a high-risk group and a low-risk group based on whether the firm's ex-ante rate is above or below the average interest rate in the credit market in the initial equilibrium. I then examine, given a decline in global banks' funding cost due to expansionary monetary policy in their home country, whether it is the high-risk firms that receive more loans from the global banks.

The specific parameter values I use for the simulation are $r^G = 1.015$, $r^{G'} = 1.005$, and $r^L = 1.040$, where the change in r^G reflects the decline in monetary policy rate in developed economies in the post-global financial crisis period and r^L reflects the average monetary policy rate in Mexico over the period. Panel (c) of Figure 11 shows a line pinpointing the firm with the average ex-ante interest rate in that parameter space. As shown, the set of marginal firms that switch into global banks in response to the funding cost change are firms in the

high-risk group. Therefore, this model recovers the result that Morais et al. (2018) find in the paper, predicting that an expansionary monetary policy in the home country of the global banks leads to a higher supply of credit to high-risk firms in the local economy. However, in contrast to their explanation, in my model the driving force for the result is substitution between global banking credit and local banking credit.

Overall Riskiness in Bank Portfolios. The prior exercise suggests that credit substitution driven by adverse selection is an important effect of monetary policy transmission. Furthermore, it could potentially confound with bank risk-taking behavior. I investigate this issue further by analyzing how a funding shock affects the overall riskiness of banks' portfolios, and decomposing the overall effect into the changes due to credit substitution and those due to bank risk-taking.

Let the riskiness of the portfolio held by a bank j be in terms of the firms' average output $R_j = \sum_{i=1}^{n}(z_i^G + z_i^L)/n$, where j denotes either a global bank or local bank, and i denotes the firm in the respective bank portfolio. Higher average output R_j implies lower risk.
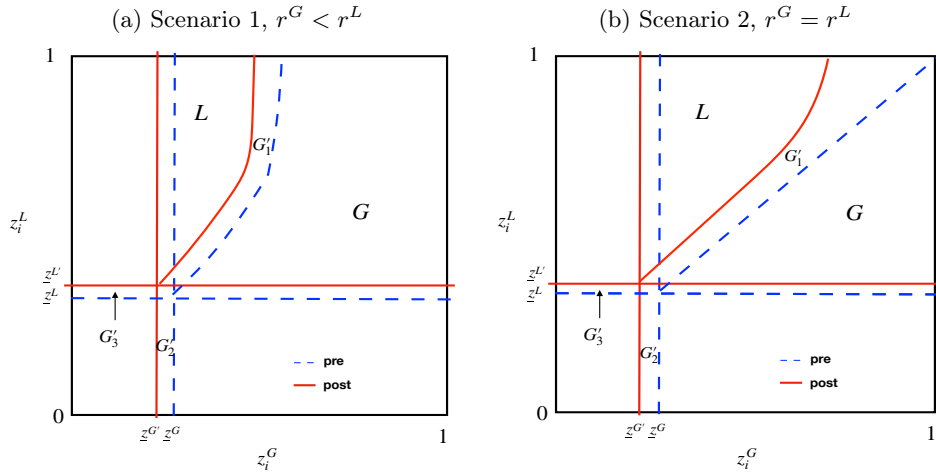
I compute R_j before and after a decline in r^G using numerical simulation, and examine the change in R_j of each bank's portfolios given the change. Specifically, I run the simulation for two sets of parameter values for the initial equilibrium. In scenario 1, $r^G < r^L$ in the initial equilibrium: $r^G = 1.015$, $r^L = 1.050$, and $r^{G'} = 1.005$ ex-post. In scenario 2, $r^G = r^L = 1.015$ in the initial equilibrium, and $r^{G'} = 1.005$. Table 2 presents the results. The local bank's portfolios become unambiguously riskier after the funding cost change due to negative spillover effects. On the other hand, the overall riskiness of the global bank's portfolio may increase or decrease depending on the relationship between r^G and r^L in the initial equilibrium.

In scenario 1, the overall riskiness of the global bank's portfolio increases given the decline in funding cost. This is due to the risk profiles of both the marginal firms that switch into the global bank and the newly added firms that were too risky to receive loans before (Region G_1' and Region G_2' in Panel (a) of Figure 12, respectively). The average risk of the firms that newly enter the credit market and borrow from the global bank is unambiguously higher than that of the infra-marginal firms that were getting loans from the global bank, driving up the overall riskiness of the global bank's portfolio. This change can be attributed to bank risk-taking. The marginal firms that switch into borrowing from the global bank, despite having higher z_i^L components conditional on z_i^G, have lower z_i^G components on average—and, as a result, higher combined average risk—than those of the infra-marginal firms. This further drives up the overall riskiness of the global bank's portfolio, and the driving force is credit substitution.

In scenario 2, the overall riskiness of the global bank's portfolio lowers. While the riskiness

of the firms that newly enter the credit market is still unambiguously higher than that of the infra-marginal firms (Region G_2' in Panel (b) of Figure 12), the average riskiness of the switching firms is lower. The average riskiness of both the z_i^L and z_i^G components of the switching firms are lower than the infra-marginal firms that were initially getting loans from global banks. The risk profile of the marginal firms dominate the risk adjustments in global bank's portfolio given the change in r^G. In other words, the effects due to credit substitution dominate the effects due to bank risk-taking in this scenario.

Figure 12: **Effects of a Decline in Funding Cost r^G**

(a) Scenario 1, $r^G < r^L$ (b) Scenario 2, $r^G = r^L$

Notes. Panel (a) Illustrates the equilibrium before and after a decline in r^G based on simulations with parameter values $r^G = 1.015$, $r^{G'} = 1.005$, and $r^L = 1.050$. Panel (a) Illustrates the equilibrium before and after a decline in r^G based on simulations with parameter values $r^G = 1.015$, $r^{G'} = 1.005$, and $r^L = 1.015$.

5 Mapping Theory to Empirics

The model presented in Sections 3 and 4 delivers three sharp empirical predictions on firm-bank sorting and credit allocation:

Prediction 1: Conditional on funding cost differences between global and local banks, global banks lend more to firms with higher return due to global risk relative to local risk, and local banks lend more to firms with higher return due to local risk relative to global risk.

Prediction 2: A shock to the funding cost of one type of bank induces the segment of firms with relatively balanced global and local risk components (i.e., the marginal firms near the thresholds $\bar{z}^L(z_i^G)$ and $\bar{z}^G(z_i^L)$) to switch to borrowing from the other type of bank.

Prediction 3: Given a decrease in global banks' funding cost, the interest rates of the infra-marginal firms that remain with the local banks are expected to increase (spillover effect).

Table 2: **Banks' Overall Risk Before and After a Decline in r^G**

		Pre	Post	Switching	New
Scenario 1	G	1.163	1.157	1.155	0.509
	L	0.943	0.917	–	–
Scenario 2	G	1.087	1.155	1.516	0.508
	L	1.155	1.085	–	–

Notes. The table shows the riskiness of the portfolios held by a global bank (G) and a local bank (L) before ("pre") and after ("post") a decline in r^G. The post effect is further decomposed by showing the riskiness of the "switching" firms and "new" firms that select into global banks after the change. Riskiness of bank portfolios is measured as $R_j = \sum_{i=1}^n (z_i^G + z_i^L)/n$, where j denotes either a global bank or local bank, i denotes all the firms in the respective bank portfolio. The higher the R_j measure, the lower the risk. In scenario 1, $r^G < r^L$ in the initial equilibrium: $r^G = 1.015$, $r^L = 1.050$, and $r^{G'} = 1.005$ ex-post. In scenario 2, $r^G = r^L = 1.015$ in the initial equilibrium, and $r^{G'} = 1.005$.

The interest rates of the infra-marginal firms that remain with the global banks are expected to decrease by more than the direct effect due to the decrease in funding cost (amplification effect). The effects on interest rates of the marginal firms that switch banks are ambiguous.

I proceed to test these predictions in the subsequent sections. First, I provide a description of the data used in the empirical analysis.

Data and Summary Statistics. The main data source for the empirical analysis is syndicated corporate loans from Loan Pricing Corporation's Dealscan database. Syndicated loans are extended by a group of banks to a borrower under a single loan contract. Within each group of lenders, the "lead arranger" is the bank that establishes a relationship with the borrowing firm, negotiates terms of the contract, and guarantees a loan amount for a price range. It then turns to "participant" lenders that fund part of the loan.[17] Ivashina and Scharfstein (2010) report that syndicated loan exposures represent about a quarter of total commercial and industrial loan exposures on US banks' balance sheets, and about a third for large US and foreign banks. De Haas and Van Horen (2013) note that syndicated loans are a key source of cross-border funding for firms from both advanced and emerging market countries.

For the purpose of this study, the ideal dataset is one that encompasses the universe of loans from firms that genuinely have access to both global and local banking credit, which are likely to be firms above a certain threshold in size. The global syndicated loans are viewed as a proxy of that universe of loans. Despite potential selection issues, syndicated loans are uniquely appropriate for this study because they capture a significant portion of cross-border lending, which would not be captured by such other loan datasets such as credit registry data.

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[17] See Sufi (2007) and Ivashina (2009) for more background description of syndicated loans.

In the Dealscan data, there is detailed information on each loan contract, including terms of the loans at origination (interest rate, whether or not the loan is secured, the maturity of the loan), the type of loan (e.g., line of credit versus term loan), the purpose of the loan, the size of the loan, and the contract activation and ending dates. The dataset also contains information on the name of the borrowers and lenders as well as the country of syndication. Using the names of the borrowers, I hand-match the Dealscan data with international firm-level databases including Orbis, Amedeus, Compustat, and Compustat Global to extract firm balance sheet data.[18] I further implement a series of data-cleaning procedures to correct for basic reporting mistakes, including dropping firm-year observations that have missing information on total assets and operating revenues, dropping firms with negative total assets or employment in any year, and dropping firm-year observations with missing information regarding their industry of activity. Finally, I also exclude firms in financial industries identified by SIC codes 60 through 64 from the sample.

