Global Banks' Networth
&
Emerging Market Fluctuations

Macro Impact & Micro Transmission

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Abstract

This paper studies the impact and transmission channels of Global Banks' credit shocks in Emerging Markets. We identify surprises in large US banks' net worth around earnings announcements and decompose them based on their co-movement with the excess bond premium (Ottonello and Song [2022]) and EMBI spreads. A credit supply shock—marked by higher net worth and lower spreads—leads to exchange rate appreciation, looser financial conditions, negative UIP deviations, and economic expansion. Conversely, a credit demand shock—marked by higher net worth and rising spreads—results in exchange rate depreciation, tighter financial conditions, positive UIP deviations, and economic contraction. Using detailed credit-registry data from Uruguay (2003–2019), we show that more indebted firms respond more strongly to credit supply shocks, highlighting the relaxation of borrowing constraints as a key transmission channel.

Keywords: Global Banks; Financial intermediaries; Emerging markets; International Spillovers; Exchange Rate; Firm Transmission;

JEL Codes: F40, F41, E44, E51.

1 Introduction

Large multinational financial institutions, often called "Global Banks," play a significant role in international capital flows, influencing economic conditions worldwide. Emerging Market Economies (EMEs) are particularly exposed to these institutions due to their less developed domestic credit markets and reliance on borrowing in U.S. dollars. For instance, data from the Bank for International Settlements (BIS) indicate that U.S. dollar-denominated credit to non-banks in EMEs has reached $4 trillion, with approximately one-third of all external liabilities of EMEs held by banks based in the United States, Europe, and Japan (see Bräuning and Ivashina [2020]).[1] Given the prominent role of Global Banks in international financial intermediation, questions have been raised regarding their function as both a source and a propagation mechanism for economic shocks.

In this paper, we examine the causal effects of changes in Global Banks' net worth on EMEs through a three-pronged approach. First, we introduce an identification strategy that leverages the co-movement of individual financial intermediaries' net worth with U.S. and EME credit spreads in a narrow window around earnings announcements. Our benchmark Global Bank net worth shock builds on the strategy proposed by Ottonello and Song [2022], allowing us to isolate an exogenous Global Bank credit supply shock. Using an event study framework and data from 71 EMEs, we find that a positive Global Bank credit supply shock is associated with exchange rate appreciation, a reduction in spreads, and an increase in equity indexes in EMEs around these earnings announcements.[2]

Second, we assess the aggregate impact of these shocks by combining the identified shocks with a monthly panel of macroeconomic and financial variables for 71 EMEs. Using VAR models and local projection regressions, we find that a positive Global Bank credit supply shock leads to improved financial conditions (appreciated exchange rates, lower borrowing rates, and higher equity indexes) and an expansion in economic activity (higher industrial output, reduced unemployment, and increased international trade). These results provide evidence that changes in Global Banks' net worth significantly influence EMEs' business cycles.

Third, we analyze the transmission channel of these shocks using a firm credit registry dataset from Uruguay covering the period 2003 to 2019. Empirically, we find that firms with higher debt burdens and closer proximity to default are the most responsive to Global Banks' net worth shocks. We interpret these results as suggesting that changes in Global Banks' net worth impact EMEs by loosening borrowing constraints.

[1] For BIS data on U.S. dollar-denominated credit to non-banks, see https://www.banque-france.fr/system/files/2023-04/820101_fsr_2020_en_article_shin.pdf.

[2] We also present an alternative identification strategy based on the co-movement between financial intermediaries' net worth and Emerging Market Bond Index (EMBI) spreads around earnings announcements.

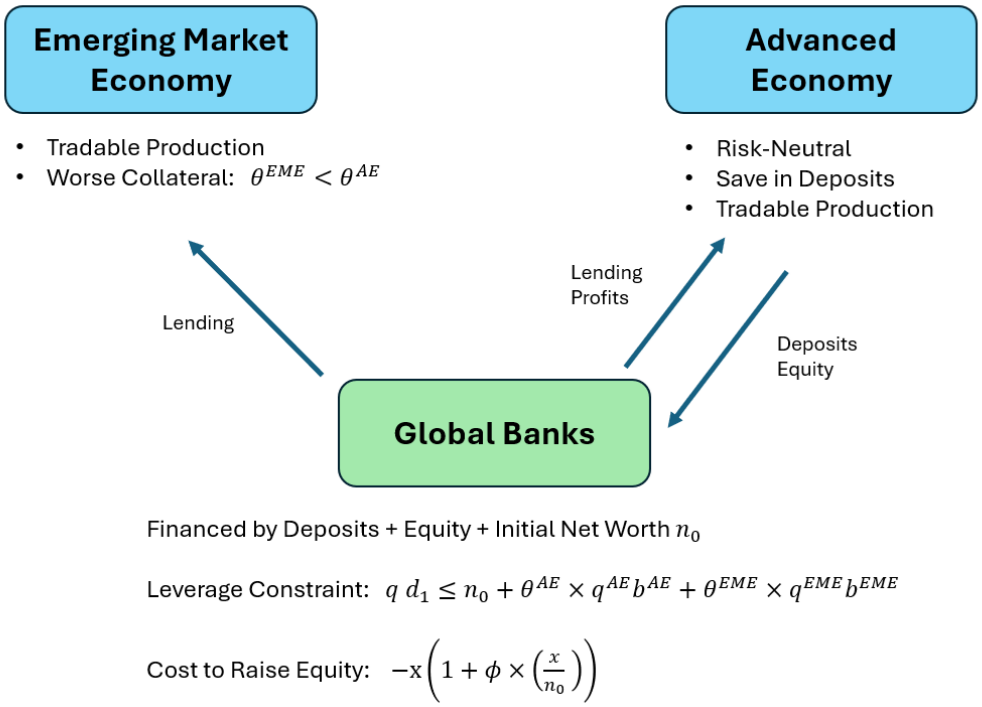
2 Identification of Global Banks' Credit Supply Shocks

This section describes our identification strategy for a causal change in global banks' net worth. The identification strategy is based on the high-frequency co-movement between bank stock price changes and Emerging Markets' spreads around earning announcements. Section 2.1 presents a stylized model of global banks, Advanced Economies, and Emerging Market Economies, which provides a theoretical basis. Section 2.2 describes the high-frequency co-movement of banks' stock prices and Emerging Market spreads and recovers a credit supply shock and a credit demand shock from Global Banks. Section 2.3 carries out an event study framework to estimate the impact of these two shocks on EME's nominal exchange rate and spreads.

2.1 A Stylized Model of Global Banks

This section of the paper presents a stylized model of global banks, which serves as the basis for our empirical identification strategy introduced in the next section. The summary of the model is presented in Figure 1 This model is a two-period version of the model introduced

Figure 1: Model Economy



by Morelli et al. [2022]. The world economy consists of an Advanced Economy (AE) and an Emerging Market Economy (EME) that live for two periods, $t = \{0, 1\}$. The model's key feature is that international lending is mediated by a global bank. AE households provide financing to global banks using a risk-free bond or deposit and equity. Global banks face

frictions in their intermediation that limit their ability to raise funds from the AE.

Environment. There are two periods $t = \{0, 1\}$; and two goods: final and capital goods, which are tradable. The Advanced Economy is populated by a unit mass of identical households and non-financial firms and a discrete set of intermediaries indexed by $i \in \mathcal{I}$. For simplicity of exposition, we assume that $\mathcal{I} = 1$. The Emerging Market Economy is populated by a unit mass of non-financial firms. Financial intermediation is carried out by the AE's intermediaries, which finance non-financial firms in both the AE and EME. To finance these loans, AE's intermediaries can use their own net worth but also raise external finance from AE households in the form of deposits, d_1, and equity, x_0, both of which are subject to frictions modeled following the literature of frictional financial intermediaries (see Gertler [2010], Morelli et al. [2022]). These frictions will play a crucial role in determining how changes in the AE's intermediary's net worth affect EME's borrowing.

Emerging Market Economy. We assume that the EME consists only of a unit measure of non-financial firms. While the lack of a deep domestic financial system is a simplification, it is in line with other modeling examples in the literature (see Morelli et al. [2022]) and with relatively low levels of financial intermediation in EMEs (see Gozgor [2014]).

In period 0, non-financial firms choose the capital to produce in the following period, k_1^{EME}. Their problem is given by:

$$\max_{k_1^{EME}, b_1^{EME}, \pi_{f,0}^{EME}} \quad \pi_{f,0}^{EME} + \beta \mathbb{E}_0 \pi_{f,1}^{EME} \tag{1}$$

subject to

$$\pi_{f,0}^{EME} = q_0^{EME} b_1^{EME} - k_1^{EME}$$
$$\pi_{f,1}^{EME} = z_1^{EME} \left(k_1^{EME}\right)^{\alpha} - b_1^{EME}$$

where b_1^{EME} denotes the non-financial firms' borrowing from the AE financial intermediaries at price q_0^{EME}. The Euler Equation characterizes non-financial firms' choice of capital

$$\frac{1}{q_0^{EME}} = \mathbb{E}_0 z_1^{EME} \alpha \left(k_1^{EME}\right)^{\alpha - 1} \tag{2}$$

We assume that the production functions between AEs and EMEs are analogous. However, we argue that the borrowing rates $\frac{1}{q_0^{AE}}$ and $\frac{1}{q_0^{EME}}$ are different and may react differently to changes in global banks' net worth.

Households in the Advanced Economy. In period $t = 0$, after perceiving their initial endowment and the net transfers from their initial ownership of non-financial firms and intermediaries, households choose their investment in financial securities: deposits on financial intermediaries, d_1, and shares of non-financial firms and intermediaries, $a_{f,1}$ and $a_{i,1}$. Households' problem is then given by:

$$\max_{d_1, a_{f,1}, a_1} \quad c_0^{AE} + \beta \mathbb{E}_0 c_1^{AE} \tag{3}$$

subject to

$$c_0^{AE} + p_{f,0}a_1 + p_0 a_1 + q_0^d d_1 = y_0 + \pi_{f,0} + p_{f,0} + \pi_{i,0} + p_{i,0}$$
$$c_1^{AE} = \pi_{f,1}a_1 + a_1\pi_1 + d_1$$

where households' initial share of non-financial firms and financial intermediaries have been normalized to one; $\pi_{f,t}$ and $\pi_{i,t}$ denote the net transfers from non-financial firms and intermediary i to households in period t; $p_{f,0}$ and $p_{i,0}$ denote the price of shares of non-financial firms and financial intermediary i in period 0, and q^d denotes the price of deposits.

Households' optimal choice of financial securities implies that

$$q_0^d = \beta, \quad p_{f,0} = \beta \mathbb{E}_0 \pi_{f,1}, \quad p_{i,0} = \beta \mathbb{E}_0 \pi_{i,1} \tag{4}$$

which determines the equilibrium deposit rate and share prices.

Advanced Economies Non-Financial Firms. Similarly to their EME counterparts, in period 0, non-financial firms choose the capital to produce in the following period, k_1. Their problem is given by:

$$\max_{k_1^{AE}, b_1^{AE}, \pi_{f,0}^{AE}} \quad \pi_{f,0}^{AE} + \beta \mathbb{E}_0 \pi_{f,1}^{AE} \tag{5}$$

subject to

$$\pi_{f,0} = q_0 b_1^{AE} - k_1^{AE}$$
$$\pi_{f,1} = z_1^{AE} \left(k_1^{AE}\right)^{\alpha} - b_1^{AE}$$

where b_1^{AE} denotes the non-financial firms' borrowing from financial intermediaries at price q_0^{AE}. The Euler Equation characterizes non-financial firms' choice of capital

$$\frac{1}{q_0^{AE}} = \mathbb{E}_0 z_1^{AE} \alpha \left(k_1^{AE}\right)^{\alpha - 1} \tag{6}$$

Advanced Economy Financial Intermediary. The AE financial intermediaries are firms owned by AE households, with an initial endowment of final goods or net worth n_0. They specialize in lending to non-financial firms in both AE and the EME. On top of this net worth, the financial intermediary can finance these loans with AE household deposits, d_1, and equity issuance, x_0. We assume that financial intermediaries face frictions in both of these sources of funds. On the deposit side, we assume that the intermediary faces a standard leverage constraint, which links their deposits to their net worth

$$q_0^d d_1 \leq \theta^{AE} q_0^{AE} b_1^{AE} + \theta^{EME} q_0^{EME} b_1^{EME} \tag{7}$$

That is, the amount that intermediaries can borrow from households is bounded by the value of their collateral. We assume that intermediaries can pledge a fraction $\theta^{AE} \in (0, 1)$ of

their holdings of AE non-financial firms and a fraction $\theta^{EME} \in (0,1)$ of the EME's non-financial firms' loans. We assume that AE's intermediaries can pledge a greater share of AE's than EME's non-financial loans $\theta^{AE} > \theta^{EME}$. This assumption introduces a home bias in asset holdings in the AE in a reduced form way, as seen in the data (see Hau and Rey [2008], Coeurdacier and Gourinchas [2016]). The assumption also captures the fact that AE securities are effectively the better collateral for financial institutions, such as Basel III regulations.

