The Financial Propagation Mechanism of Commodity Booms*

Hiroshi Toma
University of Michigan
Job Market Paper

Walter Cuba
Central Reserve Bank of Peru

This draft: November 4th, 2024

Click here for the latest version

Abstract

We examine the financial propagation mechanism in small open economies (SOEs) that links commodity price booms to the non-commodity sector via banks. We propose a mechanism in which a commodity price boom leads to an increase in deposits from commodity exporters into domestic banks, enabling banks to expand their loan supply to non-commodity firms. Then, these non-commodity firms increase their output. Using detailed bank-firm-loan microdata from Peru—an SOE that experienced a commodity price boom in the 2000s—we provide empirical evidence supporting this mechanism. We then incorporate this mechanism into a SOE model with banks to quantify its aggregate importance. After calibrating the model to Peruvian data, our simulations suggest that the mechanism explains a ninth of the observed 65% Peruvian GDP growth in the 2003–2011 commodity price boom episode.

Keywords: commodity booms, small open economies, heterogeneous banks

JEL codes: F41, G21

*The views expressed herein are those of the individual authors and do not necessarily reflect the official positions of the Central Reserve Bank of Peru.
Email: htoma@umich.edu

1 INTRODUCTION

A well-documented fact in small open economies (SOE) is that commodity prices, or more generally terms of trade, are important sources of business cycle fluctuations (Mendoza, 1995; Kose, 2002; Schmitt-Grohé & Uribe, 2018; Fernández et al., 2023). The literature has identified several mechanisms by which commodity shocks propagate to the broader economy: wealth effects (Salter, 1959; Swan, 1963; Corden & Neary, 1982), sovereign interest rate premia (Shousha, 2016; Drechsel & Tenreyro, 2018), labor reallocation (Benguria et al., 2023), among others. At the same time, many emerging market SOEs exhibit significant financial constraints, and the domestic banking system serves as a significant amplifier of shocks in these countries (Paravisini, 2008; Schnabl, 2012; Bustos et al., 2016; Morelli et al., 2022).

In this paper, we explore how a commodity price boom interacts with the bank loan supply in SOEs. More specifically, we propose a novel propagation mechanism that goes from commodity producers to non-commodity producers via the domestic banking system. We show that after a commodity boom, commodity exporters increase their deposit holdings in domestic banks, prompting banks to expand their loan supply to non-commodity firms. Then, non-commodity firms increase their output. Our proposed mechanism complements the previous studies of commodity booms in SOEs by highlighting the role of the domestic banks in the local transmission of shocks from the commodity sector to the non-commodity sector.

We document three different facts using detailed matched bank-firm-loan microdata from Peru, an SOE that experienced a mining commodity price boom in the 2000s. First, banks are heterogeneously exposed to the mining commodity sector through their different mining client portfolios. When mining commodity prices rise, banks with greater exposure to the mining sector receive more firm deposits. After an annual 100 percent increase in commodity prices, the average exposed bank registers an increase of 65 percent in firm deposits compared to a non-exposed bank.

Second, we exploit the heterogeneity in bank-borrower relationships to find that more mining-exposed banks supply more loans to non-mining firms after mining commodity prices increase. After a 100 percent hike of commodity prices, the average exposed bank increases its loan supply by 15 percent when compared to a non-exposed bank.

Third, we document that non-commodity firms more exposed to mining commodity prices through their banks increase their output after a commodity price surge. When commodity prices double, the average exposed non-commodity firm increases its total sales by 3 percent compared to a non-exposed non-commodity firm.

To quantify the aggregate importance of this mechanism, we embed it into a static SOE model with banks and an endowment commodity sector. Consistent with our empirical findings, we assume commodity exporters hold deposits in domestic banks. Furthermore, as the data suggest, banks are heterogeneous in their exposure to the commodity sector, such that each bank receives different amounts of deposits from the commodity sector after a commodity price shock.

The model contains two key financial frictions. First, non-commodity firms face a working capital constraint, which implies that they must pay for part of their expenses before production takes place. This friction creates the need for these firms to take loans from banks. Second, banks face a balance sheet constraint, so that they must obtain foreign wholesale funding to cover the loans they supply when deposits and equity are not enough. Importantly, they must pay a premium on their foreign wholesale funding that is decreasing in the amount of deposits they hold. This friction links the amount of deposits held to the interest rate banks charge for their loans.

The model's tractability allows us to derive structural equations that correspond with the regressions estimated in the empirical analysis. This way, we give a structural interpretation to the estimated coefficients and recover the values for all the bank-related parameters in the model. We calibrate the remaining parameters following the standard SOE literature and to match the change in Peruvian GDP in the 2003–2011 commodity price boom. After simulating the non-linear model using hat algebra, we successfully match the targeted moment—GDP growth— and achieve a good fit to untargeted moments.

We then conduct a counterfactual exercise where we turn off the financial propagation mechanism to quantify its aggregate importance. More specifically, we turn off the pass-through from commodity prices to firm deposits. Comparing GDP growth in the baseline and counterfactual scenarios reveals that the financial propagation mechanism accounts for a ninth of the observed GDP growth in Peru of 65 percent during the 2003–2011 commodity price boom period.

Literature review. Our paper relates to (i) the wider literature that studies the aggregate effects of terms of trade and commodity price fluctuations in small open economies (Salter, 1959; Swan, 1963; Corden & Neary, 1982; Mendoza, 1995; Kose, 2002; Schmitt-Grohé & Uribe, 2018; Fernández et al., 2023) and (ii) the literature that studies how financial frictions interact with commodity shocks (Shousha, 2016; Drechsel & Tenreyro, 2018). We contribute to the previous research by providing evidence of a new financial propagation mechanism of commodity shocks in SOE that works through the banking system.

We also connect with the recent literature that focuses on studying the transmission channels of a commodity price shock using microdata (Allcott & Keniston, 2018; Benguria et al., 2023; Silva et al., 2024). Here, our contribution lies in tracing and quantifying the importance of the financial propagation mechanism using detailed bank-firm-loan matched microdata.

Our empirical strategy is close to Peek & Rosengren (2005); Paravisini (2008); Schnabl (2012); Federico et al. (2023), who use detailed bank and loan microdata to study how banks propagate shocks across firms, sectors, and geographies. Here, we take a step further and embed our proposed financial mechanism into a general equilibrium model disciplined by microdata. Thus, we not only provide empirical evidence that supports the financial propagation mechanism, but also quantify its aggregate importance.

On the theoretical side, we build on the standard textbook SOE model of Uribe & Schmitt-Grohé (2017). Our contribution is to extend it with financial frictions and heterogeneous banks as follows. Firms need to take out loans because they are subject to a working capital constraint, following Neumeyer & Perri (2005); Jermann & Quadrini (2012). Banks are also subject to a balance sheet constraint, as they have to obtain foreign wholesale funding to cover their loans, as in Wang et al. (2022); Whited et al. (2022).