For the purpose of this empirical analysis, one of the key variables needed is one that identifies whether the lender of each loan is a global bank or a local bank. To this end, I categorize the lead lender(s) of each loan as global or local. The focus is on the lead bank(s) of each loan contract because they are the entities that are responsible for due diligence prior to loan syndication, while the participant banks rely on the information collected by the lead banks (Ivashina and Scharfstein 2010).[19]

The bank categorization is based on the following criteria:

1. Local banks: a lender is categorized as a local bank if the corresponding loan is not a cross-border loan, i.e., the borrower of the loan operates in the country where the lender resides. This includes local subsidiaries of foreign banks.[20]

2. Global banks:

   - Method 1: a lender is categorized as a global bank if the corresponding loan is a

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[18] The Amadeus and Orbis datasets are mainly used to extract information on European and other non-US firms, including private firms. Compustat is used to extract information on US firms. A well-known problem in the Orbis and Amadeus dataset is that key variables, such as employment and materials, are missing once the data are downloaded. I follow the data collection process described in Kalemli-Ozcan et al. (2015) to maximize the coverage of firms and variables for the sample. Specifically I merge data across historical disks instead of downloading historical data all at once from the WRDS website.

[19] For loans that involve multiple lead banks of which some are global banks and some are local banks, I consider a loan is given by global bank if $\geq 50\%$ of the lenders are global banks. These cases make up around 20% of the loans. Based on the model predictions, I conjecture that firms with relatively balanced global and local risk components are more likely to get loans that involve both global and local lead banks. I find empirical evidence that supports this conjecture.

[20] E.g., for firms in Germany, JP Morgan Holding Deutschland is a local bank, while JP Morgan Chase USA is a global bank. Local subsidiaries are considered separate legal entities from their parent bank, incorporated in host countries and supervised by the host regulator.

cross-border loan.

- Method 2: a lender is categorized as a global bank if the corresponding loan is a cross-border loan, or if it is considered a globally systemically important bank (G-SIB).

The resulting sample encompasses 115,166 loans, borrowed by 12,979 firms across 24 countries, in the period 2004-2017. Table 3 presents the summary statistics on the loan counts and firm counts for each country in the sample, with the loan counts decomposed into the share given by global banks and that given by local banks, based on Method 1 of the categorization criteria for global banks.[21] The majority of the countries in the sample are developed economies, where most global banking activities take place. For most of the countries, the loans are split relatively evenly between global banking credit and local banking credit.

Table 3: **Summary Statistics: Loan and Firm Count by Country (Method 1)**

Country	Loan	GB	LB	Firm	Country	Loan	GB	LB	Firm
Australia	4507	0.70	0.30	701	Japan	21341	0.29	0.71	2865
Austria	387	0.53	0.47	61	Mexico	601	0.70	0.30	137
Belgium	704	0.61	0.39	123	Netherlands	2028	0.28	0.72	406
Canada	6760	0.64	0.36	903	New Zealand	1023	0.70	0.30	127
Czech Republic	197	0.68	0.32	77	Norway	1017	0.66	0.34	253
Denmark	327	0.56	0.44	84	Poland	318	0.54	0.46	87
Finland	587	0.65	0.35	113	Portugal	254	0.65	0.35	64
France	5876	0.43	0.57	996	Spain	4380	0.60	0.40	839
Germany	5987	0.54	0.46	942	Sweden	875	0.62	0.38	190
Greece	309	0.66	0.34	47	Switzerland	790	0.58	0.42	175
Ireland	404	0.63	0.37	107	United Kingdom	6810	0.43	0.57	1528
Italy	2378	0.58	0.42	688	United States	46732	0.40	0.60	1466

Notes. Sample constructed from Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation. Sample period covers the year 2004-2017.

Table 4 presents the summary statistics on a set of firm balance sheet variables. All the variables in the table are in billions of dollars, except for age and employment. Value added, wage bill, total assets, and exporter revenue are deflated with gross output price indices with a base year of 2017. I first calculate the means and standard deviations of each variable across firms in each given year and country without weighting across firms. Entries in the table denote the means and standard deviations averaged across all years and countries. The

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[21] Table A.1 in APPENDIX B presents summary statistics on the same variables as Table 3 but with the banks categorized based on Method 2 of the categorization criteria for global banks.

summary statistics exhibit significant variation in each variable in the sample, which shows that the sample contains firms from a wide distribution of asset size and age. For all variables except exporter revenue, there does not seem to be significant difference between the firms that borrow from global banks and the ones that borrow from local banks. On the other hand, it seems that firms that borrow from global banks export significantly more than firms that borrow from local banks.

Table 4: **Summary Statistics: Firm Characteristics by Bank Type**

	Global Bank		Local Bank	
	Mean	SD	Mean	SD
Value Added	512.55	1256.45	468.55	895.09
Age	25.29	24.67	25.23	24.98
Employees	1657.34	6073.34	1719.58	5326.32
Wage Bill	209.73	1030.76	163.35	786.41
Working Capital	110.58	1089.56	123.34	1173.32
Fixed Asset	918.03	2465.80	732.76	2987.84
Total Assets	1344.5	4658.56	1134.53	4034.32
Exporter Revenue	587.00	1789.34	113.31	456.68

Notes. Value added is constructed as the difference between operating revenue and materials with negative values dropped. Age of the firm is calculated as the difference between the year of the balance sheet information and the year of firm incorporation plus one. Except for age and employment, all entries in the table are in billions of dollars. Value added, wage bill, total assets, and exporter revenue are deflated with gross output price indices with a base year of 2017. I first calculate the means and standard deviations without weighting across firms for each year in each country. Entries in the table denote the means and standard deviations averaged across all years and countries. Data from Amadeus, Orbis, Compustat, and Compustat Global. Sample period covers the year 2004-2017.

6 Empirical Analysis: Firm-Bank Sorting

In this section, I test whether the firm-bank sorting patterns predicted by the model are consistent with the observed patterns in the data (model Prediction 1). To that end, I follow an empirical strategy that tightly maps to the model set-up.

6.1 Methodology

In order to test whether global banks lend more to firms with higher return due to global risk (z_i^G) relative to local risk (z_i^L), and vice versa for local banks, I need to construct measures for z_i^G and z_i^L for each firm in the sample. Recall from the model that the production function for each firm is $z_i = z_i^G + z_i^L + u_i$. I take that as a simplified version of a typical Cobb-Douglas

production function $Y_i = z_i K_i^\gamma L_i^{1-\gamma}$, where there is one unit of K_i and L_i. The parameter z_i, in turn, can be interpreted as a firm revenue productivity measure that captures total exposure to both productivity and demand risk, and z_i^G (z_i^L) can be interpreted as total exposure to global (local) productivity and demand risk.

Estimating z_i. I start by estimating a time-varying revenue productivity measure z_{it} for each firm in each year based on the method of Solow growth accounting.[22] Specifically, I compute the z_{it} based on the following equation:

$$log\, z_{it} = log\,(Y_{it}/L_{it}) - \gamma_t log\,(K_{it}/L_{it}) \tag{4}$$

where Y_{it} denotes nominal value added divided by the 2-digit industry level output price deflator for each country where value added is constructed as the difference between operating revenue and materials with negative values dropped, L_{it} denotes the wage bill divided by the same output price deflator, K_{it} denotes fixed assets divided by aggregate price of investment goods, and the factor share γ_t uses country-specific and industry-specific shares extracted from the National Accounts of each country.

Figure A.1 plots the estimates of the productivity measure, $log\, z_{it}$, averaged across firms and time by country. As expected, average productivity is higher for the relatively more developed economies such as the US and high-income European economies.

Estimating z_i^G and z_i^L. Next I decompose the firm-specific productivity measure, z_i, which captures total exposure to productivity and demand risk, into two components: exposure to global risk (z_i^G) and exposure to local risk (z_i^L). Firms' total exposure to global risk can be considered to encompass two components, $z_i^G = \beta_i^G z^G$, where β_i^G denotes firm i's exposure to global risk and z^G denotes global risk. The same applies to firms' total exposure to local risk: $z_i^L = \beta_i^L z^L$, where β_i^L denotes firm i's exposure to local risk and z^L denotes local risk.

I implement a principle component analysis to extract estimates for z^G and z^L, following Stock and Watson (2002). Specifically, I estimate the following equation:

$$z_{ict} = \beta_{ic}^G z_t^G + \beta_{ic}^L z_{ct}^L + u_{ict} \tag{5}$$

where z_{ict} is the productivity measure for firm i in country c in year t, z_t^G is the global factor,

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[22] Gorodnichenko (2012) shows that this can be used as a robust non-parametric method to estimate productivity. He also points out that a number of existing parametric methods for estimating productivity are misspecified or poorly identified. In particular, inversion/control-function estimators (e.g., Olley and Pakes 1996, Levinsohn and Petrin 2003) can lead to inconsistent estimates because they ignore variation in factor prices. GMM/IV estimators using lags of endogenous variables as instruments (e.g., Blundell and Bond 1998) can be poorly identified because of economic restrictions on the comovement of inputs and output.

Figure 13: **Estimates of Global Factor** z^G
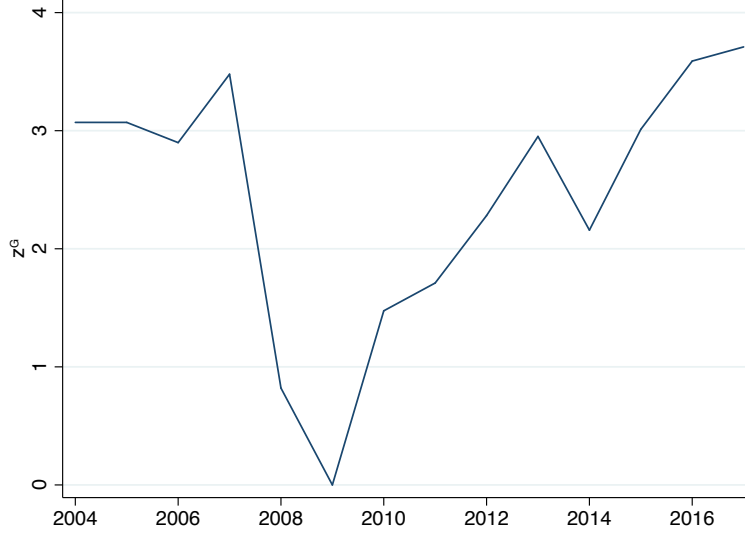
Notes. A plot of the global factor z^G, extracted from the first principle component of the z_{ict} series. The factor values have been adjusted upward by their minimum so that all the values are positive. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

z_{ct}^L is the local factor in country c, and u_{ict} is a firm-specific component.