Given its initial net worth, n_0, the problem of the financial intermediary is given by:

$$\max_{x_0, b_1^{AE}, b_1^{EME}} \quad \pi_{i,0} + \beta \pi_{i,1} \tag{8}$$

subject to

$$\begin{aligned} \pi_{i,0} &= -x_0 \left(1 + \mathbb{1}_{\{x_0>0\}} \phi \left(\frac{x_0}{n_0}\right)\right) \\ \pi_1 &= b_1^{AE} + b_1^{EME} - d_{i,1} \\ q_0^{AE} \times b_1^{AE} + q_0^{EME} \times b_1^{EME} &= n_0 + x_0 + d_1 \\ q_0^d d_1 &\leq \theta^{AE} q_0^{AE} b_1^{AE} + \theta^{EME} q_0^{EME} b_1^{EME} \end{aligned}$$

In an interior solution with $x_0 > 0$, the intermediary's optimal allocation is characterized by the following conditions

$$1 + 2\phi \frac{x_0}{n_0} = \frac{\beta}{q_0^d} + \mu \tag{9}$$

$$\frac{\mu}{\beta}\left(1 - \theta^{AE}\right) = \frac{1}{q^{AE}} - \frac{1}{q_0^d} \tag{10}$$

$$\frac{\mu}{\beta}\left(1 - \theta^{EME}\right) = \frac{1}{q^{EME}} - \frac{1}{q_0^d} \tag{11}$$

with the complementary slackness condition

$$\left(q_0^d d_1 - \theta^{AE} q_0^{AE} b_1^{AE} - \theta^{EME} q_0^{EME} b_1^{EME}\right) \mu = 0 \tag{12}$$

where μ denotes the Lagrange multiplier associated with the leverage constraint. Equation 9 implies that the intermediary equals the marginal cost of the two sources of funding, equity financing in the LHS and the shadow marginal cost of deposits in the RHS. Equations 10 and 11 imply that the intermediary equates the marginal cost of external financing with the return on lending for both lending options. These conditions imply that when the rate on lending exceeds the deposit rate, $\frac{1}{q_0^{AE}} > \frac{1}{q_0^d}$ and $\frac{1}{q_0^{EME}} > \frac{1}{q_0^d}$, the intermediary's leverage constraints binds. Additionally, if the spread between the lending rate to the AE and EME is positive

$$\frac{1}{q_0^{EME}} - \frac{1}{q_0^{AE}} = \frac{\mu}{\beta}\left(\theta^{AE} - \theta^{EME}\right) \tag{13}$$

the leverage constraint binds, i.e., $\mu > 0$.

Equilibrium Analysis. The equilibrium in this economy is then defined as follows:

Definition 1. Given the intermediary's net worth (n_0), AE and EME non-financial firms' productivity process $\{z_1^{AE}\}$ and $\{z_1^{EME}\}$, an equilibrium is a set of state-contingent AE household allocations $\{c_0, c_1, d_1, a_{f,1}, a_1\}$, AE non-financial firms' allocations $\{\pi_{f,0}^{AE}, \pi_{f,1}^{AE}, b_1^{AE}, k_1^{AE}\}$, EME non-financial firms' allocations $\{\pi_{f,0}^{EME}, \pi_{f,1}^{EME}, b_1^{EME}, k_1^{EME}\}$, AE financial intermediary' allocations $\{\pi_0^{AE}, \pi_1^{AE}, d_1, x_1, b_1^{AE}, b_1^{EME}\}$ and prices $\{q_0^d, q_0^{AE}, q_0^{EME}, p_{f,1}, p_1\}$ such that

1. Given prices, EME non-financial firms' allocations solve 1, AE household's allocations solve 3, AE non-financial firms' allocations solve 5, and AE intermediary's allocations solve 8.

2. Asset markets clear:

$$a_{f,1} = 1, \quad a_1 = 1, \quad q_0^{AE} \times b_1^{AE} + q_0^{EME} \times b_1^{EME} = n_0 + x_0 + d_1$$

We discuss the main channels through which the AE financial intermediary affects EMEs by studying the effects of fully unanticipated shocks through an EME supply and demand of funds scheme, as in Morelli et al. [2022].

On the lender's side, the supply of funds to the EME

$$\mathcal{A}^{s,EME}\left(q_0^{EME}, n_0\right) = \underbrace{\mathcal{N}\left(q_0^{EME}, n_0\right)}_{\text{Net worth, deposits, issuance}} - \underbrace{\mathcal{A}^{d,AE}\left(q_0^{EME}\right)}_{\text{Investment by AE}} \tag{14}$$

The supply of funds for the EME's non-financial firm has two main components: the proper net worth, deposits, and issuance by the AE intermediary net of the AE's non-financial firm investment. To increase the amount of funds supplied when banks are borrowing-constrained, the intermediary must either issue more equity or decrease their AE investments, both of which require higher EME returns. Issuing more equity is costly due to its increasing marginal costs (ϕ_0), and decreasing investments in AE firms is costly because it depresses the level of capital, k_1^{AE}, and increases its marginal product. The relationship between the supply of funds and the EME lending rate is upward-sloping for $\phi > 0$, i.e.,

$$\frac{\partial \mathcal{A}^{s,EME}}{\partial \frac{1}{q_0^{EME}}} > 0$$

First, this is because the net worth, deposits, and issuance increase with q_0^{EME}:

$$\mathcal{N}\left(q_0^{EME}, n_0\right) = \frac{n_0}{1-\theta^{EME}} \times \left[1 + \frac{1}{2\phi}\left(\frac{\beta}{q^{EME}} - 1 + \mu\theta^{EME}\right)\right]$$

$$\frac{\partial \mathcal{N}\left(q_0^{EME}, n_0\right)}{\partial \frac{1}{q_0^{EME}}} = \frac{n_0}{1-\theta^{EME}} \times \frac{\beta}{2\phi} > 0$$

for $\phi > 0$. Second, because an increase in $\frac{1}{q^{EME}}$ is associated with a greater $\frac{1}{q^{AE}}$ which is associated with a lower capital demand by the AE non-financial firm. To see this, note that

$$\mathcal{A}^{d,AE}\left(q_0^{EME}\right) = \left(q_0^{AE} \times \mathbb{E}_0 z_1^{AE}\right)^{\frac{1}{1-\alpha}}$$

and that, re-arranging Equation 13 we obtain:

$$\frac{1}{q_0^{AE}} = \frac{1}{q_0^{EME}} - \frac{\mu}{\beta}\left(\theta^{AE} - \theta^{EME}\right)$$

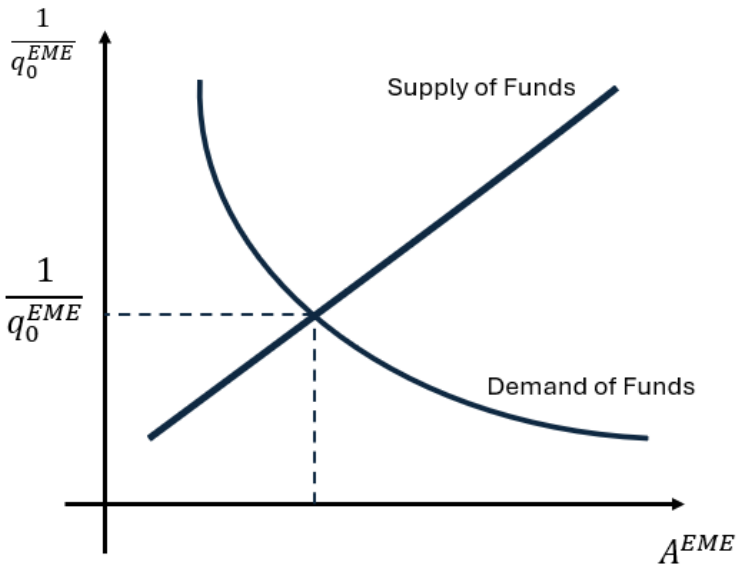
which shows that an increase in $\frac{1}{q_0^{EME}}$ is associated with an increase in $\frac{1}{q_0^{AE}}$.

On the borrower side, the demand for funds from EME non-financial firms is given by the Euler equation in Equation 2:

$$\mathcal{A}^{d,EME} = \left(q_0^{EME} \times \mathbb{E}_0 z_1^{EME}\right)^{\frac{1}{1-\alpha}} \tag{15}$$

The equilibrium and supply and demand for funds from Emerging Markets can then be studied through a graphical approach as seen in Figure 2.

Figure 2: Supply and Demand Framework



Proposition 1: If global banks face no cost of raising external finance through equity issuance, i.e. $\phi = 0$, the interest rate non-financial firms in EMEs is given by:

$$\frac{1}{q^{EME}} = \frac{1}{q^d}$$

Proof. From Equations 9 to 11 it can be seen that if $\phi = 0$, and $\beta = q_0^d$, then $\mu = 0$. This is, if there are no costs of issuance equity, then the leverage constraint never binds. If $\mu = 0$, the spreads between borrowing rates for AE and EMEs, and the deposit rates are zero.

Proposition 2: Assume that the bank's leverage constraint is binding, that the deposit rate is given by

$$q_0^d = \beta,$$

and that there are increasing marginal costs of external equity issuance (i.e. $\phi > 0$). Then an increase in the bank's net worth n_0 reduces the spread

$$S \equiv \frac{1}{q_0^{EME}} - \frac{1}{\beta}$$

that Emerging Market non-financial firms face.

When the leverage constraint binds, the pricing condition for EME loans is given by

$$\frac{1}{q_0^{EME}} = \frac{1}{\beta} + \frac{\mu}{\beta}\left(1 - \theta^{EME}\right),$$

so that the spread is

$$S \equiv \frac{1}{q_0^{EME}} - \frac{1}{\beta} = \frac{\mu}{\beta}\left(1 - \theta^{EME}\right).$$

The bank's funding condition implies that

$$1 + 2\phi\,\frac{x_0}{n_0} = \frac{\beta}{q_0^d} + \mu.$$

Since $q_0^d = \beta$, this reduces to

$$\mu = 2\phi\,\frac{x_0}{n_0}.$$

In equilibrium, an increase in n_0 allows the bank to finance more loans with its own net worth, thereby reducing the ratio x_0/n_0. That is,

$$\frac{\partial}{\partial n_0}\left(\frac{x_0}{n_0}\right) < 0,$$

and consequently,

$$\frac{\partial \mu}{\partial n_0} = 2\phi\,\frac{\partial}{\partial n_0}\left(\frac{x_0}{n_0}\right) < 0.$$

Substituting back into the expression for S, we obtain

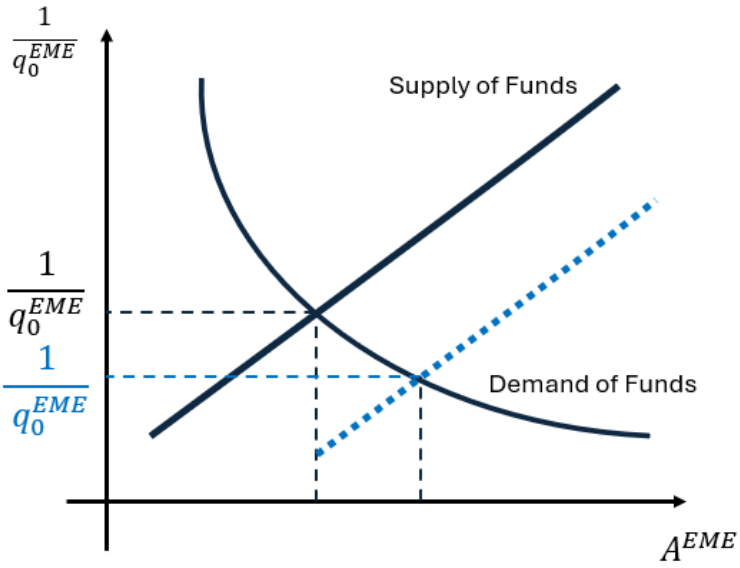
$$\frac{\partial S}{\partial n_0} = \frac{1 - \theta^{EME}}{\beta}\,\frac{\partial \mu}{\partial n_0} < 0.$$

Hence, an increase in n_0 reduces the spread S.

Figure 3 provides the intuition behind Proposition 2. The increase in the bank's net worth, n_0, shifts the supply function of EME funds to the right, as stated by Equation 14, graphed in dashed light blue. This leads to a reduction in the borrowing rate along the demand of funds curve, leading to an increase in capital accumulation. The reduction in the interest rate leads to a reduction in the spreads that EME's pay as the deposit rate is fixed.