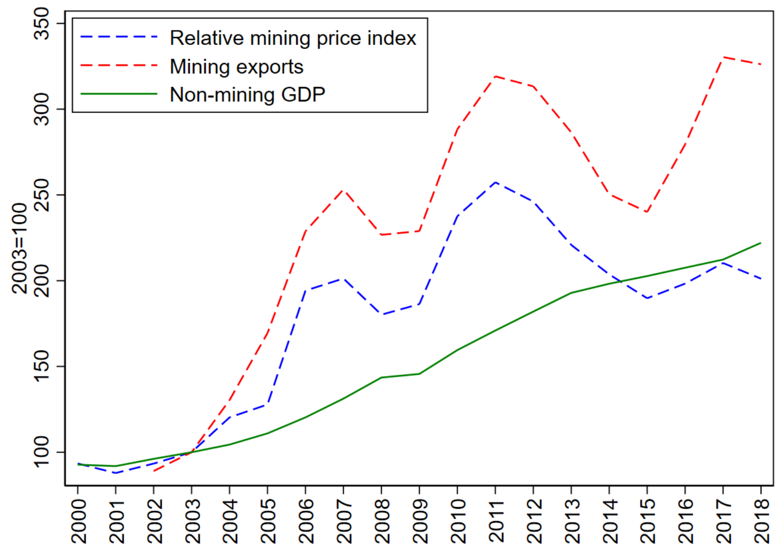
Section 2 provides details on the global mining price boom and the Peruvian economy. Section 3 introduces the data and the exposure measures we use. Section 4 presents the empirical evidence. In Section 5 we introduce the theoretical framework. Section 6 quantifies the aggregate importance of the mechanism. Finally, Section 7 concludes.

2 Setting: Global mining price boom and the Peruvian economy

From the early 2000s to the mid-2010s, the world experienced a mining commodity price boom, mainly driven by a demand expansion from China (Fernández et al., 2023). This boom represented a substantial shock for those SOEs where the mining commodity sector plays an important role. In this paper, we focus on Peru, one such economy that benefited greatly from the boom.

Peru is an ideal case study for examining the aggregate effects of commodity price shocks on commodity-exporting SOEs. First, the Peruvian economy exports a diverse basket of mining commodities: copper, gold, iron, lead, silver, tin, zinc, and aluminum, among others. Thus, we get

Figure 1: Commodity price boom



Note: For the weighted relative mining price index we first normalize the dollar prices for the commodity prices and then divide them by the Peruvian imports price index. The weights we use are the average shares each mining commodity has across the sample over total mining commodity exports. For the mining exports we first normalize the dollar value for the mining exports and then divide them by the Peruvian imports price index. The non-mining GDP is expressed in real domestic currency units and normalized.

variation across different minerals. Second, the mining commodity sector has a sizable presence in the Peruvian economy. During the boom period, the mining sector represented 60 percent of total exports and 10 percent of real GDP.[1] Then, a mining commodity price shock can produce aggregate effects. Finally, Peru holds a modest share of global markets for these commodities, meaning it is reasonable to assume Peru is a price-taker in international mining commodity markets.[2]

In Figure 1 we report a weighted mining relative price index across all minerals that Peru exports. The mining commodity prices increased sharply. For instance, at its peak in 2011, the prices more than doubled relative to its value at the start of the boom. Figure 1 also shows that mining exports increased over this period, closely following the price index.[3]

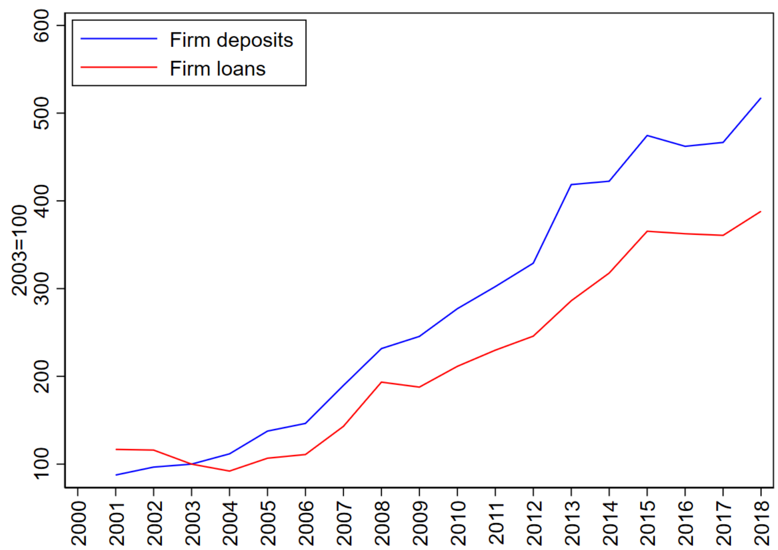
Related to this boom, Figure 1 additionally shows the evolution of non-mining GDP. We observe that this variable starts growing around the beginning of the boom and keeps increasing over the boom period. While non-mining GDP is not directly linked to the booming mining sector, we will argue later that the two are connected through the banking system.

[1] Appendix Figure A.1 shows the share of each mining commodity in the total mining exports.

[2] We present the world output shares for Peru in 2011, the peak year of the mining commodity price boom, in Appendix Table A.1.

[3] This boom was mostly price-driven rather than quantity-driven. We show individual mining price and quantity indices in Appendix Figures A.2 and A.3, respectively. Quantities remained relatively flat for most minerals, the only exceptions being copper and iron, which benefited late into the boom from large mining projects entering production.

Figure 2: Firm deposits and firm loans



Note: The series are expressed in real domestic currency units and normalized.

Figure 2 presents the evolution of relevant variables in the banking sector, namely firm deposits and firm loans. The former relates to the deposits coming from the private sector firms to the domestic banks, while the latter refers to the loans going from the domestic banks to the private sector firms. We see that both series register an increase in the early years of the boom and keep on growing over the boom episode. In the next sections, we will show that part of this growth is due to banks being connected to the booming mining sector.

3 Data

For our empirical analysis, we combine several data sources that result in a matched bank-firm-loan dataset for the Peruvian economy from 2005 to 2018 with annual frequency. First, we use firm-level customs data extracted from ADEX Data Trade. From this dataset, we identify the mining commodity exporters and their exports.

Second, we retrieve end-of-year bank balance sheet data from the Peruvian banking regulator (SBS). We focus on firm deposits, which is the total amount of deposits from private sector firms held in the banks under consideration. We have information for 9 domestic banks, whose firm deposits represented 7 percent of the Peruvian GDP on average over the analyzed period. We show the basic statistics in Appendix Table A.2.[4]

[4]The total Peruvian financial system is composed of banks and other non-banking institutions (*cajas municipales*,

Third, we use the Peruvian firm survey (EEA) to recover firm-level balance sheet information. We have information from approximately 5,600 non-mining firms that belong to the following sectors: construction, education, hotels, manufactures, restaurants, retail, services, transport and communications, and travel agencies.[5] These firms are mostly medium to large when measured by their total sales. On average, between 2005 and 2018, their aggregate sales represented 29 percent of the GDP. We present the statistics for the firms in Appendix Table A.4.

Fourth, we work with the Peruvian credit registry. This rich dataset provides end-of-year annual loan-level information on the lending institution, the borrowing non-mining firm, and the outstanding loan amount. We focus on a subsample that considers all the loans received by the non-mining firms that appear in the firm survey. The total loans in this subsample represented 102 percent of GDP on average within the analyzed period. We give more detail about the loan-level statistics in Appendix Table A.3.

Lastly, we retrieve the international commodity prices from the IMF commodity price database. We have information on aluminum, copper, gold, iron, lead, silver, tin, and zinc prices. The metals that are not considered in the commodity price database are assigned the all-metals average price index. As per the usual SOE assumption, we consider these prices to be exogenous to the Peruvian economy.