The factors can be estimated consistently with a two-step procedure. In the first step, the common global factor is obtained from the principal components of the z_{ict} series across the 24 countries in the sample. The first principle component explains 58% of the total variance, which I take as the global factor, z_t^G. Figure 13 plots the global factor.[23] As shown, it declines around 2007-2008, the period of the global financial crisis, and gradually recovers thereafter.

In the second step, I orthogonalize the global component by regressing the productivity measures z_{ict} on the global factor and taking the residuals. I then extract local (country) factors by computing the principal components based on the residualized z_{ict} series for each country. The first principle component from output for each country is taken as the local factor, z_{ct}^L. Finally, I estimate the firm-specific global and local exposure measures using OLS regressions. β_i^G and β_i^L are extracted from the loadings on the global and local factor, respectively.

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[23] To map closely to the model setup where z_i^G and z_i^L only take positive values, the factor values have been adjusted upward by their minimum so that all the values are positive.

6.2 Results

Using the estimated measures for z_i^G and z_i^L, I proceed to test the first model prediction on firm-bank sorting. Similar to the procedure I used to test the traditional theory on firm-bank sorting in Section 2 but now using the new measures, I sort firms into quartiles based on the distribution of firm exposure to global versus local risk (z_i^G/z_i^L) in each year by country, and calculate the proportion of loans given by global banks and local banks in each quartile. Figure 14 plots the resulting distribution of lending from global and local banks over the entire sample. The plot shows a stark pattern of firm-bank sorting: global banks lend more to firms with higher return given global risk (z_i^G) relative to local risk (z_i^L), and local banks lend more to firms with higher return due to local risk relative to global risk.[24]

Figure 14: **Firm-Bank Sorting, by z_i^G/z_i^L Quartile (Method 1)**
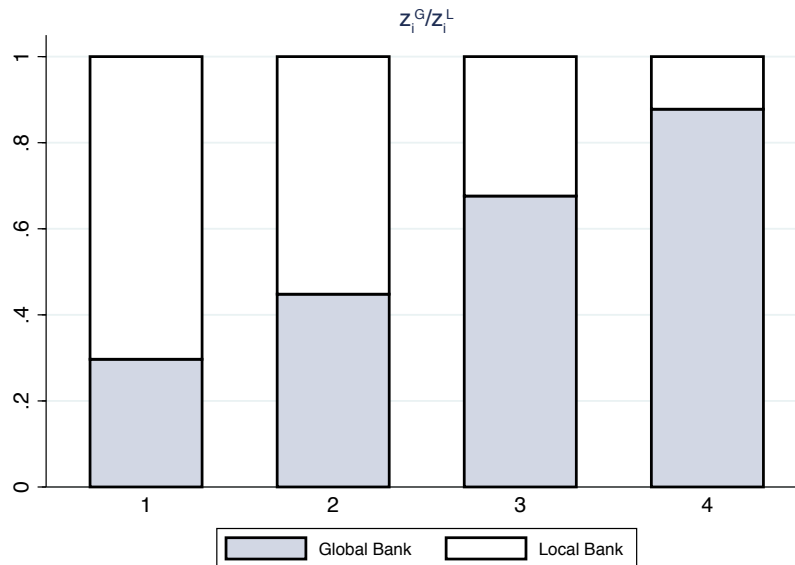
Notes. The plot shows sorting patterns between firms and global versus local banks, with firms sorted into quartiles by their exposure to global versus local risk (z_i^G/z_i^L), with the banks categorized based on Method 1 of the bank categorization criteria for global banks. Data sample consists of syndicated loans between firms global and local banks and firms across 24 countries from 2004-2017. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

As before, I further test whether the differences between global and local banks illustrated in Figure 14 and A.2 are statistically significant. For the measure on firm exposure to global versus local risk (z_i^G/z_i^L), I test whether the value-weighted mean of that variable for global

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[24] Figure A.2 parallels Figure 14, with the banks categorized based on Method 2 of the bank categorization criteria for global banks.

banks is different from that for local banks. Table 5 presents these means and their differences. The results confirm the graphical analysis: the differences in value-weighted means are statistically *significant* between global and local banks for the measure of firm exposure to global versus local risk (z_i^G/z_i^L), supporting the model prediction on firm-bank sorting.

Table 5: **Firm-Bank Sorting, by z_i^G/z_i^L Quartile: Statistical Test**

	Method 1 z_{iG}/z_{iL}	Method 2 z_{iG}/z_{iL}
Mean: Global Bank	2.905***	3.382***
	(0.046)	(0.040)
Mean: Local Bank	2.107***	2.507***
	(0.113)	(0.097)
Difference	0.798***	0.875***
	(0.122)	(0.105)
Observations	98,345	98,345

Notes. The dependent variable in each regression (Y) is the measure of firm exposure to global versus local risk, (z_i^G/z_i^L), coded 1-4 based on the quartile number to which each respective firm belong. Note the firms are sorted based on the exposure measure every year by country. Row 1 and row 2 show the means for each variable for global banks and local banks, respectively, by running a value-weighted regression of Y on a constant. For differences in means of the two types of banks, the whole data is used in the regression and a dummy for global banks is added (row 3). Standard errors reported in parentheses are clustered at the bank-level. Results in column 1 and column 2 are based on the banks categorized using Method 1 and Method 2, respectively, of the bank categorization criteria for global banks. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

The results show that the new perspective I raise in this paper, bank specialization in global versus local information, plays an important role in determining firm-bank sorting in financial systems with both global and local banks. But does the traditional theory of bank specialization in hard versus soft information still play a role? I investigate this question by studying how the measures that capture global information and the measures that capture hard information jointly predict the likelihood of getting loans from global banks. I run a set of regressions with the dependent variable being a dummy variable that takes the value 1 if the loan is given by a global bank and 0 otherwise. The independent variables in the regressions are firm exposure to global risk relative to local risk (z_i^G/z_i^L), firm asset size, and/or firm age, each coded by the quartile number to which each observation of the respective variable belongs. The results are presented in Table 6. Results in column 1 show that between firms in two consecutive quartiles based on the measure of exposure to global risk relative to local risk, the firms in the higher quartile group are 33% more likely to get loans from a global bank. Columns 2 and 3 present results from regressions that include firm asset size and firm age, respectively. The results show that, controlling for firm exposure to global risk relative to local

risk, firms that are larger and more established are significantly more likely to get loans from global banks, which is consistent with the predictions from the traditional banking theory. The results in column 4 show that each of the three measures still have predictive power on the likelihood of getting loans from global banks, even when the other two measures are also included as regressors. Overall, these results suggest that the firm-bank sorting patterns predicted by the traditional banking theory can be recovered once bank specialization in global and local information are taken into account.

Table 6: **Firm-Bank Sorting, Traditional Theory and New Perspective**

	(1)	(2)	(3)	(4)
	1(GB)	1(GB)	1(GB)	1(GB)
z_i^G/z_i^L	0.329***	0.221***	0.261***	0.198**
	(0.086)	(0.074)	(0.080)	(0.081)
Size		0.268***		0.236***
		(0.081)		(0.073)
Age			0.157**	0.138*
			(0.075)	(0.078)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	98,345	98,345	98,345	98,345

Notes. Results from regressions with the dependent variables being a dummy variable that takes the value 1 if the loan is given by a global bank and 0 otherwise. The independent variables are firm exposure to global risk relative to local risk (z_i^G/z_i^L), firm asset size, and/or firm age, each coded by the quartile number to which each observation of the respective variable belongs. Each regression controls for industry and country fixed effects. Standard errors reported in parentheses are clustered at the firm level. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

Finally, I explore the characteristics of the firms that borrow from global banks, and the characteristics of the loans are given by global banks. For the former, I study if exporters are more likely to have a higher value of z_i^G/z_i^L and thereby more likely to get loans from global banks. I run a firm-level panel regression with z_i^G/z_i^L as the dependent variable, and a dummy variable that takes the value 1 if the exporting revenue for the respective firm for a given year is nonzero and 0 otherwise as the main regressor, controlling for time and country fixed effects. The results, reported in column 1 of Table 7, show that exporting firms tend to have significantly higher z_i^G/z_i^L values, or higher exposure to global risk relative to local risk. Combined with the results from the sorting exercises, this empirical evidence suggests that exporters are more likely to get loans from global banks.

In light of these evidence, I further investigate into the loan-level data to see whether

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loans of specific purposes such as trade finance are more likely to be funded by global banks. I run a loan-level regressions with the main regressors being dummies on specific loan purposes, including project finance, working capital, trade finance, and others[25]. The dependent variable of the regression is a dummy variable that takes the value 1 if the loan is given by a global bank and 0 otherwise. The results (column 2 of Table 7) show that it is not the case that global banks mainly finance loans for the purpose of trade finance. A significant portion of the loans they finance are for general project finance and working capital.

Table 7: **Determinants of z_i^G/z_i^L and Global Banking Credit**

	(1) z_i^G/z_i^L	(2) 1(GB)
Exporter	0.565***	
	(0.103)	
Project purpose		
Project finance		0.013***
		(0.001)
Working capital		0.020***
		(0.001)
Trade finance		0.004**
		(0.002)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Country FE	Yes	Yes
Observations	129,309	98,345

Notes. Column 1 reports results from a firm-level panel regression with z_i^G/z_i^L as the dependent variable, and a dummy variable that takes the value 1 if the exporting revenue for the respective firm for a given year is nonzero and 0 otherwise as the main regressor. Column 2 reports results from a loan-level regression with a dummy variable that takes the value 1 if the loan is given by a global bank and 0 otherwise as the dependent variable, and dummy variables on loan purpose as the main regressors. Time, industry and country fixed effects are included in both regressions. Standard errors reported in parentheses are clustered at the firm level. Source: Dealscan, Amadeus, Orbis, Computstat, Compustat Global, and author's calculation.