We associate this increase in banks' net worth with a surprise increase in banks' supply of funds to EMEs. This increase in banks' net worth is associated with a decrease in borrowing rates and spreads for both Advanced Economies and Emerging Markets. Simultaneously, the increase in the bank's net worth and lending capacity will increase bank's profits

Figure 3: Increase in Banks' Net Worth



measured as $b_1^{AE} + b_1^{EME} - d_1$. In Subsection 2.2, we argue that this comparative statics is associated with a negative co-movement between surprise in banks' net worth and borrowing spreads around earning announcements.

Proposition 3: Assume that the bank's leverage constraint is binding and that the deposit rate is given by

$$q_0^d = \beta,$$

and that there are increasing marginal costs of external equity issuance (i.e. $\phi > 0$). Then an increase in Advanced Economy productivity, denoted by z_1^{AE}, increases the spread

$$S \equiv \frac{1}{q_0^{EME}} - \frac{1}{\beta},$$

that Emerging Market non-financial firms face.

When the leverage constraint binds, the pricing rule for loans to Emerging Market firms is given by

$$\frac{1}{q_0^{EME}} = \frac{1}{\beta} + \frac{\mu}{\beta}\left(1 - \theta^{EME}\right),$$

so that the spread becomes

$$S \equiv \frac{1}{q_0^{EME}} - \frac{1}{\beta} = \frac{\mu}{\beta}\left(1 - \theta^{EME}\right).$$

Thus, an increase in S is equivalent to an increase in the shadow cost μ.

Now consider the pricing condition for Advanced Economy (AE) non-financial firms. Their Euler equation implies

$$\frac{1}{q_0^{AE}} = z_1^{AE}\,\alpha\,(k_1^{AE})^{\alpha-1}.$$

On the other hand, the bank's pricing rule for AE loans when the constraint binds is

$$\frac{1}{q_0^{AE}} = \frac{1}{\beta} + \frac{\mu}{\beta}\left(1 - \theta^{AE}\right).$$

Equate these two expressions to obtain

$$z_1^{AE}\,\alpha\,(k_1^{AE})^{\alpha-1} = \frac{1}{\beta} + \frac{\mu}{\beta}\left(1 - \theta^{AE}\right).$$

Rearranging, we solve for μ:

$$\mu = \beta\,\frac{z_1^{AE}\,\alpha\,(k_1^{AE})^{\alpha-1} - \frac{1}{\beta}}{1 - \theta^{AE}}.$$

Taking the derivative with respect to z_1^{AE}, and noting that all other terms (including α, β, and $(k_1^{AE})^{\alpha-1}$)

$$\frac{\partial \mu}{\partial z_1^{AE}} = \beta\,\frac{\alpha\,(k_1^{AE})^{\alpha-1}}{1 - \theta^{AE}} > 0.$$

Since the spread is

$$S = \frac{1 - \theta^{EME}}{\beta}\,\mu,$$

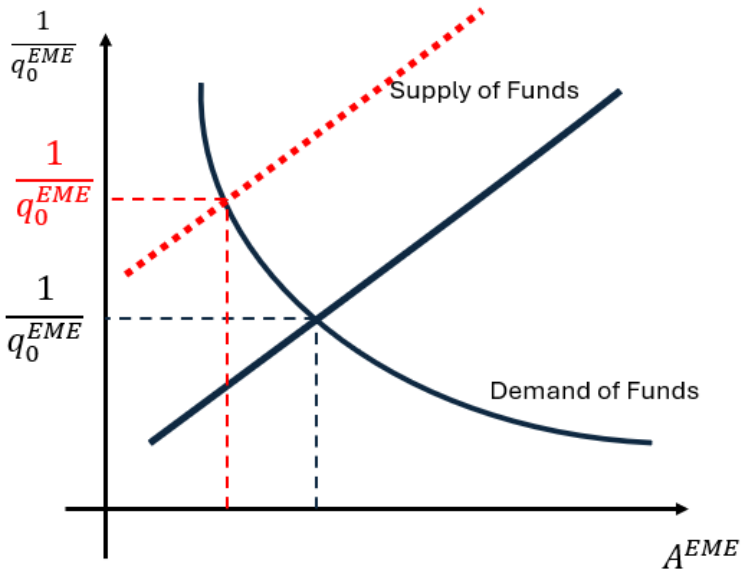
by the chain rule it follows that

$$\frac{\partial S}{\partial z_1^{AE}} = \frac{1 - \theta^{EME}}{\beta}\,\frac{\partial \mu}{\partial z_1^{AE}} > 0.$$

Thus, an increase in z_1^{AE} raises the spread S that Emerging Market borrowers face.

Figure 4 provides the intuition behind Proposition 3. From Equation 14, an increase

Figure 4: Increase in Advanced Economy's Productivity



in non-financial firms' productivity increases the demand for funds from AE and, thus, reduces

the supply of funds available for EMEs. In other words, the increase in AE's productivity effectively crowds out EMEs, as the bank's overall lending capacity is constrained. In response to a larger demand for borrowing from the AE non-financial firm, the bank increases funding through equity issuance, leading to a higher marginal cost of funding and borrowing rates for both AEs and EMEs. This reduction in the supply of funds for EMEs is reflected in higher borrowing rates along the demand curve and lower capital accumulation.

We associate this increase in AE non-financial firms' productivity with a surprise decrease in the supply of funds to EMEs driven by demand from the AE. The greater demand for funds from AEs and the greater borrowing rates lead to an increase in the bank's profits measured as $b_1^{AE} + b_1^{EME} - d_1$. In Subsection 2.2, we argue that this comparative statics is associated with a positive co-movement between surprise in banks' net worth and borrowing spreads around earning announcements.

2.2 Co-Movement between Global Banks' Networth and Spreads

This section describes the identification strategy that allows us to capture exogenous credit shocks from global banks'. Our benchmark empirical strategy is the one introduced by Ottonello and Song [2022]. We start by describing this strategy that relies on the high-frequency changes in US banks' stock prices around earning announcements and its co-movement with US private borrowing spreads. Then, we build on this strategy by introducing an alternative identification that relies on the co-movement between changes in global banks' stock prices and EMEs' sovereign spreads.

We begin by describing the methodology introduced by Ottonello and Song [2022], which exploits changes in financial intermediaries' stock prices in windows around their earning releases.[3] These financial intermediaries represent, on average, 67% of the total equity of U.S. depository institutions. Thus, the shocks represent changes in the net worth of large financial institutions in the U.S., which likely represent significant changes in the net worth of the entire U.S. and global financial markets. Across the paper, we denote this change in financial intermediaries' stock prices as "net worth surprises".

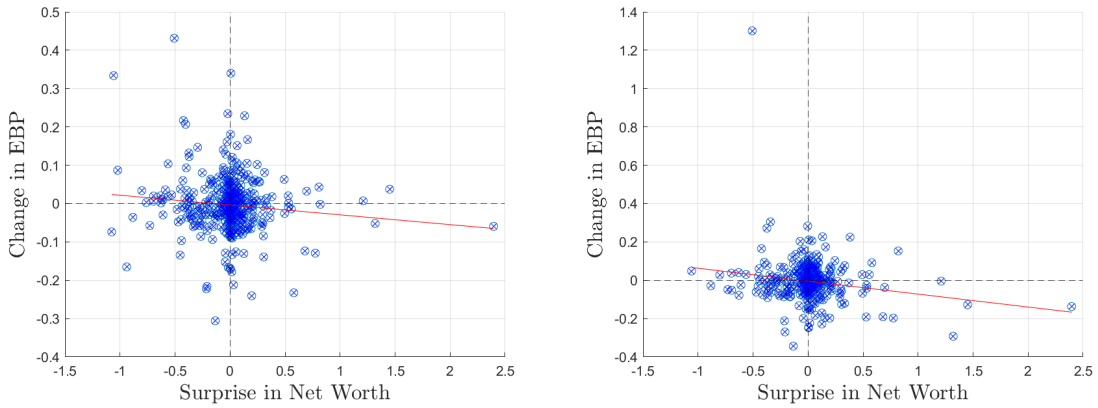
The credit supply shock is computed by decomposing "net worth surprises" into a supply and demand component. The intuition behind this decomposition relies on Propositions 2 and 3 presented above, which specify a specific co-movement between net worth and borrowing costs. On the one hand, a positive net worth surprise associated with an increase in banks' lending capacity should be associated with a decrease in borrowing spreads, i.e., negative co-movement. On the other hand, a positive net worth surprise associated with

[3]The baseline sample focuses on the commercial banks, investment banks, and securities dealers included in the S&P 500 index during the period 1998 to 2020. These intermediaries have direct involvement in financial activities in the economy. For more details, see Section 2 of their paper.

an increase in the demand for funds from the US economy, which tightens banks' lending capacity, should be associated with an increase in borrowing spreads.

In Ottonello and Song [2022], net worth surprises are decomposed into credit supply and credit demand shocks by studying the co-movement with the daily change in the excess bond premium (EBP), Gilchrist and Zakrajšek [2012]. Figure 5 presents the co-movement between the "net worth surprises" and the daily change in the EBP. While there is a negative and significant correlation between net worth surprises and the EBP, there are several observations in which positive net worth surprises are associated with increases in the daily EBP.[4] We interpret these positive co-movement events as indicative of information disclosure beyond

Figure 5: Co-Movement between Net Worth Surprises & the EBP



(a) Same Day Change (b) Two Day Change

Note: Financial intermediaries' net worth surprises are sourced directly from Ottonello and Song [2022]. Changes in daily EBP are sourced from Gilchrist et al. [2021]. The panel on the left presents the change in the EBP between the day before the surprise and the day of the surprise. The panel on the right presents the change in the EBP between the day before the surprise and the day after the surprise.

lending capacity around the banks' earning announcements. Note that if this co-movement is irrelevant and no information is disclosed, the credit supply and demand components decomposition of net worth surprises should lead to the same conclusions. In Sections 2.3 and 3, we show that the supply and demand components of financial intermediaries' net worth have qualitatively opposite international spillovers.

Table 1 presents summary statistics of the credit supply and credit demand shocks constructed by Ottonello and Song [2022] at the monthly frequency. Figure 6 presents the time series of the net worth surprises and the credit supply and credit demand shocks.

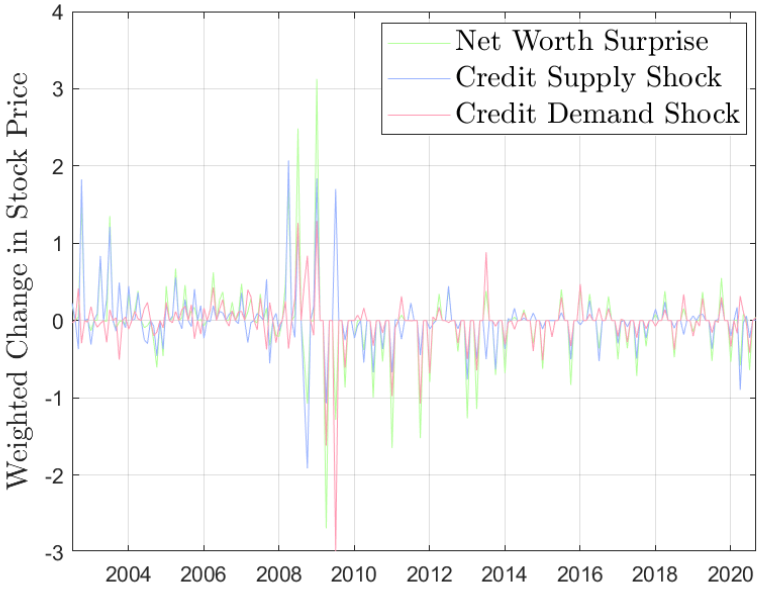
An identification strategy specifically for Emerging Markets. The previous identification strategy relies on the co-movement between the net worth surprises and the EBP as a

[4]The correlation between the net worth surprise and the change in the daily EBP is -0.1055, significant at a 0.0313 level. The correlation between the net worth surprise and the two-day change in the daily EBP is -0.1758, significant at a 0.0009 level.