All commodity prices are divided by the Peruvian import price index and normalized to 2007=100. All other variables are converted to Peruvian soles (PEN) using the average nominal exchange rate for the period and deflated by the Peruvian GDP deflator.

3.1 Exposure of banks and non-mining firms to mining sector

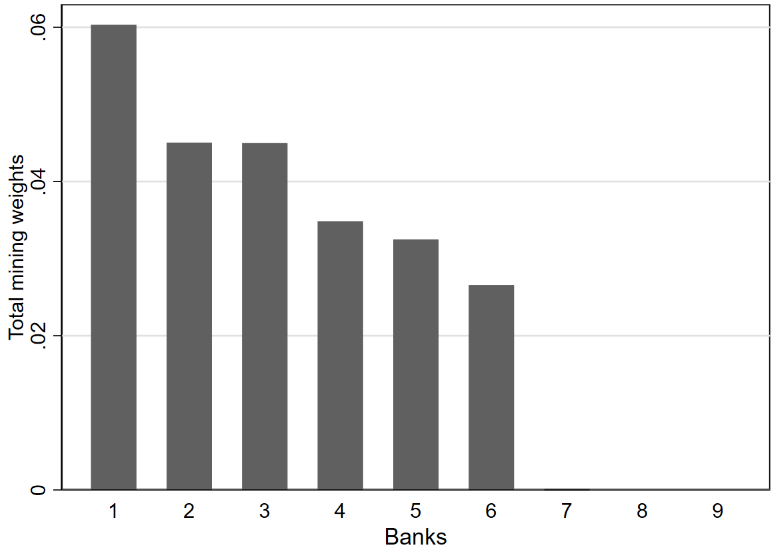
The key variable in the empirical analysis is the exposure of banks and firms to the mining commodity prices. First, we identify the mining commodity exporters in the customs data, each indexed by x. We classify a firm as a mining commodity exporter if its average mining exports are greater or equal to 50 percent of their total exports.

---

cajas rurales, and *financieras*). With respect to the total financial system, the 9 banks in our sample represented 87 percent of total assets, 87 percent of total firm loans, and 88 percent of total firm deposits on average between 2005 and 2018. We treat merged banks as single entities and combine their accounts. We exclude banks that exclusively serve foreign-owned firms or specialize in credit card and consumer loans, as they fall outside the scope of our analysis. Lastly, we do not consider the *cajas municipales*, *cajas rurales*, and *financieras*, as they were not permitted to hold firm deposits during the period of analysis due to regulatory restrictions.

[5] Although information on non-mining commodity-producing firms is available in the firm survey, we exclude these firms from the sample because their prices may be correlated with those of the mining sector. The excluded sectors include agriculture, electricity, fishing, and oil and gas.

Figure 3: Total mining weights in banks



Note: Figure shows the total weight of mining commodity firms in the total loan portfolio of the 9 banks under consideration. We use fixed 2004 weights.

Next, we define ω_{bx} as the weight of mining firm x in the total loan portfolio of bank b, with non-mining clients having 0 weight. Because our focus is on the response of deposits to a commodity boom, we would ideally use data on deposits to measure the strength of the relationship between a bank and a mining firm. Unfortunately, deposit data broken down by bank and firm does not exist. Instead, under the assumption that the bank-firm relationship influences both deposits and loans (i.e., mining firms hold deposits in the same banks from which they borrow), we use the loans from a bank to a mining firm as a proxy for the strength of their deposit-based relationship.

Moreover, the weights we use are fixed to their pre-sample values to address the concern that either banks could look for mining clients after the boom or the mining companies could look for loans after the boom.[6] We report the sum of all mining weights across banks in Figure 3, where we see that the banks under consideration are heterogeneously exposed to the mining sector.

We now combine the heterogeneous exposure of each bank b to the mining sector with the time variation of mining commodity prices. We define the weighted mining commodity price exposure index E_{bt} as

$$E_{bt} = \sum_{x} \omega_{bx} \ln \left(p_{xt} \right), \tag{1}$$

[6]To construct the constant weights, we take the 2004 end-of-year loan portfolio weights for each mining exporting company operating in that period.

where ω_{bx} is the aforementioned weight of mining firm x in total loan portfolio of bank b and p_{xt} is the relevant mineral price for mining firm x (i.e., copper price for a copper exporter, gold price for a gold exporter).[7] In line with the SOE assumption, we treat commodity prices as exogenous to Peruvian banks and firms. Since weights ω_{bx} are fixed, then time-variations in E_{bt} arise solely from changes in commodity prices, making the index exogenous to the Peruvian economy.

Likewise, we construct a measure of how non-mining firms are exposed to mining commodity prices through their associated banks. For non-mining firm i, we define the weighted mining commodity price exposure index e_{it} as

$$e_{it} = \sum_b s_{ib} E_{bt}, \tag{2}$$

where s_{ib} is the fixed pre-sample weight of bank b in the total loan portfolio of non-mining firm i. Banks with no exposure have a weight of 0.[8]

4 Empirical evidence

The goal in this section is to empirically identify the existence of the financial propagation mechanism from the commodity price boom to the rest of the economy. We use detailed micro-data from Peru to provide 3 different empirical facts after a mining commodity price increase: (i) banks that were related to mining firms received more firm deposits; (ii) banks that were related to mining firms increased their loan supply to non-mining firms; and (iii) non-firms related to exposed banks increased their output. Together, these 3 facts provide a detailed step-by-step account of the financial propagation mechanism of the commodity price boom to the non-commodity real economy of Peru.

4.1 Facts

Fact 1: More exposed banks receive more firm deposits. We first establish that banks which were exposed to the mining exporters experienced an increase in their deposits. We rely on the exogeneity assumption for mining commodity prices in SOE and exploit the heterogeneous expo-

[7] In the case of commodity exporters that export more than one mining commodity, we take the price of the most important mineral in their export basket.

[8] The weights are fixed to their 2004 values.

Table 1: Bank-level results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	$\ln(D_{bt})$	$\ln\left(D_{bt}^{dom}\right)$	$\ln\left(D_{bt}^{usd}\right)$	$\ln(D_{bt})$	$\ln(L_{bt})$	$\ln\left(D_{bt}^{hh}\right)$
E_{bt}	23.598***	23.488***	22.790***	21.663**	6.478***	-0.957
	(5.000)	(5.234)	(7.083)	(8.322)	(2.363)	(3.520)
E_{bt-1}				0.655		
				(7.714)		
FE	Bank, period	Bank, period	Bank, period	Bank, period	Bank, period	Bank, period
Obs.	121	121	121	114	120	121
Within R2	0.252	0.225	0.178	0.249	0.122	0.165

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Column 1 shows the result of estimating Equation 3. Column 2 changes the dependent variable for deposits in domestic currency. Column 3 changes the dependent variable for deposits in US dollars. Column 4 adds a lag of the independent variable to the estimation. Column 5 changes the dependent variable for total firm loans. Column 6 changes the dependent variable for household deposits.

sure to such prices across banks to estimate

$$\ln(D_{bt}) = \alpha_b + \alpha_t + \beta E_{bt} + u_{bt}, \tag{3}$$

where D_{bt} are the firm deposits, E_{bt} is the bank-level weighted mining commodity price exposure index from Equation 1, α_b is a bank fixed effect, and α_t is a period fixed effect.[9]

For any given bank b in our dataset it holds that the sum of total weights of mining firms $\sum_x \omega_{bx} \neq 1$, as no bank has a loan portfolio that consists only of mining firms. Thus, our regression is subject to an incomplete weights problem, where we do not account for the effect that the non-mining clients have over banks. This may bias the results (Borusyak et al., 2022). To control for this under our panel setting, we include an interaction of the total bank-level weights $\sum_x \omega_{bx}$ with period fixed effects in our regressions.