7 Empirical Analysis: Adverse Selection Channel of Monetary Policy Transmission

In this section, I study how shocks to bank funding cost, specifically monetary policy shocks, affect credit allocation at the extensive and intensive margins, testing model Predictions 2 and

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[25] Others include IPO related finance, real estate, stock buyback, etc. They are grouped together in one variable.

3. I take the Euro area as the empirical laboratory of this study, and analyze how US and Euro area monetary policy, through US and Euro area banks, respectively, affect credit allocation across firms in the Euro area. From the perspective of Euro area firms, US banks are global banks, and Euro area banks are local banks. Given this context, I raise two conjectures based on the model predictions and the results on firm-bank sorting from the last section:

i) Conditional on Euro area monetary policy, an expansionary US monetary policy induces firms in the Euro area with relatively balanced global and local risk components—firms in the second tercile of the z_i^G/z_i^L distribution—to switch their borrowing from Euro area banks to US banks.

ii) Conditional on Euro area monetary policy and given expansionary US monetary policy, the interest rates of the infra-marginal firms that continue to borrow from Euro area banks—firms in the first tercile of the z_i^G/z_i^L distribution (firms with relatively low z_i^G relative to z_i^L)—are expected to increase (spillover effect). The interest rates of the infra-marginal firms that continue to borrow from US banks—firms in the third tercile of the z_i^G/z_i^L distribution (firms with relatively high z_i^G relative to z_i^L)—are expected to decrease by more than the direct effect due to expansionary US monetary policy (amplification effect). The effects on interest rates of the marginal firms that switch banks—firms in the second tercile of the z_i^G/z_i^L distribution—are ambiguous.

To test the conjectures, I perform regressions of the following form, using data on loans borrowed by Euro area firms in the loan-level data and the firm-specific z_i^G/z_i^L measure:

$$\Delta Y_{it} = \sum_{q=1}^{3} \beta^q (\Delta USR_t \text{ x } T_{it-1}^q) + \sum_{q=1}^{3} \delta^q (\Delta EUR_t \text{ x } T_{it-1}^q) + \sum_{q=2}^{3} \gamma^q T_{it-1}^q + \nu_i + \sigma_t + \epsilon_{it} \quad (6)$$

where i indexes firm, t indexes the date on which a specific loan is issued, $\Delta(.)$ denotes the difference in the referred variable between the date on which the current loan is issued and the date on which the last loan was issued, Y denotes the applicable dependent variable which I explain below, USR denotes US monetary policy shocks, EUR denotes Euro area monetary policy shocks, q indexes each of the three terciles of the z_i^G/z_i^L distribution, T_{it-1}^q are dummy variables that take the value 1 when firm i's z_i^G/z_i^L measure at the time of the last loan issuance belongs to tercile q and 0 otherwise, ν_i are firm dummies, and σ_t are year dummies. The standard errors are clustered by time, to take into consideration potential correlations across firms in borrowing behavior or borrowing term changes since the monetary policy shocks are aggregate.

For measures of US and Euro area monetary policy shocks, I use intraday data on the Federal Funds 30-day futures contracts and the three-month Euribor futures contracts, re-

spectively, from Gorodnichenko and Weber (2016) and CQG Data Factory.[26] The Federal Funds futures data is based on trading on the Chicago Board of Trade (CBOT) Globex electronic trading platform. It reflects the market expectation of the average effective Federal Funds rate during that month. The Euribor futures rates is based on trading on ICE Futures Europe and reflects the market expectation of the Euribor rate for three-month Euro deposits.[27] Therefore, both series provide a market-based measure of the anticipated path of the monetary policy rates for the respective region.

In order to identify exogenous shocks to US and Euro area monetary policy, the monetary policy shocks are calculated as changes in the futures rates within a time window around the Federal Open Market Committee (FOMC) or European Central Bank (ECB) monetary policy announcements.[28] The identifying assumption is that changes in the interest rate futures within the specified windows around the announcements only reflect market responses to the monetary policy news, not changes in other domestic or foreign economic conditions. For measures of US monetary policy shock, I consider a window of 60 minutes around the announcements that starts 15 minutes (Δ^-) prior to the event, following Gorodnichenko and Weber (2016) and Nakamura and Steinsson (2018).

As for ECB monetary policy, its key target rate decision since 2001 has been announced at 13:45 CET through a press release, followed by a press conference at 14:30 pm CET. At the press conference, the ECB President and Vice-President discuss the future path of monetary policy and announce any additional non-conventional measures.[29] To give a sense of how the ECB policy rate announcement and the press conference affect the market expectation of the Euribor rate, I illustrate the three-month Euribor futures rate in high frequency on two specific announcement dates in Figure A.3. The upper panel plots the Euribor futures rate from 08:00 to 18:00 CET for April 6, 2006. At 13:45 CET, the ECB announced through a press release that it is keeping the target rate unchanged. Since this decision was expected

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[26] The US monetary policy shock measure based on intraday data on the Federal Funds futures contracts has been used in a number of papers, including Kuttner (2001), Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Gertler and Karadi (2015), Gorodnichenko and Weber (2016), Nakamura and Steinsson (2018), and Wong (2018). The Euro area monetary policy measure based on the three-month Euribor futures has been used in papers including Bernoth and Hagen (2004), Rosa and Verga (2008), and Ranaldo and Rossi (2010). They show that the three-month Euribor futures rate is an unbiased predictor of Euro area policy rate changes.

[27] To be more specific, the three-month Euribor future is a commitment to engage in a three-month loan or deposit of a face value of 1,000,000 Euros. Futures prices are quoted on a daily basis. There are four delivery dates during a year, namely the third Wednesday of March, June, September and December.

[28] I obtain the dates of the FOMC meetings from the Federal Reserve Board website at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm, and those of the ECB meetings from the ECB website at https://www.ecb.europa.eu/press/govcdec/mopo. I also verify the exact times of the monetary policy announcements using the first news article about them on Bloomberg.

[29] See Rosa and Verga (2008) for a description of the institutional features unique to ECB monetary policy announcements.

by the market, the futures rate did not exhibit significant change around the press release time. But it decreased sharply during the press conference window. This is because, contrary to market expectation of an interest rate hike later in the year, Jean-Claude Trichet told the press that "the current suggestions regarding the high probability of an increase of rates in our next meeting do not correspond to the present sentiment of the Governing Council." The decline in Euribor futures rate during the press conference time window thus reflect market's revision of its expectations. The bottom panel of Figure A.3 plots the Euribor futures rate for November 3, 2011, when the ECB unexpectedly cut interest rates by 25bps for the first time in two years. The sharp decline in the Euribor futures rate around the time of the press release reflect the change in market expectation. Given the unique institution features of ECB monetary policy announcements, I apply a window of 120 minutes that starts 10 minutes (Δ^-) prior to the press release and ends 10 minutes (Δ^+) after the press conference to construct measures of ECB monetary policy shock.

Furthermore, I consider two measures of monetary policy shocks for each region: a current period shock based on current month futures ($mp1$), and a long-term path shock based on three-month-ahead futures ($mp4$). The long-term path shock is aimed at capturing any persistent effects of current period shocks on long-term investment, which can occur when the current period shocks change expectations about the future path of monetary policy rates.

The shock measures take the general form:

$$mp_t = (f_{t+\Delta^+}^x - f_{t-\Delta^-}^x) \tag{7}$$

where t is the time when the FOMC or ECB issues an announcement, $f_{t+\Delta^+}$ is the Federal Funds futures or the Euribor futures Δ^+ minutes after t, $f_{t-\Delta^-}$ is the Federal Funds futures or the Euribor futures Δ^- minutes before t, and x denotes either 1 for current month futures or 4 for three-month-ahead futures. For the US current monetary policy shock measure ($mp1$), Equation (7) is adjusted by the term $\frac{D}{D-t}$, where D is the number of days in the month. This is because the Federal Funds futures settle on the average effective overnight Federal Funds rate.

I aggregate up the identified shocks to obtain monthly measures of monetary policy shocks, following Cochrane and Piazzesi (2002). I use the monetary policy measures from the month prior to the loan dates (t) when estimating Equation (6), to ensure time consistency.

Extensive Margin   To analyze how monetary policy shocks affect credit allocation across firms in the Euro area at the extensive margin, I estimate Equation (6) with the the dependent variable being the change in a dummy variable that takes the value 1 if the loan is given by a US bank and 0 if the loan is given by a Euro area bank between two consecutive loans for

each given firm i (denoted as ΔUSB_{it}). The main coefficients of interest are β^q and δ^q. I conjecture β^2 to be negative, and δ^2 to be positive, since, based on the model prediction, contractionary US monetary policy would induce firms in the second tercile of the z_i^G/z_i^L distribution to switch away from US banks, and contractionary ECB monetary policy would induce firms in the second tercile of the z_i^G/z_i^L distribution to switch into US banks. All the specifications include firm fixed effects to account for potential demand-driven explanations for changes in the trends of firms' borrowing behavior, as well as time fixed effects to control for common shocks.

Table 8 reports the regression results. Columns 1 and 3 show the average effects of the US and Euro area monetary policy shocks, based on measures of $mp1$ and $mp4$, respectively, on the firms' switching behavior. Results in Column 1 show that, on average, a 25-basis-point shock to the current US monetary policy rates decreases the probability of firm switching from a Euro area bank into a US bank by 3.4 percentage points, while a 25-basis-point shock to the Euro area monetary policy rates increases the probability of a firm switching from a Euro area bank into a US bank by 4.1 percentage points. The effects are larger and more significant when considering shocks to the path of monetary policy rates. Results in Column 3 show that, on average, a 25-basis-point shock to the path of US monetary policy rates decreases the probability of firm switching into a US bank by 5.2 percentage points, while such shock to the path of Euro area monetary policy rates increases the probability of a firm switching into a US bank by 5.3 percentage points.The coefficients are statistically significant at the 5% level. The findings point to evidence of firm switching in the Euro area in response to monetary policy shocks on average. In particular, firms respond slightly more to domestic monetary policy shocks.