Table 1: Summary Statistics: Ottonello and Song [2022] Shocks

	Months	Mean	Std. Dev.	Min	Max
Net Worth Surprise	145	-0.0021	0.670	-2.69	3.13
Credit Supply	145	0.0027	0.475	-1.91	2.07
Credit Demand	145	-0.0319	0.417	-2.99	1.29

Figure 6: Time Series - Ottonello and Song [2022] Shocks



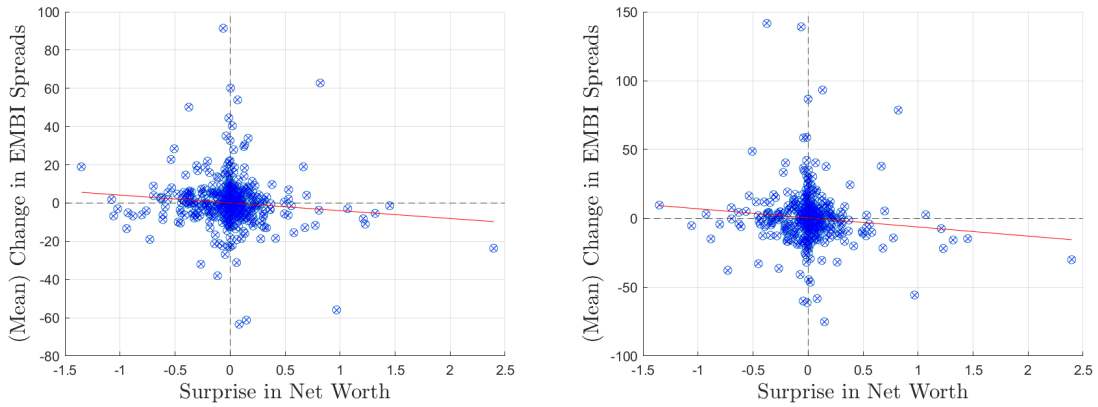
proxy of borrowing spreads. The theoretical framework in Section 2.1 predicts that borrowing spreads in both AE and EME should co-move in the same direction in response to both increases in n_0 and z_1^{AE}. This is why we use the decomposition by Ottonello and Song [2022] as our benchmark.

However, two concerns arise which might bias our results. First, daily changes in EBP might capture changes in borrowing spreads with a measurement error. This is because the EBP is constructed through a regression procedure and is thus subject to sample uncertainty. Second, net worth surprises might also capture changes in banks' relative strategies or preferences between AEs and EMEs. If this is the case, then AE and EMEs spreads might not co-move in the same direction for every earning announcement. This is why we introduce an alternative identification strategy that relies on daily changes in EMBI spreads around earning announcements.

We exploit the daily time series of EMBI spreads, which provides a measure of differences in interest rates between dollar-issued sovereign bonds for more than 73 Emerging Markets and US treasuries of similar maturity. We are left with 538 earnings announcements for which we can compute daily changes in EMBI spreads. To capture a proxy for changes in all Emerging Markets, we compute the simple average change in EMBI spreads across all

countries in our sample for each day. Figure 7 presents the co-movement between the net worth surprises and the average change in EMBI spreads. In line with the results in Figure 5,

Figure 7: Co-Movement between Net Worth Surprises & EMBI Spreads



(a) Same Day Change

(b) Two Day Change

Note: Financial intermediaries' net worth surprises are sourced directly from Ottonello and Song [2022]. Changes in daily EMBI are sourced from JP Morgan's country-level index. The panel on the left presents the change in the EBP between the day before the surprise and the day of the surprise. The panel on the right presents the change in the EBP between the day before the surprise and the day after the surprise.

there is a negative and significant correlation between net worth surprises and EMBI spreads.[5] However, once again, several observations exhibit a positive co-movement between net worth surprises and changes in EMBI spreads.

We follow Ottonello and Song [2022] and decompose net worth surprises into supply and demand components by applying the methodology introduced by Jarociński [2022] for the decomposition of monetary policy surprises. This methodology introduces two separate methods to decompose surprises according to their co-movement. The first one, called a "Poor Man's Sign Restriction" decomposes net worth surprises NWS_t as

$$\text{Shock}_t^{Supply} = \begin{cases} SNW_t & \text{if } SNW_t \times \text{Spread}_t \leq 0, \\ 0 & \text{otherwise,} \end{cases}$$

$$\text{Shock}_t^{Demand} = \begin{cases} 0 & \text{if } SNW_t \times \text{Spread}_t \leq 0, \\ SNW_t & \text{otherwise.} \end{cases}$$

This method takes the strong stance that each earning announcement can only exhibit the presence of a particular credit shock. If an earnings announcement exhibits a negative (positive) co-movement, the net worth surprise is associated with a credit supply (demand) shock and not a credit demand (supply) shock.

[5]The correlation between the net worth surprise and the mean change in the daily EMBI spread is -0.1008, significant at a 0.0193 level. The correlation between the net worth surprise and the two-day change in the daily EBP is -0.1009, significant at a 0.0292 level.

The "*rotational decomposition*" approach allows each earning announcement to contain both underlying credit shocks. The decomposition of net worth surprises into credit supply and credit demand shocks satisfies

$$M = UC, \quad \text{with} \quad U'U = \text{diagonal matrix} \quad \text{and} \quad C = \begin{pmatrix} 1 & c_{Supply} < 0 \\ 1 & c_{Demand} > 0 \end{pmatrix},$$

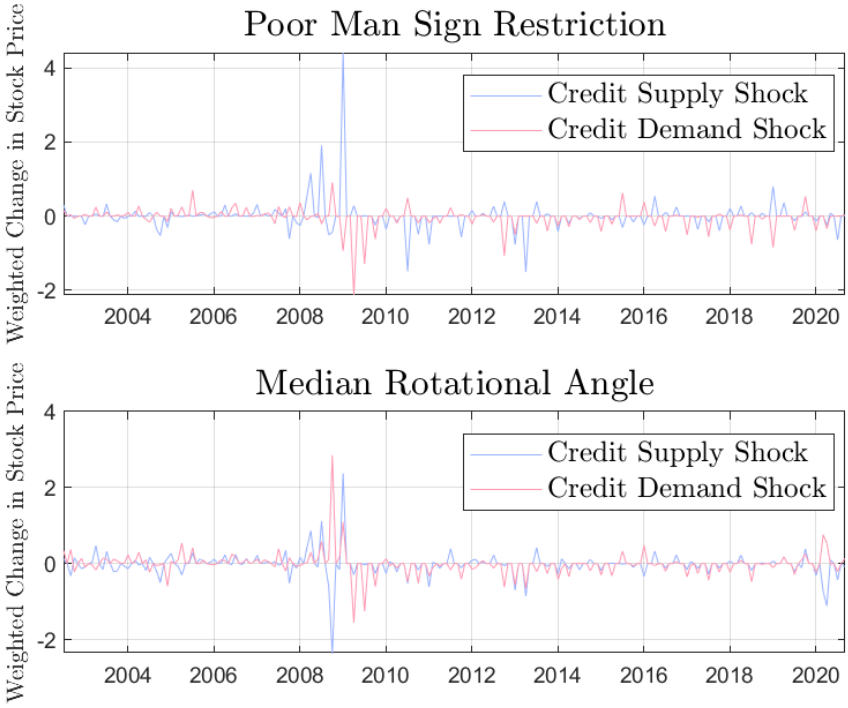
where $M = (NWS_t, \text{Spread}_t)$ is a $T \times 2$ matrix with NWS_t in the first column and the change in the EMBI spread in the second column, $U = (\text{Shock}_t^{Supply}, \text{Shock}_t^{Demand})$ is a $T \times 2$ matrix, T is the number of earning announcements, Shock_t^{Supply} and Shock_t^{Demand} are mutually orthogonal, and matrix C captures how the underlying credit shocks translate into net worth surprises and changes EMBI spreads. The decomposition in Equation 2.2 is not unique. Previous papers have chosen different approaches to this non-uniqueness. Jarociński and Karadi [2020] include the surprises in their Bayesian VAR and specify an agnostic Bayesian prior covering the space of all admissible rotations. Jarociński [2022] chooses a rotational angle that matches the ratio of variance explained by the poor man sign restriction to total net worth surprises. We choose the median rotational angle that imposes that half of the net worth surprises are explained by each shock.

Table 2: Summary Statistics: Own Shocks

	Month	Mean	Std. Dev.	Min	Max
Poor Man's Sign Restriction					
Credit Supply Shock	143	0.030	0.552	-1.510	4.407
Credit Demand Shock	143	-0.060	0.348	-2.129	0.908
Median Rotational Angle					
Credit Supply Shock	143	-0.017	0.486	-2.378	2.377
Credit Demand Shock	143	-0.013	0.441	-1.555	2.850

Table 2 presents summary statistics of the credit supply and credit demand shocks following both the poor man and median rotational angle at the monthly frequency. Figure 8 presents the time series of the net worth surprises and the credit supply and credit demand shocks. The correlation between the median rotational angle credit supply (demand) shocks and the Ottonello and Song [2022] is 0.716 (0.668). On the one hand, the strong correlation between shocks across methodologies provides reassurance that both approaches are capturing, on average, consistent shifts in supply and demand. However, the fact that the correlation is not 1 may suggest that information other than pure credit supply and demand is being systematically disclosed around earning announcements.

Figure 8: Time Series - Own Shocks



2.3 High-Frequency Results

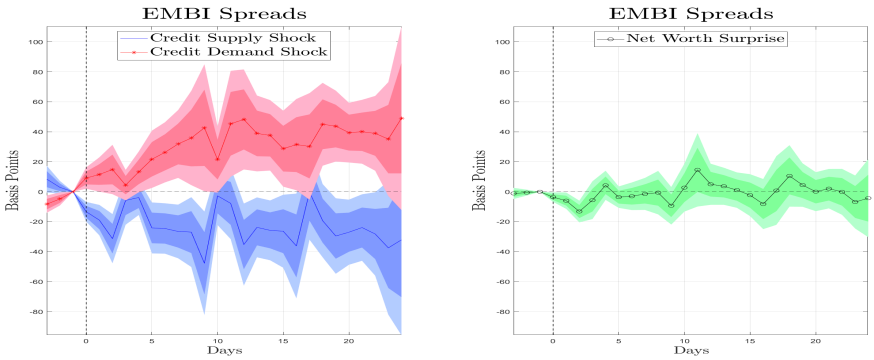
Our first empirical exercise is an event-study framework, which consists of estimating the following model

$$\Delta y_{i,t+h} = \alpha_{i,h} + \beta^{Supply} \times \text{Shock}_t^{Supply} + \beta^{Demand} \times \text{Shock}_t^{Demand} + \epsilon_{i,t+h} \tag{16}$$

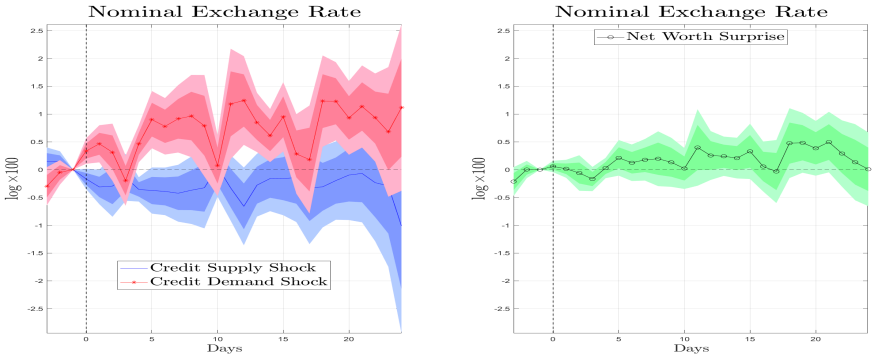
where $\Delta y_{i,t+h}$ denotes the change in an outcome variable of interest for country i between period $t-1$ and period $t+h$ (e.g., the EMBI spread, the log nominal exchange rate with the US dollar); Shock_t^{Supply} and Shock_t^{Demand} represent the supply and demand shocks (either constructed by Ottonello and Song [2022]; $\alpha_{i,h}$ is a country i is a country fixed effect, and $\epsilon_{i,t+h}$ is a random error term. We cluster standard errors in two ways to account for potential correlations within country outcomes and within announcements.

We start by describing the impact of credit supply and demand shocks in EMBI spreads and nominal exchange rates in the days around financial intermediaries' earnings announcements. Figure 9 presents the results using the shock decompositions introduced by Ottonello and Song [2022]. The first takeaway is that the co-movement between "financial intermediaries' net worth surprises" and the EBP is highly informative. If the co-movement wasn't informative, then the impact of credit supply shocks should be equal to those of credit demand shocks. On the one hand, the top left panel of Figure 9 shows that a credit demand shock (in red) leads to a persistent increase in EMBI spreads in the days after the earnings announcement. On the other hand, the top left panel of Figure 9 shows that a credit supply shock (in blue) leads to a persistent decrease in EMBI spreads in the days after the earnings

Figure 9: Event Study Analysis - Ottonello and Song [2022]



(a) EMBI Spreads



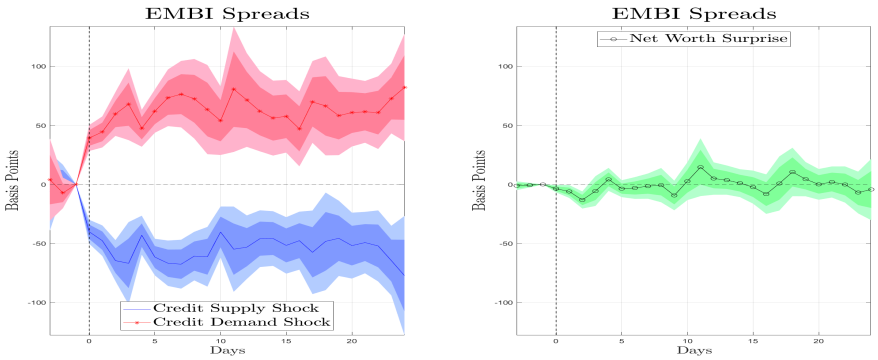
(b) Nominal Exchange Rate

Note: The figure is comprised of two panels. Each panel is comprised of two sub-panels. The top panel presents the results for EMBI spreads. The bottom panel presents the results for the nominal exchange rate with the US dollar in terms of units of the local currency. An increase implies a depreciation of the local currency with respect to the US dollar. The left sub-panels present the results of decomposing the surprises into credit supply shocks (blue) and credit demand shocks (red). Results present the estimated parameters in Equation 16.