For this regression, we use data at the bank-level. Column 1 of Table 1 shows there is a positive elasticity between the firm deposits of a bank and its exposure to mining commodity prices. Given an average ω_{bx} of 0.04 across exposed banks (see Figure 3), a 100 percent increase in mining commodity prices would result in an increase of 65 percent in firm deposits within exposed banks ($E_{bt} > 0$) compared to non-exposed banks ($E_{bt} = 0$).[10]

While we only have information for total firm deposits across all sectors and not mining-

[9]Firm deposits refer to deposits that originate from firms. Therefore, it excludes other types of deposits, such as those that come from households.

[10]The calculation we perform is $\beta \times \overline{\omega_{bx}} \times [\ln(2)] \approx 65\%$, where $\overline{\omega_{bx}} = 0.04$ is the average mining commodity weight across exposed banks.

specific firm deposits, we argue that the positive effect we find is mostly due to the mining sector increasing their firm deposit holdings after mining commodity prices increase. The identification strategy we use relies on two elements that should isolate the effects coming from the mining sector. First, the mining exposure weights ω_{bx} guarantee we only focus on banking relationships with mining commodity firms. Second, the commodity prices p_x are relevant for mining commodity firms and not necessarily firms from other sectors.[11]

Fact 2: More exposed banks supply more loans to non-mining firms. We now turn to analyzing whether exposed banks supply more loans to their non-mining firm clients. For this, we follow the Khwaja & Mian (2008) identification strategy, which relies on non-mining firms being matched to multiple banks. More specifically, we estimate

$$\ln\left(L_{ibt}\right) = \alpha_{ib} + \alpha_{it} + \zeta E_{bt} + u_{ibt}, \tag{4}$$

where L_{ibt} are the outstanding loans from bank b to non-mining firm i, E_{bt} is the bank-level weighted mining commodity price exposure index from Equation 1, α_{ib} firm-bank fixed effect that controls for the special relationship the pair could have, and α_{it} firm-period fixed effect that controls for any loan demand shocks. We also include an interaction of the total bank-level weights with period fixed effects to control for the incomplete weights problem.

In this part, we use data at the bank-firm level. The combination of fixed effects results in a within-firm specification, where the sample only consists of firms that have loans with more than one bank. Then, by assuming mining commodity prices are exogenous to the Peruvian economy and exploiting the within-firm and across-bank variation, the coefficient ζ identifies the loan supply shock coming from the banks. Moreover, we trim the dependent variable at 1 and 99 percent each period.

Column 1 of Table 2 presents the result. We find a positive elasticity between the loans a bank gives to its non-mining clients and the exposure of that bank to mining commodity prices. For a non-mining firm, a 100 percent increase in mining commodity prices would correspond with an increase of 15 percent in loans supplied from exposed banks ($E_{bt} > 0$) when compared to non-exposed banks ($E_{bt} = 0$).[12]

Fact 3: More exposed non-mining firms produce more. We now ask about what occurs with

[11] According to professionals from the Peruvian mining industry who were interviewed, mining companies must hold deposits in domestic banks for several operational motives: Paying suppliers, workers, and taxes, as well as financing reinvestment and other precautionary motives.

[12] The calculation we perform is $\zeta \times \overline{\omega_{bx}} \times [\ln(2)] \approx 15\%$.

Table 2: Loan-level results

	(1)	(2)	(3)	(4)
Dep. var.	$\ln(L_{ibt})$	$\ln(L_{ibt})$	$\ln(L_{ibt})$	$\mathbb{I}^{entry}_{ibt}$
E_{bt}	5.240*	10.509***	9.633***	-0.001
	(2.835)	(2.951)	(3.562)	(0.370)
E_{bt-1}			-5.035	
			(3.450)	
FE	Firm × bank, firm × period	Firm × bank, sector × region × period	Firm × bank, firm × period	Firm × bank, firm × period
Obs.	75,011	105,806	73,121	143,867
Within R2	0.002	0.001	0.002	0.004

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm-bank and firm-period in parentheses. Column 1 shows the result of estimating Equation 4. Column 2 changes the set of fixed effects. Column 3 adds a lag of the independent variable to the estimation. Column 4 examines the extensive margin.

the production of non-mining firms related to exposed banks. First, we measure production using total sales in deflated monetary units. Second, we maintain the exogeneity assumption for the mining commodity prices and leverage the heterogeneity in loan portfolios across non-mining firms to estimate

$$\ln(p_{it}y_{it}) = \alpha_i + \alpha_t + \kappa e_{it} + u_{it}, \quad (5)$$

where $p_{it}y_{it}$ represents the total sales of non-mining firm i, e_{it} is the firm-level weighted mining commodity price exposure index from Equation 2, α_i is a firm fixed effect, and α_t is a period fixed effect. As in the previous cases, this regression is also subject to the missing weights problem, for which we add an interaction of the total weights with period fixed effects. For this regression, we use firm-level data. We also trim the dependent variable at 1 and 99 percent in each period.

Column 1 of Table 3 shows the result. There is a positive elasticity between the total sales of a non-mining firm and its exposure to the mining commodity prices through banks. A 100 percent increase in mineral prices would imply a 3 percent increase in the total sales of exposed firms ($e_{it} > 0$) with respect to non-exposed firms ($e_{it} = 0$).[13]

[13]The calculation we perform is $\kappa \times \overline{\omega_{bx}} \times \overline{s_{ib}} \times [\ln(2)] \approx 3\%$, where $\overline{s_{ib}} = 0.97$ is the average weight exposed banks have in the firm loan portfolios.

Table 3: Firm-level results

	(1)	(2)	(3)	(4)
Dep. var.	$\ln(p_{it}y_{it})$	$\ln(p_{it}y_{it})$	$\ln(p_{it}y_{it})$	$\ln(w_t h_{it})$
e_{it}	1.004***	1.062***	0.694***	1.035***
	(0.320)	(0.339)	(0.250)	(0.300)
e_{it-1}			0.634**	
			(0.257)	
FE	Firm, period	Firm, period	Firm, period	Firm, period
Obs.	38,163	34,275	36,758	38,163
Within R2	0.001	0.003	0.001	0.001

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm in parentheses. Column 1 shows the result of estimating Equation 5. Column 2 changes the set of fixed effects. Column 3 adds a lag of the independent variable to the estimation. Column 4 changes the dependent variable for the wage bill.

4.2 Additional bank-level results

Firm deposits by currency. In Peru, firms can hold deposits in either domestic currency or dollars. The average of firm deposits in domestic currency over total firm deposits is 48 percent for the 2005-2018 period. To assess whether deposit responses differ by currency, we estimate Equation 3, but differentiate deposits by domestic currency (D_{bt}^{dom}) or dollars (D_{bt}^{usd}). For consistency, dollar-denominated deposits are converted into domestic currency. Columns 2 and 3 of Table 1 show that different currencies do not imply significantly different responses with respect to the mining commodity prices, as the estimated coefficients are similar between them and are also close to the main result of Column 1.