Turning to the coefficients of interest, columns 2 and 4 in Table 8 show the estimations of how these effects vary for firms in different terciles of the z_i^G/z_i^L distribution (Equation (6)). Across both specifications, the effects of US and Euro area monetary policy shocks on the probability of firm switching are around two times larger in the second tercile of the z_i^G/z_i^L distribution than the other terciles, and highly significant. The point estimates of β^2 imply that a 25-basis-point shock to the current and long-term US monetary policy rate decreases the probability of firm switching into a US bank by 6.0 and 7.6 percentage points, respectively, for firms in the second tercile of the z_i^G/z_i^L distribution. For those firms, the point estimates of δ^2 imply that a 25-basis-point shock to the Euro area monetary policy increases the probability of firm switching into a US bank by 6.6-8.5 percentage points. The effects are again larger when considering shocks to the path of monetary policy rates, suggesting that firm investments respond more to changing expectations about the future path of monetary policy rates. The results for the other two terciles are mostly statistically insignificant.

Overall, the results suggest that most of the firm switching effects are concentrated in the second tercile of the z_i^G/z_i^L distribution, where firms have relatively balanced exposure to global risk relative to local risk. This evidence supports the model prediction on the effects of bank funding shocks on credit allocation across firms at the extensive margin.

Intensive Margin Next, I turn to analyzing how monetary policy shocks affect credit allocation across firms in the Euro area at the intensive (interest rate) margin. I implement Equation (6) with the dependent variable being the change in the interest rate spread between two consecutive loans for each given firm i (denoted as ΔR_{it}).[30] The spread describes the amount the borrower pays in basis points over the LIBOR. The main coefficients of interest are again β^q and δ^q. The model predicts that, conditional on Euro area (US) monetary policy and given contractionary US (Euro area) monetary policy, the interest rates of the infra-marginal firms that continue to borrow from Euro area (US) banks decrease, reflecting a (positive) spillover effect. Thus, β^1 (which summarizes the group of firms that are more likely to be borrowing from Euro area banks) and δ^3 (which summarizes the group of firms that are more likely to be borrowing from US banks) are conjectured to be negative. The model also predicts that, under the above scenario, the interest rate spreads of the infra-marginal firms that continue to borrow from US (Euro area) banks increase, reflecting a (negative) amplification effect. Thus, β^3 and δ^1 are conjectured to be positive.

Since these predictions are based on the assumption that there is stronger pass-through from US monetary policy to the interest rates offered by US banks, and similarly Euro area monetary policy to Euro area banks, I first perform a series of regressions to validate these assumptions. Columns 1, 2, 4 and 5 in Table 9 report the results from regressions of changes in firm interest rate spreads (ΔR_{it}) on changes in US and Euro area monetary policy shock (ΔUSR and ΔEUR, respectively), a dummy variable that takes the value 1 for US or Euro area banks and 0 otherwise ($1(USB)$ or $1(EUB)$), and interactions of these two variables: either an interaction between US monetary policy shock and the US bank dummy variable ($USR*1(USB)$), or one between Euro area monetary policy shock and the Euro area bank dummy variable ($\Delta EUR*1(EUB)$). The results confirm the assumption. Columns 1 and 4 show that a 25-basis-point shock to the current and long-term US monetary policy rate disproportionately increases the interest rate spread charged by the US banks by around 25 and 33 basis points, respectively, on average relative to other banks. Results in columns 2 and 5 show that a 25-basis-point shock to the current and long-term Euro area monetary policy rate disproportionately increases the interest rate spread charged by Euro area banks by 34

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[30] To make the interest rate spreads as comparable as possible, the type of loan facilities (e.g., revolving line, bank term loan, and institutional term loan) between two consecutive loans are matched.

and 37 basis points, respectively, on average relative to other banks.

Turning to the coefficients of interest, columns 3 and 6 in Table 9 report the results of how the effects of monetary policy shocks on interest rate spreads vary for firms in different terciles of the z_i^G/z_i^L distribution (Equation (6)). As predicted, the coefficients β^1 and δ^3 are negative across all specifications. Specifically, a 25-basis-point shock to the current US monetary policy rate decreases the interest rate spread for the infra-marginal firms that continue to borrow from Euro area banks by 22 basis points, while such a shock to the Euro area monetary policy rate decreases the interest rate spread for the infra-marginal firms that continue to borrow from US banks by 25 basis points. The effects are larger and more significant when considering shocks to the path of monetary policy rates (column 6). A 25-basis-point shock to the long-term US (Euro area) monetary policy rate decreases the interest rate spread for the infra-marginal firms that continue to borrow from Euro area (US) banks by 27 (32) basis points. These results point to a (positive) spillover effect.

Furthermore, the coefficients β^3 and δ^1 are positive across all specifications, as predicted, and highly statistically significant. Specifically, a 25-basis-point shock to the current US monetary policy rate increases the interest rate spread for the infra-marginal firms that continue to borrow from US banks by 25 basis points. The effect increases to 32 basis points given a 25-basis-point shock to the path of US monetary policy rate. Similarly, a 25-basis-point shock to the current and long-term Euro area monetary policy rate increases the interest rate spread for the infra-marginal firms that continue to borrow from Euro area banks by 34 and 40 basis points, respectively. These results point to a (negative) amplification effect. Furthermore, the effects on interest rates of the firms in the second tercile of z_i^G/z_i^L distribution, which, based on the results from Table 8, is mostly comprised of marginal firms that switch banks, are ambiguous, as predicted.

Overall, the results in Table 9 support the model prediction on the effects of bank funding shocks on credit allocation across firms at the intensive margin. Combined with the results on the extensive margin effects, they point to evidence of a novel adverse selection channel of monetary policy transmission.

Table 8: **Monetary Policy Shocks and Credit Allocation: Extensive Margin**

| | (1) | (2) | (3) | (4) |
	$mp1$	$mp1$	$mp4$	$mp4$
ΔUSR	-0.134*		-0.209**	
	(0.071)		(0.083)	
ΔEUR	0.164**		0.211**	
	(0.074)		(0.089)	
$\Delta USR * T^1$		-0.049		-0.054
		(0.119)		(0.128)
$\Delta USR * T^2$		-0.241**		-0.302**
		(0.120)		(0.131)
$\Delta USR * T^3$		-0.117		-0.163
		(0.118)		(0.127)
$\Delta EUR * T^1$		0.057		0.062
		(0.118)		(0.137)
$\Delta EUR * T^2$		0.264**		0.339***
		(0.118)		(0.135)
$\Delta EUR * T^3$		0.173		0.220*
		(0.116)		(0.127)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,454	11,454	11,454	11,454
R-squared	0.067	0.068	0.067	0.068

Notes. Regressions with the dependent variable being the change in a dummy variable that takes the value 1 if the loan is given by a US bank and 0 if the loan is given by a Euro area bank between two consecutive loans for each given firm i (denoted as ΔUSB). USR denotes US monetary policy shocks, and EUR denotes Euro area monetary policy shocks. T^q is a dummy variable that takes the value 1 when the firm's z_i^G/z_i^L measure at the time of the last loan issuance belongs to tercile q and 0 otherwise. For the specifications in columns 1 and 2, the monetary policy measures used are current period shocks constructed from current month futures ($mp1$). For the specifications in columns 3 and 4, the monetary policy measures used are long-term path shocks constructed from three-month-ahead futures ($mp4$). Year and firm fixed effects are included in all specifications. Standard errors reported in parentheses are clustered by time. Source: Dealscan, Amadeus, Orbis, Computstat, Compustat Global, and author's calculation. Significance at the 1 percent, 5 percent, and 10 percent levels is indicated by ***, **, and *, respectively.

Table 9: **Monetary Policy Shocks and Credit Allocation: Intensive Margin**

	(1)	(2)	(3)	(4)	(5)	(6)
	$mp1$	$mp1$	$mp1$	$mp4$	$mp4$	$mp4$
$\Delta USR * 1(USB)$	98.543**			132.458***		
	(43.765)			(47.986)		
$\Delta EUR * 1(EUB)$		136.633***			147.375***	
		(42.543)			(49.864)	
$\Delta USR * T^1$			-89.354*			-108.564*
			(48.542)			(54.875)
$\Delta USR * T^2$			62.796			78.342
			(52.769)			(60.875)
$\Delta USR * T^3$			98.427**			126.653**
			(46.293)			(58.975)
$\Delta EUR * T^1$			136.864**			158.539***
			(56.249)			(57.986)
$\Delta EUR * T^2$			76.563			83.457
			(52.087)			(59.357)
$\Delta EUR * T^3$			-101.876*			-127.978**
			(54.681)			(54.975)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,367	3,367	3,367	3,367	3,367	3,367
R-squared	0.051	0.051	0.052	0.051	0.051	0.052

Notes. Regressions with the dependent variable being the change in the interest rate spread between two consecutive loans for each given firm i (denoted as ΔR). USR denotes US monetary policy shocks, and EUR denotes Euro area monetary policy shocks. $1(USB)$ and $1(EUB)$ are dummy variables that takes the value 1 for US and Euro area banks, respectively, and 0 otherwise. T^q is a dummy variable that takes the value 1 when the firm's z_i^G / z_i^L measure at the time of the last loan issuance belongs to tercile q and 0 otherwise. For the specifications in columns 1-3, the monetary policy measures used are current period shocks constructed from current month futures ($mp1$). For the specifications in columns 4-6, the monetary policy measures used are long-term path shocks constructed from three-month-ahead futures ($mp4$). The specifications in column 1 and 4 include USR, $1(USB)$, and EUR as regressors. The specifications in column 2 and 5 include USR, $1(EUB)$, and EUR as regressors. Year and firm fixed effects are included in all specifications. Standard errors reported in parentheses are clustered by time. Source: Dealscan, Amadeus, Orbis, Computstat, Compustat Global, and author's calculation. Significance at the 1 percent, 5 percent, and 10 percent levels is indicated by ***, **, and *, respectively.