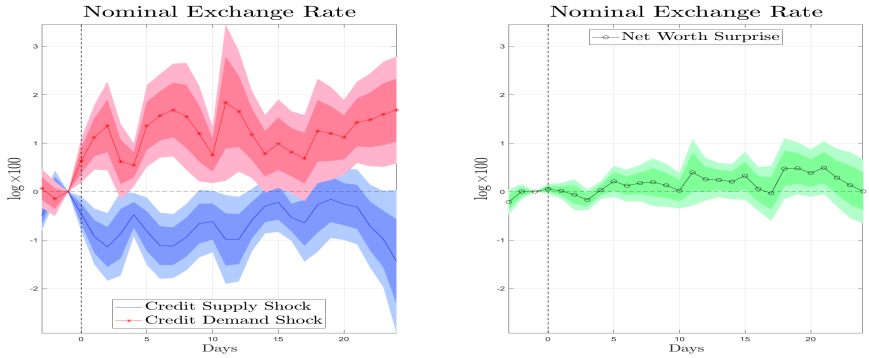
announcement. The top right panel of Figure 9 shows that failing to account for the co-movement between "financial intermediaries' net worth surprises" and the EBP would lead to the conclusion that an increase in financial intermediaries' net worth only leads to a small and not persistent decrease in EMBI spreads. The bottom panels of Figure 9 show similar results for the nominal exchange rate. A credit demand shock leads to a depreciation of the local currency, while a credit supply shock leads to an appreciation of the local currency. Again, failing to decompose surprises in intermediaries' net worth would lead to the conclusion that there is little to no impact on Emerging Markets' exchange rates.

Figure 10 presents the results when identifying supply and demand shocks according to the co-movement of "financial intermediaries' net worth surprises" and EMBI spreads instead of the EBP. Once again, the co-movement between the two variables is highly informative of the impact that surprises in intermediaries' net worth have in Emerging Markets in

Figure 10: Event Study Analysis - Own Shocks



(a) EMBI Spreads



(b) Nominal Exchange Rate

Note: The figure is comprised of two panels. Each panel is comprised of two sub-panels. The top panel presents the results for EMBI spreads. The bottom panel presents the results for the nominal exchange rate with the US dollar in terms of units of the local currency. An increase implies a depreciation of the local currency with respect to the US dollar. The left sub-panels present the results of decomposing the surprises into credit supply shocks (blue) and credit demand shocks (red). Results present the estimated parameters in Equation 16.

the days after the earnings announcements. The resulting dynamics are in line with those in Figure 9, i.e., a credit demand shock leads to higher EMBI spreads and depreciation, while a credit supply shock leads to lower EMBI spreads and appreciation. Quantitatively, the impact is larger under our own identification strategy. The peak impact under our identification strategy is twice as large for EMBI spreads (80 basis points vs 40 basis points) and 50% larger for the nominal exchange rate (1.5% vs 1%), respectively. However, this is not surprising because our outcome variable, the EMBI spreads, is part of our identification strategy.

In summary, this section presented evidence that surprises in financial intermediaries' net worth have a significant impact on Emerging Market financial conditions in the days after earning announcements. First, we showed that while there is a negative correlation between intermediaries' net worth surprises and EMBI spreads, a large number of earning

announcements exhibit a positive co-movement between the two variables. Second, we build on the identification strategy introduced by Ottonello and Song [2022] and introduce an identification strategy that decomposes net worth surprises into credit supply and credit demand shocks by exploiting the co-movement with EMBI spreads. We show that this co-movement is highly informative, with credit supply and demand shocks having qualitatively opposite impacts on Emerging Markets' EMBI spreads and exchange rates.

3 Macro Impact of Global Banks' Credit Supply

In this section of the paper, we quantify the macroeconomic impact of global banks' credit shocks. To do so, we combine the shocks described in the previous section with an unbalanced panel of macroeconomic and financial variables from 65 economies from January 1998 to September 2020. We estimate the aggregate impact through Bayesian VAR models and instrumental variable local projection regressions.

3.1 Sample Details & Econometric Specification

We start by describing the datasets and econometric methods used in this section.

Datasets & Country Sample. For the purpose of comprehensively estimating the international spillovers of global banks' credit supply shocks, we construct a sample of both macroeconomic and financial variables EMEs. To do so, we select all the countries that have data on the sample of macroeconomic and financial variables from either the IMF or OECD datasets for the time sample of credit supply shocks from January 1998 to September 2020.

Next, we discuss the choice of macroeconomic and financial variables. This choice is driven by data availability, given that several EMEs do not have significant coverage. The smallest variable specification includes the nominal exchange rate with the US dollar, a domestic price index, and an industrial production index. This leaves us with 43 Emerging Market Economies (see Table 3) and 22 Advanced Economies (see Table 4). This sample allows us to present results for the largest possible sample across both EMEs and AEs.

Next, we extend this benchmark sample with several additional variables specifically for EMEs: (i) EMBI spreads, (ii) equity index, (iii) domestic monetary policy rates, (iv) domestic lending rates, (v) banking credit, (vi) unemployment rate, (vii) exports and imports in current dollars, (viii) country-specific export and import price indexes. Our benchmark sample and extended variable specifications are in line with the sample size in the literature.[6].

Variables are sourced from IMF and OECD datasets to ensure methodological con-

[6]For instance, this is a similar sample size and variable specification to that in Camara [2021].

Table 3: Emerging Market Economies

Country Name	# Periods	Country Name	# Periods
Bangladesh	273	Mexico	273
Barbados	202	Mongolia	165
Bosnia and Herzegovina	153	Montenegro	189
Brazil	273	Nicaragua	186
Bulgaria	249	North Macedonia, Republic of	273
Chile	273	Pakistan	273
China, P.R.: Mainland	129	Paraguay	189
Colombia	273	Peru	244
Croatia, Rep. of	273	Philippines	273
Côte d'Ivoire	191	Romania	273
Dominican Rep.	165	Russian Federation	273
Ecuador	249	Senegal	153
El Salvador	261	Serbia, Rep. of	240
Estonia, Rep. of	156	Tunisia	256
Guatemala	201	Türkiye, Rep of	273
Honduras	249	Uganda	177
Hungary	273	Ukraine	225
India	273	Uruguay	212
Jordan	253	Uzbekistan, Rep. of	93
Kazakhstan, Rep. of	192	Venezuela, Rep. Bolivariana de	109
Malawi	215	Vietnam	153
Malaysia	255		

Note: The columns titled "# Periods" reflect the number of months for which each country reports all three variables between January 1998 to September 2020.

sistency.[7] We also introduce five US-specific control variables: (i) the excess bond premium Gilchrist and Zakrajšek [2012], (ii) the 10-year treasury rate, (iii) the federal funds rate, (iv) log industrial production, (v) the PCE price index. These variables are sourced from FRED.

Local projection regression. We start by quantifying the international spillovers of Global Banks' credit shocks by estimating instrumental variable local projection regressions á la Jordà [2023]. This exercise allows me to estimate the international spillovers of US interest rates for the largest possible sample in terms of the time and country dimensions.

The main local projection regression estimated is an instrumental variable specification

$$y_{i,t+h} = \beta_h \times EBP_t + \sum_{j=1}^{J_y} \delta_i^j y_{i,t-j} + \sum_{j=1}^{J_x} \alpha_i^j x_{i,t-j} + \sum_{j=1}^{J_x^{US}} \alpha_{US}^j x_{US,t-j} + \mu_i + \epsilon_{i,t} \tag{17}$$

where $y_{i,t+h}$ represents the outcome variable from country i's at time horizon of h months

[7] Data from IMF's International Financial Statistics and OECD Statistics is supplemented with constructed long-term interest rates where needed by combining a country's EMBI Spread and Kenneth French's short-term US risk-free rate (Camara et al. [2024]).

Table 4: Advanced Economies

Country Name	# Periods	Country Name	# Periods
Australia	237	Malta	96
Canada	273	Norway	273
Cyprus	120	Poland, Rep. of	273
Czech Rep.	273	Singapore	273
Denmark	273	Slovak Rep.	132
Iceland	242	Slovenia, Rep. of	110
Israel	273	Sweden	273
Japan	273	Switzerland	120
Korea, Rep. of	273	United Kingdom	273
Latvia	183	United States	273
Lithuania	204		

Note: The columns titled "# Periods" reflect the number of months for which each country reports all three variables between January 1998 to September 2020.

from date t. The specification includes J_y lags of the outcome variable, y_i, J_x lags of the other "country-specific" variables x_i and J_x^{US} lags of the US-specific control variables. For the benchmark sample, I set the lags on the dependent and other control variables at 2, i.e., $J_y = J_x = J_x^{US} = 2$.[8] I also introduce a country-fixed effect. We estimate the impact of a Global Bank's Credit Supply or Demand shock by instrumenting the EBP_t separately for each of the shocks recovered above.

Alternatively, we estimate the impact of the Global Bank's Credit Supply or Demand shock by estimating the following local projection regression

$$\begin{aligned} y_{i,t+h} =& \beta_h^{Supply} \times \text{Shock}_t^{\text{Supply}} + \beta_h^{Demand} \times \text{Shock}_t^{\text{Demand}} + \\ &+ \sum_{j=1}^{J_y} \delta_i^j y_{i,t-j} + \sum_{j=1}^{J_x} \alpha_i^j x_{i,t-j} + \sum_{j=1}^{J_i} \left(\phi_i^j \text{Shock}_{t-j}^{\text{Supply}} + \varphi_i^j \text{Shock}_{t-j}^{\text{Demand}} \right) + \\ &+ \sum_{j=1}^{J_x^{US}} \alpha_{US}^j x_{US,t-j} + \mu_i + \epsilon_{i,t} \end{aligned} \tag{18}$$

where we introduce the credit shocks, $\text{Shock}_t^{\text{Supply}}$ and $\text{Shock}_t^{\text{Demand}}$, directly into the regression. Coefficients β_h^{Supply} and β_h^{Demand} give the impulse response of outcome variable y at horizon h of a Global Bank Credit Supply shock and Demand shock, respectively. The rest of the variables and coefficients are as defined above.

VAR models. We also estimate the international spillovers of Global Banks' credit shocks through both panel VAR and country-by-country VAR models. First, we estimate a pooled panel Bayesian VAR model as in Canova and Ciccarelli [2013]. This pooled model imposes common parameter values across countries to capture the average impact of shocks across

[8] We choose two lags considering the Bayesian Information Criterion (BIC) and the Hannan-Quinn (HQ) information criteria.

countries. The panel VAR model is estimated for a balanced panel of EMEs that are present for the full sample from September 2002 to September 2020. For each country, the vector of variables Y_t consists of two vectors.

Second, we estimate a series of country-by-country VAR models. For this estimation, we estimate a standard Bayesian model, as described above, with both U.S. and country-specific variables. Several papers in the international macroeconomics literature have followed this approach to allow for the potential heterogeneous impact of shocks across countries, see Degasperi et al. [2020], Camara [2021].