Lagged effects. Our main specification does not account for potential lagged effects of past shocks on current deposits. To address this, we estimate Equation 3 incorporating a the lag of the weighted mining commodity price exposure index. Because of the lag, we shorten our sample to cover the 2006-2018 period for this specification. Column 4 of Table 1 shows that the lagged value of the independent variable is not statistically significant, whereas the current value remains significant. This allows us to rule out the possibility of significant lagged effects of mining price exposure on firm deposits.

Total firm loans. We estimate Equation 3 using the total of firm loans L_{bt} given by each bank to private sector firms as the dependent variable. Column 5 of Table 1 displays that total firm loans also increase after a commodity price shock. This suggests the loan-level result we found for Fact 2 also holds at the aggregate bank-level.

Household deposits. While our main focus is on firm deposits, we also analyze the response of household deposits to the changes in mining commodity prices. Specifically, we estimate Equation 3, but substitute the dependent variable to the deposits made by households D_{bt}^{hh} in the different banks. Column 6 of Table 1 shows there is not a statistically significant effect of mining commodity prices on household deposits.

4.3 Additional loan-level results

Alternative fixed effects. Our within-firm identification we use (Khwaja & Mian, 2008) relies on our sample consisting only of firms that have loans with more than one bank. This discards firms with only one banking relationship. Following Degryse et al. (2019), we can use a different combination of fixed effects to prevent this issue. In particular, we estimate Equation 4 but replace α_{it} with α_{srt}, where s denotes 2-digit ISIC sector and r denotes geographic region. We present the results in Column 2 of Table 2. The result of the main regression holds, albeit with two differences. First, the number of observations increases because now we include firms that have loans with only one bank. Second, the magnitude of the coefficient is larger. Then, we may interpret the main regression as a lower bound for the effect of mining commodity prices on loan supply.

Lagged effects. To assess potential lagged effects of past mining price exposure on current loans, we estimate Equation 4 adding a lag of the independent variable. Moreover, the sample is now restricted to 2006-2018 due to the addition of the lag. Column 3 of Table 2 shows that the lagged independent variable is not statistically significant, while the current variable remains significant. We interpret this as evidence that bank exposure to mining commodity prices affects loan supply contemporaneously, with no significant lagged effects.

Extensive margin. The focus of our analysis so far has been on the intensive margin. Here, we modify our within-firm specification to explore if there is also an effect on the extensive margin. Specifically, we introduce the indicator variable $\mathbb{I}_{ibt}^{entry}$, which is equal to 1 if a new relationship is formed between firm i and bank b in period t. We also expand the sample to include all possible bank-firm pairs. For a given bank-firm pair, the sample covers all the periods from 2005 until a relationship is formed. We estimate Equation 4 using $\mathbb{I}_{ibt}^{entry}$ as the dependent variable. We present the results in Column 4 of Table 2, where we do not find a statistically significant effect of mining commodity prices in the extensive margin. Within our medium to large firm sample, loan supply responds to mining commodity prices on the intensive margin, but not on the extensive margin.

4.4 Additional firm-level results

Alternative fixed effects. In our main regression, we did not account for sector-related and geographic region-related unobservables. Thus, we estimate Equation 5, but control for sector-related and geographic region-related unobservables by replacing fixed effect α_t with α_{srt}, where s denotes 2-digit ISIC sector and r denotes region. Column 2 of Table 3 presents the results. We find a similar coefficient to that of the main regression, which suggests sector-related and geographic region-related unobservables do not significantly influence the sensitivity of firm-level production to mining commodity prices.

Lagged effects. We examine whether lagged values of the independent variable affect the current production of non-commodity firms. We estimate Equation 5 with an additional lag of the weighted mining commodity price exposure index. The consideration of the lag also requires us to shorten the sample to 2006-2018. We present the results in Column 3 of Table 3, where we see that the current and lagged values of the independent variables are statistically significant. Moreover, we see that the sum of both coefficients is close to that of the baseline specification in Column 1, suggesting that the baseline specification captures both the contemporaneous and lagged effects of mining price shocks.

Wage bill. The main input in our theoretical model is labor. Then, we explore the relationship between non-mining firm wage bill $w_t h_{it}$ and the exposure to mining commodity prices. Since the number of workers or hours worked is not precisely recorded in our dataset, we use the wage bill as a proxy for labor. Column 4 of Table 3 shows the results of estimating Equation 5 with the wage bill as the dependent variable. We find a positive elasticity between the wage bill of a non-mining firm and its exposure to the mining commodity prices through banks. This suggests that mining-exposed firms do not only produce more when mining commodity prices go up, but they also increase their hiring.

5 Model

In this section, we introduce a static SOE model that captures the financial propagation mechanism of commodity booms and quantifies its aggregate importance. The model consists of a representative household, a discrete number of non-tradable intermediate goods producers, a loan aggregator, a discrete number of banks, a representative non-commodity exporter, and a representative commodity exporter. The household owns all the firms and banks. Importantly, the non-tradable intermediate goods producers are the model-equivalent to the non-commodity firms we have in the data.

The economy has a fixed endowment of the commodity good. At the same time, the economy imports goods, and banks can obtain wholesale funds from foreign markets. We take the importable good as the numeraire. Following the SOE assumption, the economy takes the international commodity price as given.

In line with our empirical findings, we assume commodity exporters hold deposits in domestic banks and that they will increase such deposits after an increase in commodity prices. Moreover, as indicated by the data, banks exhibit varying degrees of exposure to the commodities sector. Then, each bank will receive different amounts of deposits from the commodity sector according to their exposure after a shock to the commodity prices.

There are two key financial frictions in the model. First, non-tradable firms produce with a linear technology that uses only labor. However, they face a working capital constraint. This means these firms have to pay for a fraction of their wage bill before actual production takes place (Neumeyer & Perri, 2005; Jermann & Quadrini, 2012). Then, non-tradable intermediate firms need to take out loans from banks to finance such expenses.

Second, banks face a balance sheet constraint (Wang et al., 2022; Whited et al., 2022). Banks typically fund their loans with deposits and equity. However, when deposits and equity are not enough, banks must turn to foreign wholesale money markets. Because foreign lenders are concerned about domestic banks possibly defaulting, there will be a premium that domestic banks must pay. This premium is decreasing in the amount of deposits held. Importantly, this friction connects the interest rates that banks charge on loans to the amounts of deposits that are held.

The frictions we introduce in the model have several effects. After a commodity price boom that increases the deposit holdings, banks will require less foreign wholesale funding. First, this will reduce the premiums banks pay, so they will charge lower interest rates to the domestic firms. Second, because the stock of foreign wholesale funding falls, there are fewer financial outflows to the foreign sector and more resources in the domestic economy, which implies imports will be larger. Because imports are complements with the domestic non-tradable goods, this will increase domestic production.

Timewise, the model operates as follows. At the beginning of the single period, the commodity price is revealed. The commodity producers export their endowment at the given price and deposit part of their income flow in domestic banks. We further assume this deposit bears no interest. Then, all agents decide how much to consume, how much labor to supply, and how much to produce. Households fund banks with equity. Given the previous decisions, banks take foreign wholesale funding and lend to non-tradable intermediate firms. At the end of the single period, firms produce and pay back loans. Banks pay back wholesale funding and return deposits. Then, the household receives the profits from the firms and the banks. Next, banks are liquidated, and the household is given back the equity. Finally, the household consumes.