8 Conclusion

The rise of global banking has transformed financial systems and corporate financing across the world over the past two decades. This paper provides a new theory on the mechanism driving credit allocation in globalized financial systems, and tests it using cross-country loan-level data. I show that bank specialization in global versus local information—information on global versus local risk factors—plays a key role in determining firm-bank sorting and credit allocation in financial systems with both global and local banks.

I first point out that that the traditional theory of bank specialization in hard or soft information is insufficient to explain observed sorting patterns between firms and global versus local banks, revealing a puzzle in the mechanism driving global banking credit. Given the puzzle, I develop a model of banking in which there are global and local banks, and firms that have return dependent on exposure to global and local risk. Each bank faces a problem of asymmetric information: global banks have the technology to extract information on global risk factors but not local risk factors, and vice versa for local banks. The model shows that this double information asymmetry creates a segmented credit market affected by double adverse selection: banks are adversely selected against by firm selection, as firms select into borrowing from the bank which observes the more favorable component of their risk exposure.

I further apply the model to analyze the macroeconomic implications of the adverse selection problem, studying the impact on credit allocation of funding shocks to banks. The model demonstrates that, given a monetary policy shock, adverse selection affects credit allocation at both the extensive and intensive margins. It induces firms with relatively balanced global and local risk components to switch banks, and generates spillover and amplification effects through adverse interest rates. I test the model using a cross-country firm-bank loan-level dataset matched with firm balance sheet data. I find firm-bank sorting patterns, and evidence of firm switching behavior and interest rate changes given US and Euro area monetary policy shocks, that support the model predictions. The results point to a novel adverse selection channel of international monetary policy transmission.

Overall, the evidence substantiates that bank specialization in global versus local information is a key mechanism driving credit allocation in globalized banking systems. This mechanism has potentially important policy implications. Relative to the traditional view that firms and banks sort based on hard versus soft information, this new mechanism suggests that global banks' balance sheet may be more loaded on global risk than previously thought, since firms with returns more dependent on global risk are more likely to select into borrowing from them. This, in turn, calls for considerations from policy-makers for bank regulations on exposure limits and macroprudential policies.

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APPENDIX A   MODEL SOLUTION AND PROOFS

I.A   Equilibrium Solution

Propositions 1–3 lead to a full characterization of the equilibrium solution on $\mathcal{R}^G$ and $\mathcal{R}^L$. Based on these characterizations, I solve for the equilibrium interest rates $\mathcal{R}^G(z_i^G)$ and $\mathcal{R}^L(z_i^L)$, and thresholds $\bar{z}_i^L = \bar{z}^L(z_i^G)$ and $\bar{z}_i^G = \bar{z}^G(z_i^L)$, for $z_i^G \in [\underline{z}^G, 1]$ and $z_i^L \in [\underline{z}^L, 1]$ as follows.

First, let $\mathbb{R}^G(z_i^G, \bar{z}_i^L)$ and $\mathbb{R}^L(z_i^L, \bar{z}_i^G)$ be the implicit functions which give the rate at which each banks' expected profit (Equation (3a) and (3b)) would be zero for a given observed component combined with a given threshold on the unobserved component[31]:

$$\mathbb{R}^G(z_i^G, \bar{z}_i^L) = \mathcal{R}^G(z_i^G) \text{ s.t. } E_G[\pi_G(z_i^G, \bar{z}_i^L, \mathcal{R}^G(z_i^G))] = 0;$$
$$\mathbb{R}^L(z_i^L, \bar{z}_i^G) = \mathcal{R}^L(z_i^L) \text{ s.t. } E_L[\pi_L(z_i^L, \bar{z}_i^G, \mathcal{R}^L(z_i^L))] = 0.$$

Based on Proposition 2, for each given z_i^G, the corresponding threshold $\bar{z}_i^L$ is the z_i^L for the firm (z_i^G, z_i^L) for which $\mathcal{R}^L(z_i^L) = \mathcal{R}^G(z_i^G)$. By symmetry, $\bar{z}^G(\bar{z}_i^L) = z_i^G$. Therefore, the equilibrium rate $\mathcal{R}^G(z_i^G)$ and threshold $\bar{z}_i^L$ are the solutions to the system of equations:

$$\mathbb{R}^G(z_i^G, \bar{z}_i^L) = \mathbb{R}^L(\bar{z}_i^L, z_i^G). \tag{A.1}$$
$$\mathcal{R}^G(z_i^G) = \mathbb{R}^G(z_i^G, \bar{z}_i^L).$$

Similarly, for each given z_i^L, the equilibrium rate $\mathcal{R}^L(z_i^L)$ and threshold $\bar{z}_i^G$ are the solutions to the system of equations:

$$\mathbb{R}^L(z_i^L, \bar{z}_i^G) = \mathbb{R}^G(\bar{z}_i^G, z_i^L). \tag{A.2}$$
$$\mathcal{R}^L(z_i^L) = \mathbb{R}^L(z_i^L, \bar{z}_i^G).$$

Furthermore, I apply Proposition 2 to solve for $\underline{z}^G$ and $\underline{z}^L$, the cut-offs below which the expected profits of the firms are too low for the global bank and local bank to break even in expectation, regardless of the rate charged. At these cut-off points, the maximum expected profits of the banks are zero, all firms default given the equilibrium interest rates. The next lemma establishes that the cut-offs $\underline{z}^G$ and $\underline{z}^L$ are thresholds to each other.

Lemma 2. $\underline{z}^G = \bar{z}^G(\underline{z}^L)$, and $\underline{z}^L = \bar{z}^L(\underline{z}^G)$.

Given Lemma 2, $\underline{z}^G$ and $\underline{z}^G$ are the solutions to the system of equations:

$$\int_0^{\underline{z}^L} \int_0^1 (\underline{z}_i^G + z_i^L + u_i) \, dF_{\underline{z}^L}(u_i, z_i^L) = r^G;$$

$$\int_0^{\underline{z}^G} \int_0^1 (z_i^G + \underline{z}_i^L + u_i) \, dF_{\underline{z}^G}(u_i, z_i^G) = r^L.$$

where $F_{\underline{z}^L}(.)$ and $F_{\underline{z}^G}(.)$ denote the cumulative distribution function of the relevant variable

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[31] The implicit equations are fully written out in the appendix as Equations (A.5a) and (A.5b).

conditional on $z_i^L \leq \underline{z}^L$ and $z_i^G \leq \underline{z}^G$, respectively. The solutions to this system is:

$$\underline{z}^G = \frac{1}{3}(4r^G - 2r^L - 1) \qquad \text{and} \qquad \underline{z}^L = \frac{1}{3}(4r^L - 2r^G - 1). \tag{A.3}$$

The bounds $\underline{z}^G$ and $\underline{z}^L$ define the cut-offs on z_i^G and z_i^L, respectively, below which global banks and local banks would not make loans. They are increasing in the banks' own funding cost and decreasing in the funding cost faced by the other bank type. In other words, facing higher funding cost induces the respective banks to be more restrictive on the riskiest firm to which they lend, while higher funding cost faced by the other bank type induces them to lend to riskier firms. Interestingly, each banks' own funding cost has a stronger effect on the respective lower bound than the other banks' funding cost. Figure 7 illustrates the cut-offs $\underline{z}^G$ and $\underline{z}^L$ in a space that summarizes all the firms in the economy. Given the cut-offs, firms in Region A are not offered loans. Firms in Region B can only receive loans from local banks, and firms in Region C can only receive loans from global banks.

I.B Proofs

Proof of Proposition 1. Based on Equations (2a) and (3a), $\mathcal{R}^G(z_i^G)$ is given implicitly by the global bank's expected profit function:

$$E_G[\pi_G(z_i^G)] = \left[\int\limits_{G_c} \left(\int\limits_{G_a} (z_i^G + z_i^L + u_i) \, dF(u_i) + \int\limits_{G_b} \mathcal{R}^G(z_i^G) \, dF(u_i) \right) dF(z_i^L) \right] - r^G = 0$$

$$\text{where} \quad G_a = \left\{ u_i \mid 0 \leq u_i < \min(\max(0, \mathcal{R}^G(z_i^G) - z_i^G - z_i^L), 1) \right\}$$

$$G_b = \left\{ u_i \mid \min(\max(0, \mathcal{R}^G(z_i^G) - z_i^G - z_i^L), 1) \leq u_i \leq 1 \right\}$$

$$G_c = \left\{ z_i^L \mid z_i^L : (z_i^G, z_i^L) \in S_G \right\}$$

$$\tag{A.4}$$

Equation (A.4) can be decomposed into two regions over z_i^G:

1. No loans: z_i^G such that $z_i^G + E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G] + 1/2 < r^G$.

2. Loans: z_i^G such that $z_i^G + E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G] + 1/2 \geq r^G$.

Equilibrium rates $\mathcal{R}^G(z_i^G)$ are defined in region 2.

Analyzing $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial z_i^G}$: An increase in z_i^G lowers the probability of default and increases the bank's expected return. Thus $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial z_i^G} > 0 \; \forall z_i^G$.

Given that, I first prove that $\mathcal{R}^G$ is weakly decreasing in z_i^G. Assume otherwise: there exists $z_j^G > z_i^G$ such that $\mathcal{R}^G(z_j^G) > \mathcal{R}^G(z_i^G)$. Given perfect competition with free entry, $E[\pi_G(z_i^G)] = 0$ for $\mathcal{R}^G(z_i^G)$. Because $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial z_i^G} > 0$, another global bank could offer at most

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the same $\mathcal{R}^G(z_i^G)$ for z_j^G and at least break even. Therefore, it could offer $\mathcal{R}^G(z_j^G) \leq \mathcal{R}^G(z_i^G)$, which is a contradiction. $\mathcal{R}^L$ is similarly weakly decreasing in z_i^L.

Analyzing $\frac{\partial E_G[z_i^L | (z_i^G, z_i^L) \in S^G]}{\partial \mathcal{R}^G(z_i^G)}$: An increase in the rate $\mathcal{R}^G(z_i^G)$ may cause some marginal values of z_i^L to switch from selecting the global to the local bank. Since both $\mathcal{R}^G(z_i^G)$ and $\mathcal{R}^L(z_i^L)$ are non-increasing, those that do will be those with the lowest $\mathcal{R}^L(z_i^L)$ and therefore the highest z_i^L, lowering the expected value of z_i^L over firms which select the global bank. Therefore, $\frac{\partial E_G[z_i^L | (z_i^G, z_i^L) \in S^G]}{\partial \mathcal{R}^G(z_i^G)} \leq 0$.