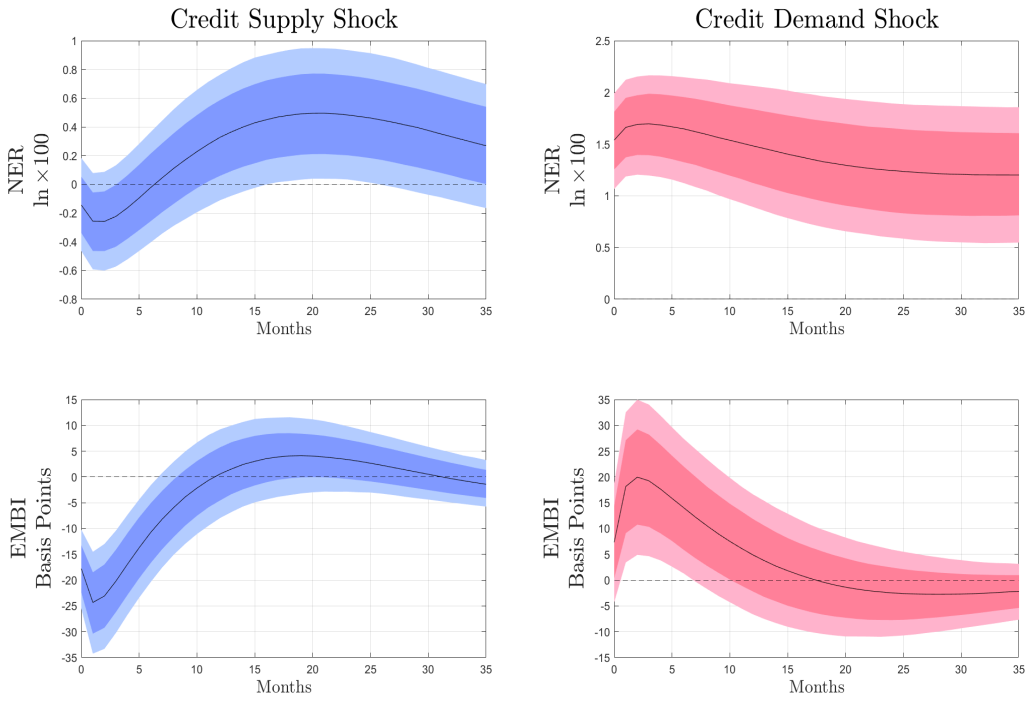
3.2 Macro Level Results

This section presents our first novel results, which quantify the macroeconomic or aggregate impact of a global bank credit supply shock on EMEs. We present the impulse response functions using the identification strategy by Ottonello and Song [2022]. We present the impulse response functions using our own identified shocks in Appendix A.

Panel VAR results. First, we study how persistent the impact of credit supply and demand shocks on Emerging Markets' exchange rates and EMBI spreads. To do so, we estimate the impulse response functions of these two variables at the monthly frequency. Figure 11 presents the results. Both credit supply and demand shocks persistently impact Emerging Markets' financial conditions, with responses away from zero for large periods of time after the shock. A credit supply shock leads to an initial exchange rate appreciation of 0.2%, which lasts six months after the shock. A credit supply shock leads to a hump-shaped reduction in EMBI spreads, falling by as much as 30 basis points one to two months after the shock. EMBI spreads return to pre-shock levels a year after the shock. Overall, credit supply shocks lead to an improvement in the Emerging Market's financial conditions, which last up to a year after the initial shock. Oppositely, credit demand shocks lead to a persistent deterioration of Emerging Market financial conditions. In particular, an initial jump in the exchange rate of 1.5%, which persists for more than 2 years after the initial shock, and a hump-shaped increase in EMBI spreads, peaking at 20 basis points.

Next, we show that these credit shocks percolate into the real economy. We do this by expanding the set of variables to include the consumer price index, the industrial production index, and the equity index. Figure 12 presents the results. First, the left column shows that the credit supply shock associated with an exchange rate appreciation and a decrease in the EMBI spreads is also associated with significant real effects. A credit supply shock leads to a persistent increase in industrial production and the equity index. In particular, a credit supply shock associated with a 25 basis point decrease in the EBP leads to an expansion in the industrial production index, which peaks at 1.25% and is above pre-shock levels for 15 months after the initial shock. Similarly, a credit supply shock associated with a 25 basis

Figure 11: Persistent Impact on EMBI Spreads & NER
Ottonello and Song [2022]

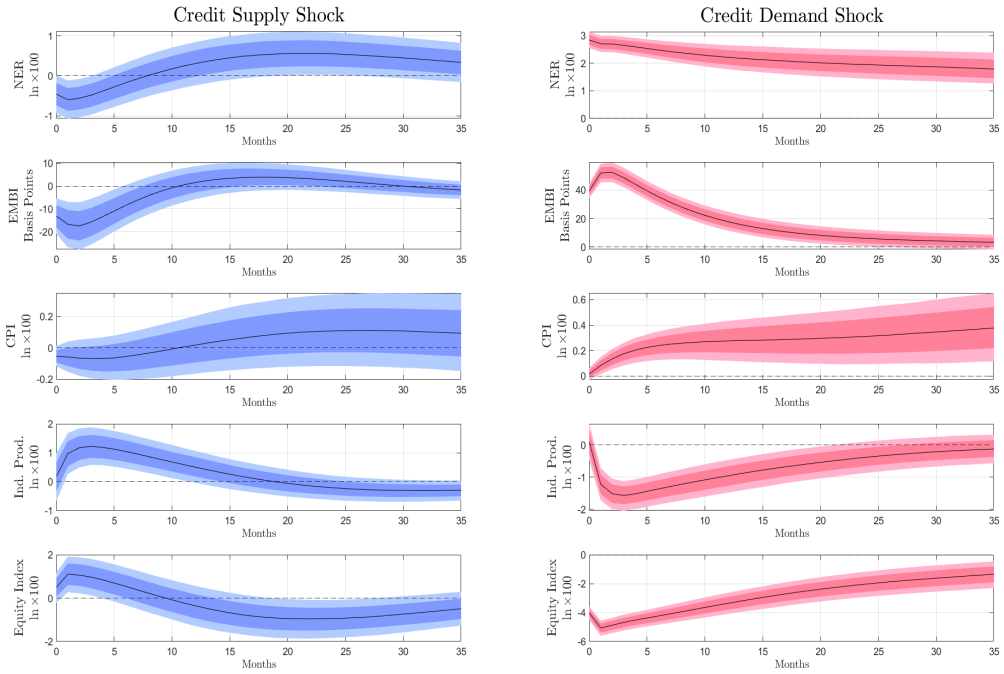


Note: The figure is comprised of four sub-figures organized in two columns and two rows. The left column presents the results for the credit supply shocks (in blue) associated with a decrease of 25 basis points in the EBP. The right column presents the results for the credit demand shocks (in red) associated with an increase of 25 basis points in the EBP. The top row presents the results for the nominal exchange rate. The bottom row presents the results for EMBI spreads. Countries in the sample: Argentina, Brazil, Chile, China, Colombia, Dominican Republic, Egypt, Hungary, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Turkey, Ukraine, and Uruguay.

point decrease in the EBP leads to an expansion in the equity index, which peaks at 1.5% and returns to pre-shock levels 9 months after the initial shock.

Second, the right column shows that the credit demand shock associated with an exchange rate depreciation and an increase in the EMBI spreads is also associated with significant real effects. A credit demand shock leads to a persistent decrease in industrial production and the equity index. In particular, a credit demand shock associated with a 25 basis point increase in the EBP leads to a reduction in the industrial production index, which peaks at 1.5% and is below pre-shock levels for 24 months after the initial shock. Similarly, a credit demand shock associated with a 25 basis point decrease in the EBP leads to a significant fall in the equity index, which reaches 5% and doesn't return to pre-shock levels even after 36 months.

Figure 12: Persistent Impact on EMBI Spreads & NER
Ottonello and Song [2022]



Note: The figure is comprised of ten sub-figures organized in two columns and five rows. The left column presents the results for the credit supply shocks (in blue) associated with a decrease of 25 basis points in the EBP. The right column presents the results for the credit demand shocks (in red) associated with an increase of 25 basis points in the EBP. The rows present the results (in order) for the nominal exchange rate, EMBI spreads, the consumer price index, the industrial production index, and the equity index. Countries in the sample: Brazil, Chile, Colombia, Hungary, Mexico, Philippines, Poland, Turkey and Ukraine.

4 Examining the Transmission Channel

In this section, we present our firm-level results that shed light on the transmission channel of the Global Bank credit shocks. First, we describe the credit registry dataset from Uruguay that covers firm-bank level data for the period April 2003 to December 2019. Second, we present the different econometric specifications used to study the micro-level transmission channel. We show that

4.1 Data Description & Econometric Specification

Data sources. We use two datasets containing detailed information at the loan, bank, and firm levels, covering every month from April 2003 to December 2019. Both datasets are managed by the Central Bank of Uruguay, which regulates and supervises the banking sector.

The first dataset, known as the Credit Register (*Central de Riesgos Crediticios*),

is administered by the Central Bank of Uruguay. This comprehensive register includes all loans issued within the financial system, offering detailed data at the loan level, such as the loan amount, currency, maturity, borrower's identity, country of residence, economic sector, and the financial institutions with which the borrower has a loan and collateral. It also includes the credit risk category that each institution must assign to each borrower every month following the regulation.[9] It is similar in structure to other credit registries collected worldwide and widely used in the academic literature. We complement this dataset with external information that allows us to classify firms into four size categories: (i) Micro, (ii) Small, (iii) Medium, and (iv) Large firms.

The second dataset contains balance sheet and income statement information of all financial institutions operating in Uruguay, which is publicly available on the Central Bank of Uruguay's website.[10] We use this data as complementary to the credit registry dataset, including bank-level variables as controls in our firm-level regressions.

Aggregate dynamics. Figure 13 presents the evolution of firm loans and the role of both domestic and foreign capital banks during the period 2003-2019. The top panels show a significant increase in firm borrowing, on average, in foreign (left panel) and local (right panel) currencies. Note that this increase has also shown transitory slowdowns, as can be seen between 2008 and 2010 during the Great Financial Crisis and between 2016 and 2018 during the Federal Reserve's exit from the zero lower bound. These transitory fluctuations suggest the exposure of the Uruguayan banking system to the global financial conditions.

The bottom panel of Figure 13 shows the decomposition of firm loans by banks' origin: (i) domestic banks (in blue) include both public and private banks; (ii) foreign capital (in orange) include banks which were incorporated with foreign capital but are independent entities from their headquarters; (iii) foreign subsidiaries (yellow) which act as representatives of their headquarters. From this panel, it is clear that foreign capital banks have increased their role in the market for firm loans, explaining, on average, two-thirds of the market. While foreign banks can help increase credit intermediation and facilitate economic growth, this might also expose the Uruguayan economy to changes in foreign financial conditions.[11] We explore the role of these banks as specific sources of transmission of global bank credit shocks in Section 4.3.

Firm level summary statistics. Table 5 presents summary statistics on firms' bank loans. The top panel presents data on firms' total debt, the share of debt in foreign currency, and the ratio of firms' assets pledged as collateral to debt. From this top panel, it is clear that there is significant heterogeneity in firm debt. For instance, the median firm has a debt of $7,576$, and

[9] https://www.bcu.gub.uy/Servicios-Financieros-SSF/Normas%20y%20Plan/Marco%20Contable.pdf, page 26.

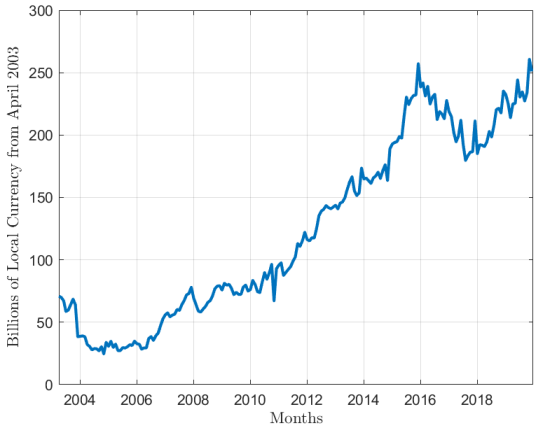
[10] https://www.bcu.gub.uy/Servicios-Financieros-SSF/Paginas/Boletin-SSF.aspx.

[11] See Caldara et al. [2024] for an example of how exposure to foreign banks amplifies the impact of US monetary policy shocks.

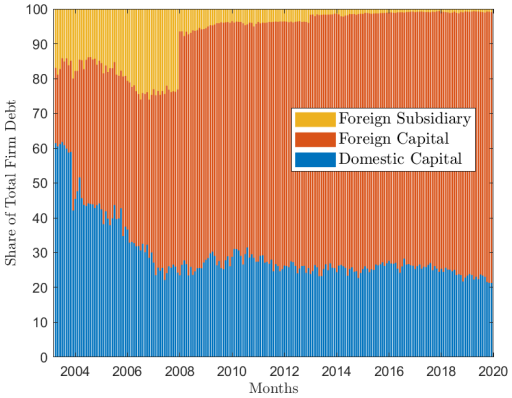
Figure 13: Evolution of Firm Bank Loans in Uruguay 2003-2019



(a) Foreign Currency Loans



(b) Local Currency Loans



(c) Composition of Loans by Origin of Bank

Note: For the top panel, foreign currency loans are converted to USD at the monthly frequency. Local currency debt is deflated by a domestic price index and is expressed in terms of purchasing power of April 2003. For the bottom panel, the shares of firm loans are computed in dollar terms for every month in the sample.

the 95^{th} percentile at more than $320,000$. In terms of the share of debt in foreign currency, while the vast majority of firms have debt in both domestic and dollar currencies, around a third of the firms only have debt in domestic currency, and close to a quarter have only debt in dollar currency. In terms of the ratio of collateral pledged to total debt, close to half of all firms have no collateral pledged, in line with the findings of Camara and Sangiacomo [2022], and the median ratio of total collateralized assets to debt at 20%.