5.1 Household

The representative household consumes the final consumption good c at relative price p, supplies labor h at relative wage w and owns the firms and the banks, for which it receives total profits π.[14] Moreover, following the standard SOE literature, we assume the household has GHH preferences (Greenwood et al., 1988), so labor supply is independent of consumption.

The household solves the problem

$$\max_{c,h} \frac{1}{1-v}\left(c - \frac{h^{1+\psi}}{1+\psi}\right)^{1-v},$$

subject to

$$pc = wh + \pi,$$

where v measures the relative risk aversion and ψ is the inverse of the labor supply elasticity.

The final consumption good is a bundle of the importable good c_m and the bundle of the non-tradable good y_n, such that

$$c = \left[(1-\Lambda_n)^{\frac{1}{\gamma}} c_m^{\frac{\gamma-1}{\gamma}} + \Lambda_n^{\frac{1}{\gamma}} y_n^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}},$$

where γ is the elasticity of substitution and Λ_n is the weight of the non-tradable good.

The non-tradable consumption bundle is composed of a discrete number of differentiated non-tradable intermediate goods y_i, so that

$$y_n = \left(\sum_i \Lambda_i^{\frac{1}{\sigma}} y_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

[14]The household provides equity K_b to fund the banks at the beginning of the period and receives it back at the end of the period when banks are liquidated. Since equity is an outflow for the household at the beginning, but then reverts as income after liquidation of the banks, it cancels out in the household budget constraint. However, equity still appears on the bank balance sheets. In the simulations, we treat equity as exogenous and set it to match the change observed in the data.

where σ is the elasticity of substitution and Λ_i denotes the weights, with $\Lambda_i \geq 0$ and $\sum_i \Lambda_i = 1$. The relative price of this bundle is p_n.

5.2 Non-tradable intermediate firms

There is a discrete number of non-tradable intermediate good firms indexed by $i \in [1, \ldots, I]$ that engage in monopolistic competition and are owned by the household. These firms represent the non-commodity firms from our dataset. They use labor h_i to produce y_i with productivity A_i and charge relative price p_i.

These firms are also subject to a working capital constraint, which means they must pay a proportion θ of the wage bill wh_i in advance, before production takes place (Neumeyer & Perri, 2005; Jermann & Quadrini, 2012). Thus, these firms need to take out loans from banks to finance their production expenses. The firms produce and pay off their loans plus interest at the end of the period.

The problem of the firm is

$$\max_{p_i, y_i, h_i} \pi_i = p_i y_i - \left(1 + \theta r_i^L\right) wh_i,$$

subject to

$$y_i = \left(\frac{p_i}{p_n}\right)^{-\sigma} \Lambda_i y_n,$$

$$y_i = A_i h_i,$$

where A_i is the productivity and r_i^L is the loan interest rate each firm faces.

Additionally, for each non-tradable intermediate firm we define loan demand as

$$L_i = \theta wh_i.$$

5.3 Commodity exporter

We assume there is a representative commodity exporter, fully owned by the household.[15] It receives an endowment $y_x = 1$ and exports it at exogenous price p_x. This firm does not hire labor

[15] In Appendix B.6 we explore the possibility of the domestic household not wholly owning the commodity exporting firm.

to operate.[16]

As suggested by Fact 1, we assume that the commodity exporter holds deposits in the domestic banks. Additionally, the amount of deposits held is sensitive to the commodity prices. We discuss this feature more extensively in the bank section. As a simplification, we further assume these deposits bear no interest rate. At the end of the period, the commodity producer gets its deposits back from banks and transfers the export revenue to households.

5.4 Non-commodity exporter

While commodity exports constitute a significant share of total exports in SOE, they do not encompass all export activity. Thus, we introduce a representative non-commodity exporter which is owned by the household. Similar to its commodity-exporting counterpart, the non-commodity exporter receives an exogenous endowment X_{nm} that it exports at price $p_{nm} = 1$. We set this price as a simplification because, in the simulations, it will not be relevant whether changes in non-commodity exports were caused by quantities or prices. Moreover, the non-commodity exporter does not use labor to operate.

5.5 Loan aggregator

Non-tradable intermediate firms obtain their loans L_i from firm-specific and perfectly competitive loan aggregators, which are owned by the household. Each loan aggregator specializes in serving a single non-tradable intermediate firm $i \in [1, \ldots, I]$, by sourcing bank-level loans L_{ib} from banks b at interest rate r_b^L to convert them to a loan bundle L_i using CES technology (Gerali et al., 2010; Andrés et al., 2013; Ulate, 2021) and charge an interest rate r_i^L. The CES assumption mirrors two facts from firm and bank relationships. First, firms may obtain loans from more than on banks. Second, there is imperfect substitability across different banks as they may be specialized in certain sectors, or may have special relationships with specific firms (Paravisini et al., 2023).

The problem of the loan aggregator is

$$\max_{L_{ib}} \left(1 + r_i^L\right) L_i - \sum_b \left(1 + r_b^L\right) L_{ib},$$

[16] This is based on the observation that, in our Peruvian setting, the mining sector hires few workers. For instance, in 2007, this sector hired 1 percent of the total labor force.

subject to loan bundle

$$L_i = \left[\sum_b (s_{ib})^{\frac{1}{\varepsilon}} (L_{ib})^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where s_{ib} are fixed weights and ε is the elasticity of substitution across banks.[17] Moreover, for a given firm i, it must hold that $s_{ib} \geq 0$ and $\sum_b s_{ib} = 1$. We allow the weights s_{ib} to be zero, so firms do not necessarily have to source loans from all banks.

5.6 Banks

There is a discrete number of banks indexed by $b \in [1, \dots, B]$, with each offering a differentiated variety of loans. Banks operate in a monopolistically competitive fashion and are owned households. Banks choose loans L_b, interest rate r_b and foreign wholesale funding N_b subject to their balance sheet and the loan demand coming from loan aggregators.

Banks are subject to a balance sheet friction (Wang et al., 2022; Whited et al., 2022). Their balance sheet has loans on the asset side, which have to be funded on the liabilities side through firm deposits D_b from commodity producers, equity K_b from households and foreign wholesale funding N_b. This implies that when deposits and equity are insufficient to fully cover loans, domestic banks have to go to foreign money lenders to obtain foreign wholesale funding.

The cost of the foreign wholesale funding has two parts. First, the cost depends on the foreign interest rate r. Second, because domestic banks could default, foreign lenders will charge them a premium $\phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right)$, where ϕ is a cost function parameter and $\mathcal{B}_b$ is a constant that serves as a benchmark.[18] The functional form $\phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right)$ captures the idea that when deposits are abundant, the need for foreign wholesale funding is lower and domestic banks are charged lower premiums in foreign markets.

The problem banks solve is

$$\max_{r_b^L, L_b, N_b} \pi_b = \left(1 + r_b^L\right) L_b - D_b - \left[1 + r + \phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \right] N_b,$$

subject to balance sheet

$$L_b = D_b + K_b + N_b,$$

[17] Column 4 of Table 2 shows there is no effect of the mining commodity price shock on the extensive margin of loans. Thus, we do not consider this margin within the model.