Analyzing $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)}$: An increase in $\mathcal{R}^G(z_i^G)$ drives the expected return to the global bank through two effects:

1. It increases the return in all outcomes where previously there was no default.

2. It decreases the expected value of z_i^L for firms which will select the global bank, which decreases the expected return in case of default.

Absent other constraints, at any point, $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)}$ could be dominated by either term and be positive, negative, or zero.

Now I prove that $\mathcal{R}^G$ is strictly decreasing in z_i^G (where loans are made, in region 2). Assume otherwise: there exists $z_j^G > z_i^G$ such that $\mathcal{R}^G(z_j^G) \geq \mathcal{R}^G(z_i^G)$. Consider again the perfect competition and free entry among global banks. $E_G[\pi_G(z_i^G)] = 0$ for $\mathcal{R}^G(z_i^G)$. Because $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial z_i^G} > 0$, if $\mathcal{R}^G(z_j^G) = \mathcal{R}^G(z_i^G)$ there would be excess profit: $E_G[\pi_G(z_j^G)] > 0$. Regardless of the sign of $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)}$, another bank could charge a lower rate $\mathcal{R}^G(z_j^G)$ without losing money in expectation:

- If $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)} \leq 0$, decreasing the rate would leave profit unchanged or *increased* and clearly be possible.

- If $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)} > 0$, a competing global bank could trade the excess profit to offer a lower rate and capture the market while still at least breaking even.

Therefore $\mathcal{R}^G(z_j^G) < \mathcal{R}^G(z_i^G)$, which is a contradiction.

The proof that $\mathcal{R}^L$ is strictly decreasing in z_i^L is entirely analogous.

Further analysis. Consider the two effects which drive $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)}$. The first is trivially continuous. The second is continuous because $\mathcal{R}^L$ being strictly decreasing means that differential changes in $\mathcal{R}^G(z_i^G)$ cannot have discontinuous effects on selection S^G.

Consider also the implicit function of $\mathcal{R}^G(z_i^G)$ where the the bank profit is zero: $E_G[\pi_G(z_i^G)] = 0$. By the implicit function theorem, $\frac{d\mathcal{R}^G(z_i^G)}{dz_i^G} = -\frac{\partial E_G[\pi_G]}{\partial z_i^G} / \frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)}$. We know that

$\frac{d\mathcal{R}^G(z_i^G)}{dz_i^G} < 0$ ($\mathcal{R}^G$ is strictly decreasing) and $\frac{\partial E_G[\pi_G]}{\partial z_i^G} > 0$. Therefore, $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)} > 0$, and the positive profit effect of increasing $\mathcal{R}^G(z_i^G)$ dominates the negative selection effect.

Finally, considering the regions over z_i^G, the boundary between the two regions occurs when $z_i^G + E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G] + 1/2 = r^G$. Since $\frac{\partial E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G]}{\partial \mathcal{R}^G(z_i^G)} < 0$ and $\frac{d\mathcal{R}^G(z_i^G)}{dz_i^G} < 0$, $E_G[z_i^L \mid (z_i^G, z_i^L) \in S^G]$ is increasing in z_i^G. Therefore there is a unique $\underline{z}_i^G = r^G - E_G[z_i^L \mid (\underline{z}_i^G, z_i^L) \in S^G] - 1/2$. Equilibrium rates $\mathcal{R}^G(z_i^G)$ are defined for all $\underline{z}_i^G \le z_i^G \le 1$.

All analyses apply to the analogous terms for local banks.

Proof of Proposition 2.

1) In an equilibrium market configuration that supports both types of banks, there must exist a set of marginal firms that are indifferent between the contracts by global banks and local banks, which occur when $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(z_i^L)$. Let $f(z_i^G, z_i^L) = \mathcal{R}^G(z_i^G) - \mathcal{R}^L(z_i^L) = 0$. By Proposition 1, $\frac{\partial f(z_i^G, z_i^L)}{\partial z_i^L} = -\frac{\partial \mathcal{R}^L(z_i^L)}{\partial z_i^L} > 0$ for $z_i^L \in [\underline{z}_i^L, 1]$. By the implicit function theorem, for each $z_i^G \in [\underline{z}_i^G, 1]$, there exists a threshold function $\bar{z}^L$: $z_i^G \mapsto \bar{z}_i^L$, such that $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(\bar{z}_i^L)$.

The proof on the existence of a threshold function $\bar{z}^G$: $z_i^L \mapsto \bar{z}_i^G$ such that $\mathcal{R}^L(z_i^L) = \mathcal{R}^G(\bar{z}_i^G)$ is analogous.

2) Consider a marginal firm that faces $\mathcal{R}^G(z_i^G) = \mathcal{R}^L(z_i^L)$. As z_i^L decreases, $\mathcal{R}^L(z_i^L)$ increases by Proposition 1, while $\mathcal{R}^G(z_i^G)$ remains constant. Since now $\mathcal{R}^L(z_i^L) > \mathcal{R}^G(z_i^G)$, those firms would select a global bank. Therefore, firms with $z_i^L < \bar{z}_i^L \in S^G$. Conversely, as z_i^L increases, $\mathcal{R}^L(z_i^L)$ decreases by Proposition 1, while $\mathcal{R}^G(z_i^G)$ remains constant. Since $\mathcal{R}^L(z_i^L) < \mathcal{R}^G(z_i^G)$, those firms would select a local bank. Therefore, $S^G = \{(z_i^G, z_i^L) : z_i^L \le \bar{z}^L(z_i^G)\}$, and $S^L = \{(z_i^G, z_i^L) : z_i^L > \bar{z}^L(z_i^G)\}$

The proof that $S^L = \{(z_i^G, z_i^L) : z_i^G < \bar{z}^G(z_i^L)\}$ and $S^G = \{(z_i^G, z_i^L) : z_i^G \ge \bar{z}^G(z_i^L)\}$ is analogous.

Proof of Proposition 3. The equilibrium interest rate functions are solution to the bank expected profits equations subject to zero profits conditions and firm selection:

$$E_G[\pi_G(z_i^G)] = \left[\int_{G_c} \left(\int_{G_a} (z_i^G + z_i^L + u_i)\, dF(u_i) + \int_{G_b} R^G(z_i^G)\, dF(u_i) \right) dF(z_i^L) \right] - r^G = 0,$$

$$\text{where } \ G_a = \left\{ u_i \mid 0 \le u_i < \min(\max(0, R^G(z_i^G) - z_i^G - z_i^L), 1) \right\},$$

$$G_b = \left\{ u_i \mid \min(\max(0, R^G(z_i^G) - z_i^G - z_i^L), 1) \le u_i \le 1 \right\},$$

$$G_c = \left\{ z_i^L \mid 0 < z_i^L \le \bar{z}^L(z_i^G)) \right\};$$

(A.5a)

$$E_L[\pi_L(z_i^L)] = \left[\int_{L_c} \left(\int_{L_a} (z_i^G + z_i^L + u_i)\, dF(u_i) + \int_{L_b} R^L(z_i^L)\, dF(u_i) \right) dF(z_i^G) \right] - r^L = 0,$$

$$\text{where } \ L_a = \left\{ u_i \mid 0 \le u_i < \min(\max(0, R^L(z_i^L) - z_i^G - z_i^L), 1) \right\},$$

$$L_b = \left\{ u_i \mid \min(\max(0, R^L(z_i^L) - z_i^G - z_i^L), 1) \le u_i \le 1 \right\},$$

$$L_c = \left\{ z_i^G \mid 0 < z_i^G \le \bar{z}^G(z_i^L)) \right\}.$$

(A.5b)

Analyzing $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^L(\bar{z}^L(z_i^G))}$: An increase in $\mathcal{R}^L(\bar{z}^L(z_i^G))$ shifts marginal firms from the local to global bank at $(z_i^G, \bar{z}^L(z_i^G))$. This increases the threshold value $\bar{z}^L(z_i^G)$ at z_i^G. As a result, the expected profit of the global bank increases, all else held constant, so $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^L(\bar{z}^L(z_i^G))} > 0$.

The analysis that $\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)} > 0$ is outlined in the proof for Proposition 1.

By the implicit function theorem, $\frac{d\mathcal{R}^G(z_i^G)}{d\mathcal{R}^L(\bar{z}^L(z_i^G))} = -\frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^L(\bar{z}^L(z_i^G))} \Big/ \frac{\partial E_G[\pi_G(z_i^G)]}{\partial \mathcal{R}^G(z_i^G)} < 0.$

Proof of Lemma 2. At $\underline{z}^G$, the equilibrium rate $\mathcal{R}^G(\underline{z}^G)$ is such that all firms which approach global banks default: $\mathcal{R}^G(\underline{z}^G) = \underline{z}^G + \bar{z}^L(\underline{z}^G) + 1$. Similarly at $\underline{z}^L$, $\mathcal{R}^L(\underline{z}^L) = \bar{z}^G(\underline{z}^L) + \underline{z}^L + 1$. It is clear that at least one entry $\underline{z}^j$ must be the threshold for the other $\underline{z}^k$: $\bar{z}^j(\underline{z}^k) = \underline{z}^j$.

Without loss of generality, let $j = G$ and $k = L$: $\bar{z}^G(\underline{z}^L) = \underline{z}^G$. Assume otherwise, $\bar{z}^L(\underline{z}^G) > \underline{z}^L$. Given $\bar{z}^G(\underline{z}^L) = \underline{z}^G$, $\mathcal{R}^L(\underline{z}^L) = \underline{z}^G + \underline{z}^L + 1$. It follows $\mathcal{R}^G(\underline{z}^G) = \underline{z}^G + \bar{z}^L(\underline{z}^G) + 1 > \underline{z}^G + \underline{z}^L + 1 = \mathcal{R}^L(\underline{z}^L)$. This implies $\mathcal{R}^L(\bar{z}^L(\underline{z}^G)) > \mathcal{R}^L(\underline{z}^L)$, which contradicts the strict monotonicity of $\mathcal{R}^L$. At the same time, $\bar{z}^L(\underline{z}^G) < \underline{z}^L$ is a contradiction, since local banks make no loans to firms with $z_i^L < \underline{z}^L$ by definition. Therefore, $\underline{z}^L = \bar{z}^L(\underline{z}^G)$.