The middle panel of Table 5 describes the role of short (under 90 days), medium (between 90 and 365 days), and long-term (over a year at origination) debt. The vast majority of firms exhibit short-term debt, with the median firm showing 67% of its total debt in short-term debt. The second and third rows of this panel show that nearly half of the firms in the sample do not have any medium or long-term debt. This is in line with previous literature,

Table 5: Firm Summary Statistics

	# Firms	p10	p25	p50	p75	p90	p95
Total Debt in USD	107,794	169	1,693	7,576	30,391	123,860	328,551
Share of Debt in USD	83,226	0%	0%	45%	99%	100%	100%
Collateral-Assets to Debt	59,992	0	0	0.19	1.34	3.64	8.17
Short-Term Debt	98,853	0.01%	29.4%	66.8%	100%	100%	100%
Medium-Term Debt	63,362	0%	0%	2.6%	24.7%	57.5%	91.6%
Long-Term Debt	51,658	0%	0%	0%	38.6%	83.6%	100%
Firm-Bank	160,986	1	1	1	1.02	1.6875	2
Firm-Bank-Currency	276,059	1	1	1	1.06	1.6	2.4
Firm-Bank-Currency-Term	432,456						
Total Observations	**6,612,819**						

Note: The statistics on Total Debt in USD (first row) are computed by converting total debt to USD at the monthly frequency and then averaged out for all the periods the firm is in the sample. Short-term debt is comprised of debt with less than 90 days in term at the moment of origin of the loan. Medium-term debt is comprised of debt with more than 90 days but less than a year in term at the moment of origin of the loan. Long-term debt is comprised of debt with more than a year in term at the moment of origin of the loan.

which shows the vastly shorter maturity of firm debt in Emerging Markets (compared to the US and other Advanced Economies) and its role in exposing economies to changes in global financial conditions .[12]

The bottom panel of Table 5 describes the links between firms and banks. The median firm only borrows from one bank, and only the top 25% have an average of more than one bank during the sample.

Econometric specification. We estimate variants of the baseline empirical specification:

$$\Delta \log L_{i,b,c,t+j} = \alpha_{i,j} + \alpha_{b,j} + \beta_t^{Supply} \times (x_{i,b,t-1} - \bar{x}_{i,b}) \times \text{Shock}_t^{Supply} +$$

$$+ \beta_t^{Demand} \times (x_{i,b,t-1} - \bar{x}_{i,b}) \times \text{Shock}_t^{Demand} +$$

$$+ \Gamma' Z_{i,b,c,t-1} + e_{i,b,c,t} \tag{19}$$

where $\alpha_{i,j}$ is a firm time fixed effect that captures a firm-specific demand for loans; $\alpha_{b,j}$ is a bank time fixed effect that captures a bank-specific supply for loans; Shock_t^{Supply} and Shock_t^{Demand} are the credit supply shocks identified in the previous sections; $x_{i,b,t-1}$ is the ratio of debt-to-collateral values of firm i with bank b in period $t-1$; $\bar{x}_{i,b}$ is the average value

[12] See Camara and Sangiacomo [2022], Ivashina et al. [2022].

of $x_{i,b,t-1}$ for a firm-bank relationship over the sample; and $Z_{i,b,c,t-1}$ is a vector of controls. Our coefficients of interest are β_t^{Supply} and β_t^{Demand}, which measures how the semi-elasticity of loans with respect to global banks' credit supply and demand shocks depends on within-firm variations in the debt-to-collateral ratio. Throughout, we cluster standard errors in two ways to account for correlation within firms and within quarters.

We control for a number of factors that may simultaneously affect firms' loans and financial position. The firm time fixed effect, $\alpha_{i,t}$, captures a firm-specific demand for loans, which captures firm i's time t specific loan demand across banks. The bank time fixed effect, $\alpha_{b,t}$, captures bank-specific supply for loans, which captures bank b's time t specific supply of loans across firms. This fixed effect captures banks' differential exposure to global banks' credit supply shocks, for instance, through their balance sheet. The vector $Z_{i,b,c,t-1}$ captures other controls, such as dummy variables for the specific currency, lagged values of the interaction terms, and other controls.

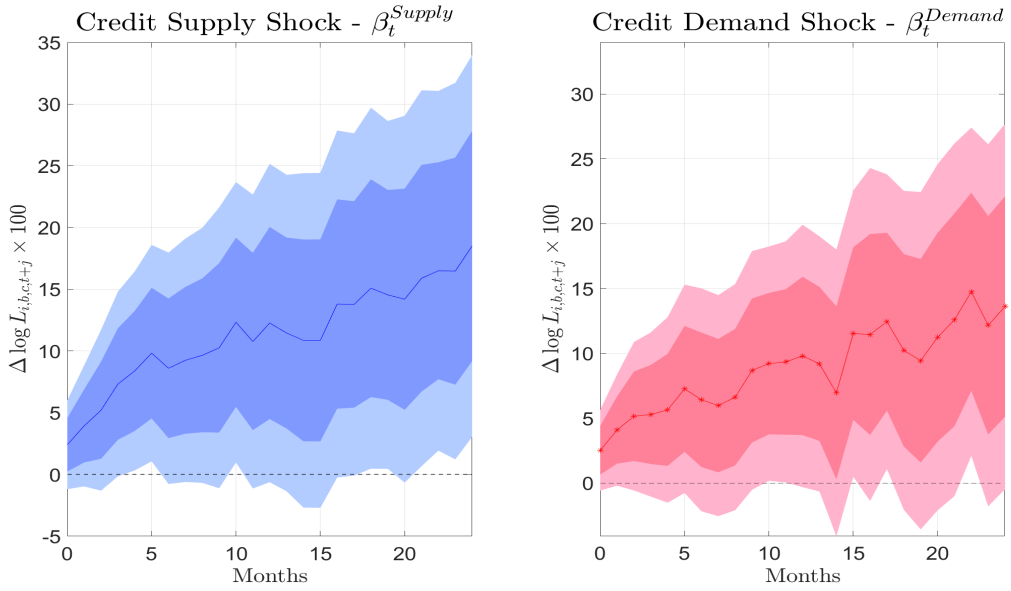
Studying the interaction between credit shocks and the within-firm variation in financial, i.e., $(x_{i,b,t-1} - \bar{x}_{i,b})$, ensures that our results are not driven by permanent heterogeneity in responsiveness across firms. Firms in the data may be ex-ante heterogeneous in how they respond to these global credit shocks according to their financial position $x_{i,b,t-1}$. For example, firms in risky markets may be permanently more exposed to fluctuations in global financial markets and also permanently more likely to exhibit large leverages. If we had instead interacted the level of financial position with the credit shock, i.e., $x_{i,b,t-1} \times \text{Shock}_t^{Supply}$ or $x_{i,b,t-1} \times \text{Shock}_t^{Demand}$, then our results would be partly determined by such permanent differences in responsiveness. By demeaning financial position within firms, our estimates are instead driven by how a given firm responds to credit shocks when it has relatively higher or lower default ratios of debt to collateral than usual.

4.2 Transmission Results

This section presents our main micro-level results that describe the transmission channels of the Global Bank's credit supply shocks. First, we show relatively more indebted firms are more responsive to credit supply shocks. We show that this differential impact is quantitatively significant, with a firm one standard deviation above its average debt-to-collateral ratio experiencing an increase in credit XXX larger. We argue that this result is evidence that credit supply shocks are transmitted by relaxing firms' borrowing constraints. Second, we show that this result is asymmetric for credit demand shocks, i.e., that relatively less indebted firms are more responsive to them.

Figure 14 presents the dynamic heterogeneous response to both credit supply and demand shocks according to firms' debt-to-collateral ratio. We begin by describing the heterogeneous impact of credit supply shocks. The left panel of Figure 14 shows that firms with

Figure 14: Differential Response according to Debt-to-Collateral
Ottonello and Song [2022]



Note: The figure is comprised of two sub-figures. The left panel presents the results for the credit supply shock. The right panel presents the results of the credit demand shock. The figures present the estimated parameters β_t^{Supply} and β_t^{Demand} from Equation 19.

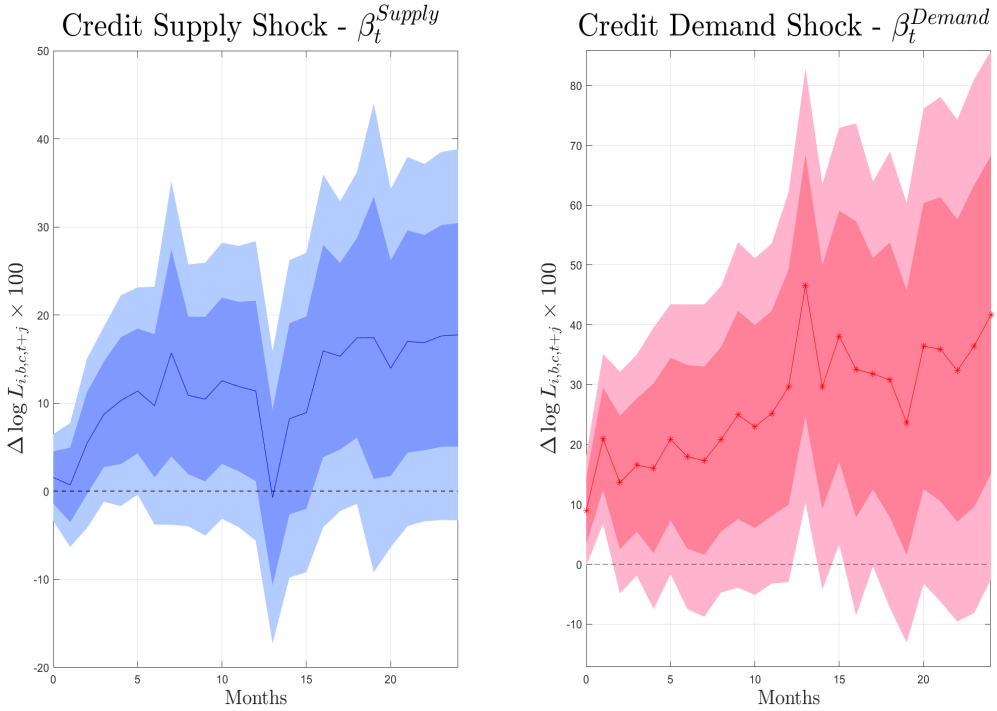
higher debt-to-collateral ratios are more responsive to credit supply shocks. This heterogeneous impact is significantly different from zero at 90% level for several periods ahead, with increasing point estimates across time. From this figure, a firm with one standard deviation higher debt-to-collateral ratio has an elasticity of debt-to-credit supply shock 10% larger.

Second, we describe the heterogeneous impact of credit demand shocks. The right panel of Figure 14 shows that firms with higher debt-to-collateral ratios are less responsive to credit demand shocks. This heterogeneous impact is significantly different from zero at 90% level for several periods ahead, with increasing point estimates across time. From this figure, a firm with one standard deviation higher debt-to-collateral ratio has an elasticity of debt-to-credit demand shock around 7.5% smaller. This result is at odds with the results for the credit supply shock, which suggests that credit supply and credit demand shocks are transmitted differently in Emerging Market Economies.

Estimating the average elasticity & the role firm indebtedness.

Results using our own shocks. Figure 15 shows that our results are robust when estimating Equation 19 replacing the shocks by Ottonello and Song [2022] with our own shocks.

Figure 15: Differential Response according to Debt-to-Collateral Own Shocks



Note: The figure is comprised of two sub-figures. The left panel presents the results for the credit supply shock. The right panel presents the results of the credit demand shock. The figures present the estimated parameters β_t^{Supply} and β_t^{Demand} from Equation 19.