[18] We may think of constant benchmark $\mathcal{B}_b$ as capturing the reputation of the domestic bank has in foreign markets or the relationships the domestic bank may have with foreign lenders. For technical reasons related to recovering the model parameters from our empirical results, we require $\frac{\mathcal{B}_b}{D_b} > 1$ and $\phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \approx 0$ (see Appendix B.3).

and total loan demand

$$L_b = \sum_i \left[\left(\frac{1 + r_b^L}{1 + r_i^L} \right)^{-\varepsilon} s_{ib} L_i \right].$$

The optimal interest rate r_b^L charged is

$$1 + r_b^L = \frac{\varepsilon}{\varepsilon - 1} \left[1 + r + \phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \right],$$

where we see that the introduction of the balance sheet friction connects the interest rate banks charge with the amount of firm deposits they hold. The larger the amount of deposits held, the lower the premium paid by the bank for the foreign wholesale funding and the lower the interest rate charged to firms.

Consistent with the empirical evidence from Equation 3 above, we posit the following reduced-form relationship between deposits D_b and commodity prices p_x:

$$\ln (D_b) = \alpha_b + \beta \omega_{bx} \ln (p_x),$$

where α_b is a constant. As suggested by the data, this equation captures the idea that commodity exporters hold deposits in domestic banks and will increase their holdings when they income increases.

5.7 Market clearing conditions, balance of payments and real GDP

The markets for the final consumption good c, the non-tradable consumption bundle y_n, intermediate non-tradable good y_i, loan bundle L_i, and bank loans L_{ib} clear by assumption. Additionally, the labor market clearing condition states that total labor supply h must be equal to the total labor demanded by each non-tradable intermediate firm h_i, such that

$$h = \sum_i h_i.$$

The imports are defined by the balance of payments equation

$$c_m = p_x y_x + X_{nm} + \sum_i L_i - \sum_b D_b - \sum_b \left[1 + r + \phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \right] N_b,$$

where $p_x y_x + X_{nm} - c_m$ is the trade balance and $\sum_b \left[1 + r + \phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \right] N_b - \left(\sum_i L_i + \sum_b D_b \right)$ is the financial account.

Lastly, we define real GDP as

$$GDP = \overline{p_n} y_n + \overline{p_x} y_x + X_{nm} - c_m,$$

where $\overline{p_n}$ and $\overline{p_x}$ are constant relative prices.

5.8 Equilibrium

We solve the model using the exact hat algebra method of Dekle et al. (2008). For a given variable x in levels, we define $\widehat{x} = \frac{x'}{x}$ as the change between final state x' and initial state x. Likewise, for a given interest rate i we define $1 + \widehat{i} = \frac{1+i'}{1+i}$.

Given a commodity price shock $\widehat{p_x}$, the market foreign interest rate $\widehat{r}$, non-tradable firm-level TFP $\left\{\widehat{A_i}\right\}_i$, equity $\left\{\widehat{K_b}\right\}_b$, non-mining exports $\widehat{X_{nm}}$, parameters and ratios; the equilibrium of the model is a set of relative prices $\widehat{p}, \widehat{w}, \widehat{p_n}, \{\widehat{p_i}\}_i$; a set of interest rates $\{r_i^L\}_i, \{r_b^L\}_b$; and a set of allocations $\widehat{h}, \widehat{c}, \widehat{c_m}, \widehat{y_n}, \left\{\widehat{h_i}, \widehat{y_i}, \widehat{L_i}\right\}_i, \left\{\widehat{D_b}\right\}_b, \left\{\widehat{L_{ib}}\right\}_{i,b}$; such that the final consumption good, non-tradable good, loans, and labor markets clear; and the bank balance sheets hold. We present the equilibrium conditions in Appendix B.1 and the conditions expressed in terms of hat algebra in Appendix B.2.

5.9 Calibration

We divide the parameters into the non-bank block, the bank block, ratios, and shocks. We present the complete parametrization in Tables 4 and 5. Based on the matched bank-firm-loan dataset from Peru, we calibrate the model for 5 representative non-tradable firms, 9 banks and a representative commodity exporter.[19] For the non-bank block we use the standard values in the SOE literature (Uribe & Schmitt-Grohé, 2017). For the ratios, we calibrate them to match the averages in Peruvian data in the period 2005-2018.

Next, we provide detail on how we obtain the values for the bank block parameters based on the data and the regressions of Section 4, as well as on how we calibrate the shocks.

Working capital financed by banks θ. We proceed in two parts. First, from the firm survey, we recover total expenses Z, which include intermediate consumption, investment, wage bill and

[19] We sort non-commodity firms from the firm survey according to their sales and average them by quintiles. Each representative non-tradable firm in the model is calibrated to match the average firm by quintile from the data.

Table 4: Parameters (1)

	Non-bank block	
ψ	Inverse of labor supply elasticity	0.455
γ	Elasticity of substitution in final consumption basket	0.5
Λ_n	Weight of non-tradables in final consumption basket	0.564
σ	Elasticity of substitution in NT basket	6
	Bank block	
β	Commodity price to deposit elasticity	23.598
ε	Elasticity of substitution across banks in loan bundle	6.159
ϕ	Bank cost function parameter	0.036
θ	Working capital financed by loans	0.236
	Trade balance	
χ_x	Exports / Imports	1.108
η_x	Mining exports / Exports	0.569
χ_L	Total firm loans / Imports	0.814
χ_D	Total firm deposits / Imports	0.338
χ_N	Total wholesale funding / Imports	0.229
δ_b^L	Loans by bank / Total loans	By bank
δ_b^D	Deposits by bank / Total deposits	By bank
δ_i^L	Loans by firm/ Total loans	By firm
r^*	Foreign real interest rate	0.0135
ν	Country spread	0.0215
	GDP weights	
Ω_n	(Consumption + Investment + Gov. exp.) / GDP	0.967
Ω_x	Exports / GDP	0.282
Ω_m	Imports / GDP	0.249
	Firm weights in total labor and price index	
Λ_i^h	Wage bill / Total wage bill	By firm
Λ_i	Sales / Total sales	By firm
	Bank weights in firm loan portfolio	
s_{ib}	Individual loans / Total loans, by firm	By firm and bank
	Bank exposure to commodity prices	
ω_{bx}	Mining loans / Total loans, by bank	By bank
	Bank balance sheet	
Ω_b^N	Wholesale funding / Firm loans	By bank
Ω_b^D	Firm deposits / Firm loans	By bank
Ω_b^K	Equity / Firm loans	By bank
ω_{ib}^L	Individual loans / Total loans, by bank	By firm and bank

Note: All ratios calculated using deflated data and expressed in domestic currency. Because foreign wholesale funding N_b is not properly measured in the data, we calculate a proxy as $N_b = L_b - D_b - K_b$.

Table 5: Parameters (2)

	Shocks	
$\widehat{p_x}$	Commodity price shock	2.57
$\widehat{A_i}$	TFP	1.08
$\widehat{r}$	Foreign interest rate	-0.04
$\widehat{K_b}$	Bank equity	2.21
$\widehat{X_{nm}}$	Non-mining exports	2.10

Note: We provide details on the data underlying the shocks in Appendix B.4.

financial expenses. Let the financial expenses be $\theta r^L Z$ and r^L the interest rate paid.