The proof that $\underline{z}^G = \bar{z}^G(\underline{z}^L)$ is analogous.

Proof of Lemma 1. Let $r^G = r^L$. The expected profit equations for global banks and local banks subject to the break even conditions and firm selection, given by Equations (A.5a) and (A.5b), respectively, are symmetric. The result that $\bar{z}^L(z_i^G) = z_i^G$ and $\bar{z}^G(z_i^L) = z_i^L$ follows.

Proof of Corollary 2. Let $r^G = r^L$. Assume firm i selects into borrowing from a global bank. Based on firm selection criteria from Equations (2a) and 2b and Assumption 1, $\mathcal{R}^G(z_i^G) \leq \mathcal{R}^L(z_i^L)$, which implies $z_i^G \geq z_i^L$ by Proposition 1 and Lemma 1. Now assume $z_i^G \geq z_i^L$. Based on Equations (A.5a) and (A.5b), $R_{Gi}(z_i^G) \leq R_{Li}(z_i^L)$, which implies firm i selects into borrowing from a global bank.

The proof that a firm selects a local bank if and only if $z_i^L > z_i^G$ is analogous.

APPENDIX B   ADDITIONAL FIGURES AND TABLES

Table A.1: **Summary Statistics: Loan and Firm Count by Country (Method 2)**

| Country	Loan	GB	LB	Firm	Country	Loan	GB	LB	Firm
Australia	4507	0.70	0.30	701	Japan	21341	0.45	0.55	2865
Austria	387	0.53	0.47	61	Mexico	601	0.70	0.30	137
Belgium	704	0.69	0.31	123	Netherlands	2028	0.54	0.46	406
Canada	6760	0.64	0.36	903	New Zealand	1023	0.70	0.30	127
Czech Republic	197	0.68	0.32	77	Norway	1017	0.66	0.34	253
Denmark	327	0.56	0.44	84	Poland	318	0.54	0.46	87
Finland	587	0.65	0.35	113	Portugal	254	0.65	0.35	64
France	5876	0.67	0.33	996	Spain	4380	0.68	0.32	839
Germany	5987	0.68	0.32	942	Sweden	875	0.66	0.34	190
Greece	309	0.66	0.34	47	Switzerland	790	0.69	0.31	175
Ireland	404	0.70	0.30	107	United Kingdom	6810	0.69	0.31	1528
Italy	2378	0.67	0.33	688	United States	46732	0.70	0.30	1466

Notes. Sample constructed from Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation. Sample period covers the year 2004-2017.

Figure A.1: **Estimates of Average Productivity Measure** $log\ z_{it}$ **by Country**
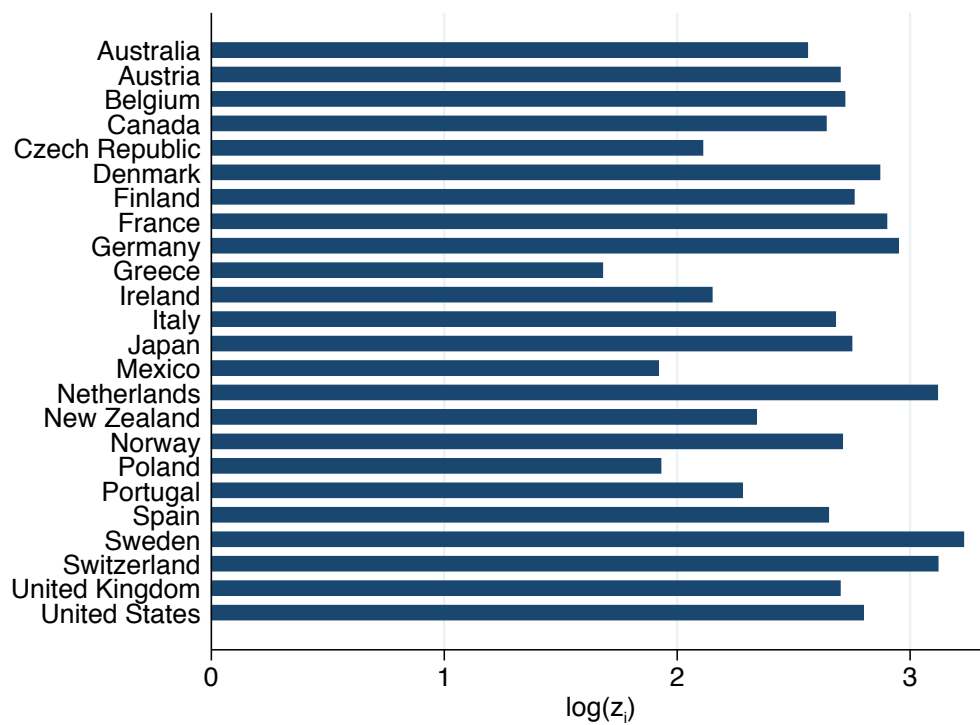

Notes. Estimates of the productivity measure $log\ z_{it}$ averaged across firms and years by country, calculated based on Equation (4). Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

Figure A.2: **Firm-Bank Sorting, by** z_i^G/z_i^L **Quartile (Method 2)**
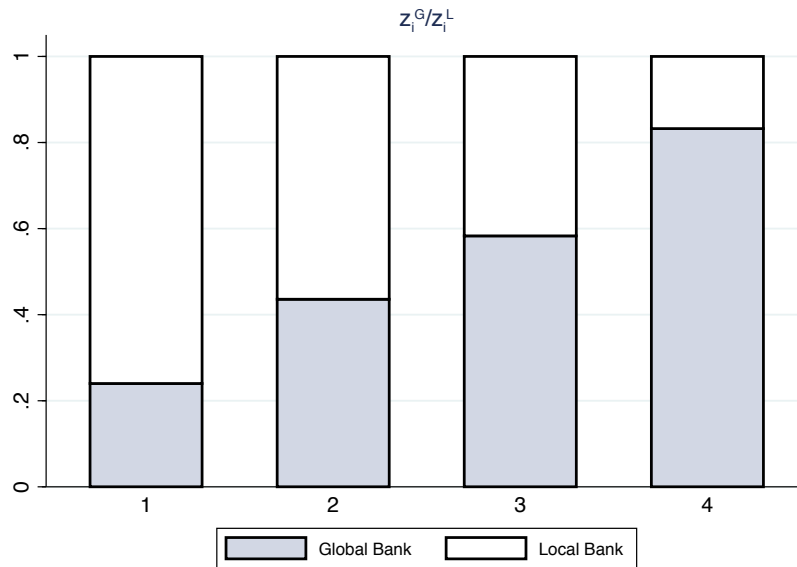
z_i^G/z_i^L

Global Bank   Local Bank

Notes. The plot shows sorting patterns between firms and global versus local banks, with firms sorted into quartiles by their exposure to global versus local risk (z_i^G/z_i^L), uses variables that are constructed based on Method 2 of the bank categorization criteria for global banks. Data sample consists of syndicated loans between firms global and local banks and firms across 24 countries from 2004-2017. Source: Dealscan, Amadeus, Orbis, Compustat, Compustat Global, and author's calculation.

Figure A.3: **Three-Month Euribor Rates around ECB Announcements**
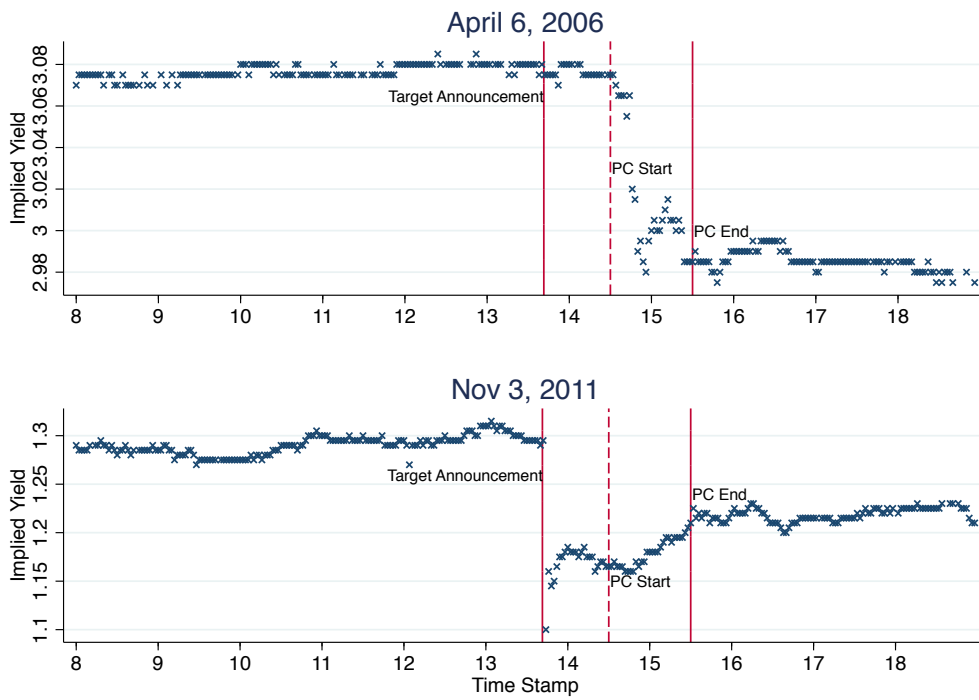
Notes. The figure plots the three-month Euribor rates on April 6, 2006 (upper panel) and November 3, 2011 between 08:00 and 18:00. Vertical lines represent the target policy rate announcement (13:45), the start of the press conference (14:30), and the end of the press conference (15:30). All times are in CET. Source: CQG Data Factory.