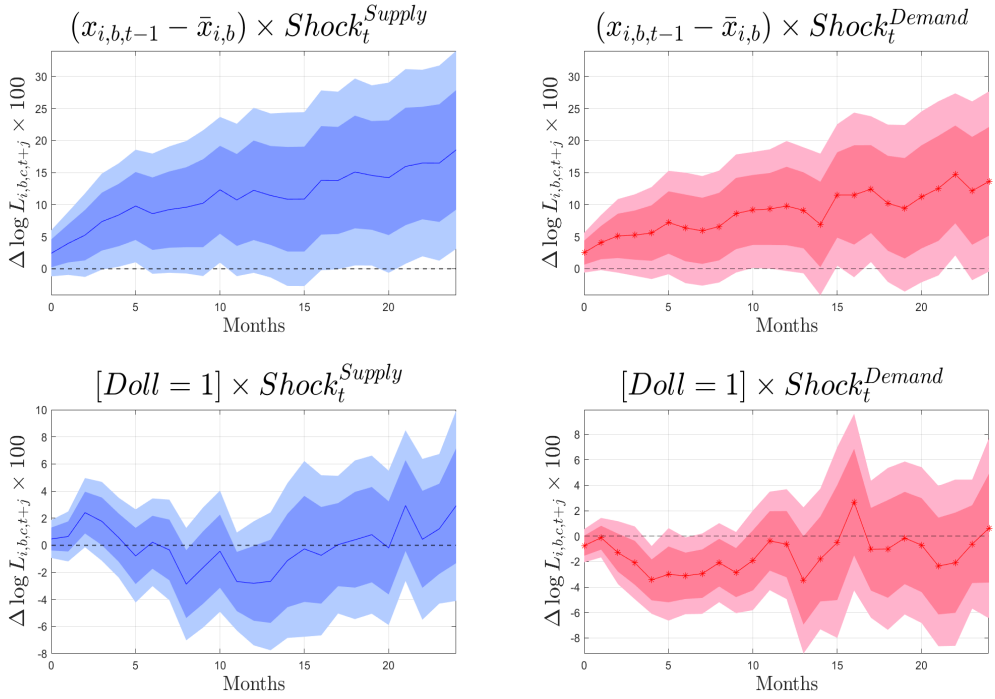
4.3 Additional Results

Results exploiting heterogeneous response by loan currency. We turn to estimate whether loan responses are persistently different across loans' currencies. To do so, we expand the baseline econometric specification to include additional interaction terms. See the econometric specification below.

$$\begin{aligned}\Delta \log L_{i,b,c,t+j} = \alpha_{i,j} + \alpha_{b,j} + \beta_t^{Supply}\left(x_{i,b,t-1} - \bar{x}_{i,b}\right) \times \text{Shock}_t^{Supply} + \\ + \beta_t^{Doll,Supply} \times \mathbb{1}\left[Doll = 1\right] \times \text{Shock}_t^{Supply} + \\ + \beta_t^{Demand}\left(x_{i,b,t-1} - \bar{x}_{i,b}\right) \times \text{Shock}_t^{Demand} + \\ + \beta_t^{Doll,Demand} \times \mathbb{1}\left[Doll = 1\right] \times \text{Shock}_t^{Demand} + \\ + \Gamma' Z_{i,b,c,t-1} + e_{i,b,c,t} \end{aligned} \tag{20}$$

Figure 16 presents the results of estimating Equation 20. The first row shows that our benchmark results are robust, where firms with higher debt-to-collateral ratios are relatively more reactive to credit supply shocks and relatively less reactive to credit demand shocks. The bottom left panel shows that a loan's currency does not seem to react heterogeneously to

Figure 16: Diff. Response: Debt-to-Collateral & Currency
Ottonello and Song [2022] Shocks



Note: The figure is comprised of four sub-figures organized in two columns and two rows. The left column presents the results of the credit supply shock. The right column presents the results of the credit demand shock. The top row presents results for differential response according to the debt-to-collateral ratio. The bottom row presents results for differential response according to the currency of the loan. The figures present the estimated parameters β_t^{Supply} and β_t^{Demand} from Equation 20.

credit supply shocks, with estimates close to zero with large confidence intervals. However, the bottom right panel shows that loans in dollar currency seem more reactive to credit demand shocks, falling more than 3% compared to local currency loans. This relatively larger impact is statistically different from zero during the first year after the shock.

Results using interactions with the level of financial position. So far, we show that our results are robust to our specification of firms' relative indebtedness. In our benchmark specification, we exploit within-firm time-series variation in firms' debt-to-collateral ratio. Next, we test that our results are robust to estimating the interaction between our credit

shocks and the actual level of debt-to-collateral ratio. Our econometric specification becomes

$$\Delta \log L_{i,b,c,t+j} = \alpha_{i,j} + \alpha_{b,j} + \beta_t^{Supply} x_{i,b,t-1} \times \text{Shock}_t^{Supply} +$$

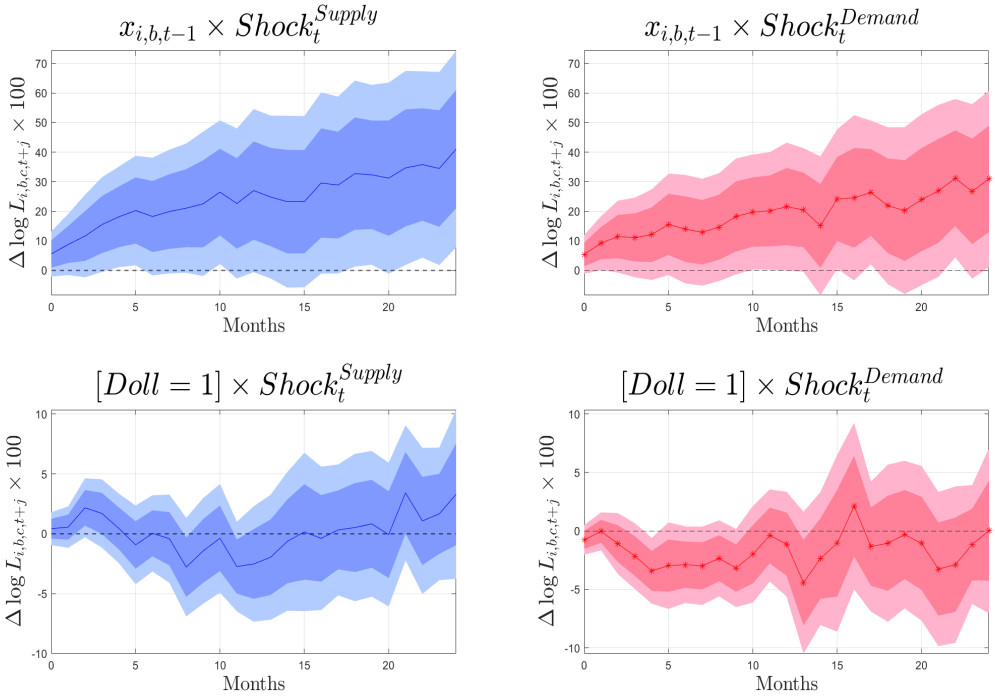
$$+ \beta_t^{Demand} x_{i,b,t-1} \times \text{Shock}_t^{Demand} +$$

$$+ \Gamma' Z_{i,b,c,t-1} + e_{i,b,c,t} \tag{21}$$

where we also introduce interactions with the loan currency.

Figure 17 presents the results of estimating Equation 21. Results are in line with

Figure 17: Diff. Response to the Level of Debt-to-Collateral Ratio



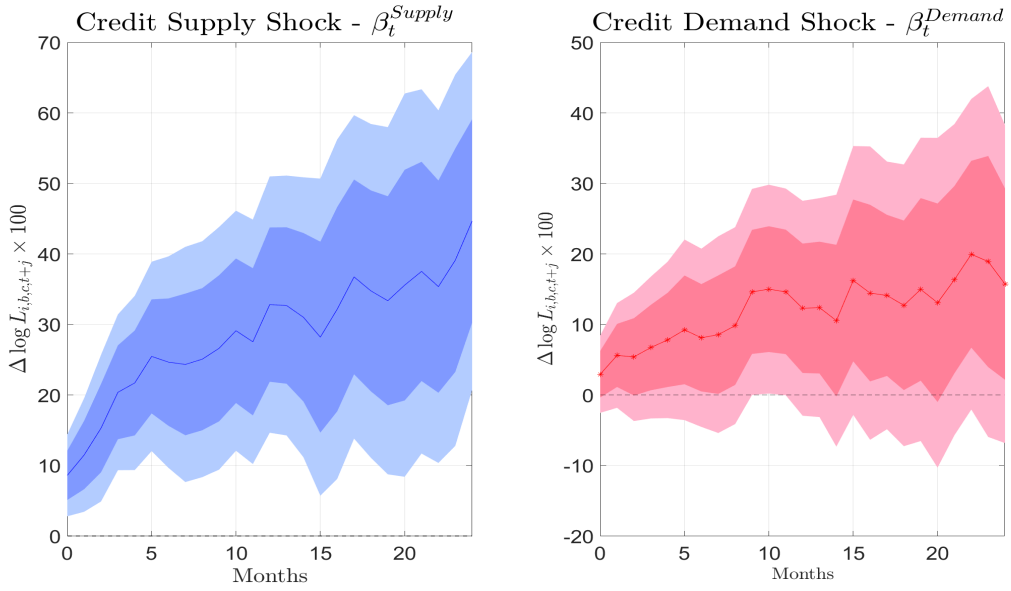
Note: The figure is comprised of four sub-figures organized in two columns and two rows. The left column presents the results of the credit supply shock. The right column presents the results of the credit demand shock. The top row presents results for differential response according to the debt-to-collateral ratio. The bottom row presents results for differential response according to the currency of the loan. The figures present the estimated parameters β_t^{Supply} and β_t^{Demand} from Equation 21.

those in our benchmark specification.

Results after the GFC. Lastly, we show that our results are robust after the Great Financial Crisis. To do so, we re-estimate Equation 19 for a sample starting in January 2010.

Figure 18 presents the results of this robustness check. Comparing the estimates with those in Figure 14, the estimated coefficients are larger for the sample starting in 2010.

Figure 18: Differential Response according to Debt-to-Collateral
Ottonello and Song [2022]



Note: The figure is comprised of two sub-figures. The left panel presents the results for the credit supply shock. The right panel presents the results of the credit demand shock. The figures present the estimated parameters β_t^{Supply} and β_t^{Demand} from Equation 19 for a sample starting in January 2010.

On the one hand, this could be driven by the increasing influence of Global Banks in Emerging Markets over time. On the other hand, this could be driven by the fact that the start of our sample coincides with a large recession in the US in which sovereign default risk might have insulated the Uruguayan economy from fluctuations in global banks' net worth.

5 Conclusion

This paper provides new evidence on the causal impact of global banks' net worth on Emerging Market Economies through financial and real economy channels. By leveraging high-frequency co-movement between global bank stock prices and credit spreads around earnings announcements, we develop an identification strategy that isolates exogenous global bank credit supply shocks. Our findings demonstrate that these shocks significantly affect financial conditions in EMEs, leading to exchange rate appreciation, lower borrowing costs, and increased equity valuations. At the macroeconomic level, we show that global bank credit supply shocks generate persistent effects on economic activity, including higher industrial output, reduced unemployment, and increased trade.

Our firm-level analysis highlights a crucial transmission mechanism: firms with higher leverage and closer proximity to default are more responsive to global bank credit supply shocks. This suggests that improvements in global banks' net worth relax borrowing

constraints in EMEs, amplifying the impact of these shocks on economic activity. Additionally, we document that the response to credit demand shocks differs significantly, reinforcing the importance of distinguishing between credit supply and demand dynamics in understanding the international transmission of financial shocks.

Taken together, our results highlight the central role of global banks in shaping business cycles in emerging markets. Policymakers should recognize that fluctuations in global banks' net worth can have significant spillover effects, influencing credit conditions and macroeconomic stability in EMEs. Future research could explore heterogeneity in transmission mechanisms across different institutional and financial structures, as well as the potential role of macroprudential policies in mitigating adverse spillovers from global financial shocks.

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A VAR Model Details

First, we estimate the impulse response functions through a pooled panel Bayesian VAR model as in Canova and Ciccarelli [2013] to capture the average impact of surprises in banks' networth in AEs and EMEs. The model is briefly described below,

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{N,t} \end{pmatrix} = \begin{pmatrix} A^1 & 0 & \cdots & 0 \\ 0 & A^1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A^1 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{N,t-1} \end{pmatrix} + \cdots$$
$$+ \begin{pmatrix} A^p & 0 & \cdots & 0 \\ 0 & A^p & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A^p \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{N,t-p} \end{pmatrix} + \begin{pmatrix} C \\ C \\ \vdots \\ C \end{pmatrix} x_t + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \vdots \\ \epsilon_{N,t} \end{pmatrix} \tag{22}$$

where $y_{i,t}$ denotes an $n \times 1$ vector of n endogenous variables of country i at time t and A^j is an $n \times n$ matrix of coefficients providing the response of country i to the j^{th} lag at period t. Note that by assuming that $A_1^j = A_n^j = A^j$ for $j = 1, \ldots, n$ implies the assumption that the estimated coefficients are common across countries. x_t is a vector $m \times 1$ of exogenous variables, C is a $Nn \times 1$ vector of constant terms which are also assumed to be common across countries.[13] The vector of country specific variables is comprised of: (i) the nominal exchange rate with respect to the U.S. dollar; (ii) a long term interest rate; (iii) an equity index; (iv) an industrial production index; (v) a consumer price index. The vector of exogenous variables is comprised by the two shocks to the networth of banks described above.

[13] The model described in Equation 22 can be re-written into a conventional VAR model. This single VAR model is estimated for the whole set of units. Priors are assumed to follow the standard Normal-Inverse Wishart distribution. The prior over C is set to have a mean of 0 and a dispersion of 100. The model is estimated using the BEAR toolbox from the ECB. See Dieppe et al. [2016].