Second, we need to obtain a value for r^L. The only interest rate data available for Peru in our period of analysis is the average real interest rate for loans across all banks. We take the average between 2005 and 2018 to set $r^L = 0.11$.[20] With this, we recover a firm-level value for θ. Next, we drop the outliers (observations with $\theta > 1$). Finally, we calculate the average across all firms and years to find $\theta = 0.236$.

Commodity price to deposit elasticity β. We refer to the estimation of Equation 3 to recover this elasticity, where we found $\beta = 23.598$. This implies that a hike in the mining commodity price increases the amount of deposits held by the mining-exposed banks.

Elasticity of substitution across banks in loan bundle ε and bank cost function parameter ϕ. To recover these two parameters, we start from the loan-level and firm-level equilibrium conditions of the model and derive expressions that correspond with Equations 4 and 5. We show the detailed steps in Appendix B.3.

Thus, we are able to express the estimated coefficients ζ and κ in terms of the structural parameters of the model, so that $\zeta = \varepsilon\phi\beta$ and $\kappa = (\sigma - 1)\,\theta\phi\beta$. Given we know the numerical values of estimated coefficients β, ζ and κ, as well as calibrated parameters σ and θ, we find $\varepsilon = 6.159$ and $\phi = 0.036$.

Shocks. In the next section, we simulate a commodity price shock $\widehat{p_x} = 2.57$, which is equal to the observed change in the weighted mining relative price index across all minerals that Peru exports between 2003 and 2011. We choose 2003 as the starting point because it marks the beginning of the boom, while we pick 2011 as the end point of the simulation as it the period when the mining commodity prices reached their peak, as seen in Figure 1.

We target the observed change in Peruvian GDP between 2003 and 2011 by choosing the TFP levels. We set $\widehat{A_i} = 1.08$ for all i. Within the model, we also have additional shocks that help us

[20] This is a weighted average between domestic currency-denominated and dollar-denominated loans.

match the data. We set these shocks to match their observed changes in the data between 2003 and 2011. We set the market foreign interest rate $\widehat{r} = -0.04$, the equity $\widehat{K_b} = 2.21$ for all b, and the non-mining exports $\widehat{X_{nm}} = 2.10$.[21]

6 Quantifying the aggregate importance of the financial propagation mechanism

In this section, we conduct simulations using the hat algebra version of the model to quantify the aggregate importance of the financial propagation mechanism during commodity booms. Specifically, we first simulate the model with the financial propagation mechanism activated, using the calibration and shocks defined in the previous section. Next, we simulate the model under the same calibration and shocks but with the financial propagation mechanism turned off. We define the aggregate importance of the financial propagation mechanism as the difference in GDP growth rates between these two scenarios.

6.1 Main simulation

Table 6 reports the results of the main simulation. Columns 1 and 2 show the moments coming from the data and the model, respectively. First, our baseline simulation hits the targeted moment. This way, the baseline simulation predicts a GDP growth $\widehat{GDP}$ of 65 percent, as we see in the data. Second, related to the untargeted moments, we focus on the change in imports $\widehat{c_m}$, non-tradable output $\widehat{y_n}$, non-tradable price index $\widehat{p_n}$, average loans $\widehat{L_i}$, average deposits $\widehat{D_b}$, average wholesale funding $\widehat{N_b}$, and average loan interest rate $\widehat{r_b^L}$. Our baseline simulation gets fairly close to the untargeted moments.[22]

Within our model, a commodity price boom that raises firm deposits reduces the need for banks to rely on foreign wholesale funding. First, this decreases the premiums banks pay for foreign wholesale funding, enabling them to charge lower interest rates to non-tradable intermediate firms. This lowers the production costs of non-tradable intermediate firms, reducing the prices they charge and increasing the demand they face. This constitutes an interest rate channel effect that drives GDP upward.

In second place, because the amount of foreign wholesale funding decreases, there are fewer

[21] We provide details on the data underlying the shocks in Appendix B.4.

[22] We provide details on the data-based moments in Appendix B.4.

financial outflows to the foreign sector and more resources remain in the domestic economy. This leads to an increase in imports. Because imports are complements with the domestic non-tradable goods, the demand for non-tradable goods rises as well. This is a wealth channel effect that also contributes to GDP growth.

To quantify the aggregate importance of the financial propagation mechanism of commodity booms, we perform a counterfactual simulation where we simulate the model with the same calibration and shocks as before, but turn off the financial propagation mechanism. In terms of the model, this means setting $\beta = 0$. Therefore, firm deposits do not vary when there is a mining commodity price shock. We present the results of the counterfactual simulation in Column 3, while Column 4 shows the difference between the baseline and the counterfactual scenarios.

Under the counterfactual scenario, GDP still grows, but at a lower rate than in the baseline scenario. The difference between the two cases, which we interpret as the aggregate importance of the financial propagation mechanism of commodity booms, is 7 percentage points or approximately a ninth of the observed GDP growth under the baseline case. We now turn to explain this difference. In the counterfactual scenario, there is still a positive wealth shock to the economy that generates an increase in loan demand. However, with the financial propagation mechanism turned off, deposits do not increase, so that banks now require more foreign wholesale funding. First, this drives up their premiums and interest rates charged. Then, non-tradable intermediate firms do not take out loans as much as in the baseline. Second, a higher amount of debt increases the financial outflows to the foreign sector and reduces the resources available in the domestic economy, which implies fewer imports and a lower demand for non-tradable goods. These two channels reduce the GDP growth rate.[23]

6.2 Commodity price shock-only simulation

In this section, we isolate the effects of a commodity price shock by simulating the model with only this shock, excluding any other disturbances. This way, the model economy is subject to a pure wealth increase coming from the commodity price shock, more in line with the standard SOE macroeconomic models. To do so, we conduct the simulation by introducing a positive commodity price shock $\widehat{p_x} = 2.57$ to the model, under the same baseline calibration outlined earlier, but turning off the other shocks (i.e., $\widehat{A_i} = 1$ for all i, $\widehat{K_b} = 1$ for all b, $\widehat{X_{nm}} = 1$, and $\widehat{r} = 0$).

Table 7 presents the results after the commodity price shock. Under the baseline case, with

[23] In Appendix B.6 we explore the sensitivity of the model results under alternative parametrizations.

Table 6: Main simulation

Variable	(1) Data, 2003-2011	(2) Baseline: Fin. mech.	(3) CF: No fin. mech. ($\beta = 0$)	(4) Baseline minus CF
Targeted moment				
$\widehat{GDP}$	1.65	1.65	1.58	0.07
Untargeted moments				
$\widehat{c_m}$	2.24	2.19	1.98	0.21
$\widehat{y_n}$	1.71	1.84	1.72	0.12
$\widehat{p_n}$	1.29	1.41	1.33	0.08
Ave. $\widehat{L_i}$	2.34	2.65	2.30	0.34
Ave. $\widehat{D_b}$	3.02	2.64	1.00	1.64
Ave. $\widehat{N_b}$	8.56	6.06	8.23	-2.17
Ave. $\widehat{r_b^L}$	-0.05	-0.07	-0.04	-0.03

Note: Column 1 shows data moments. Column 2 shows moments from baseline simulation with financial propagation mechanism. Column 3 shows moments from counterfactual simulation with no financial propagation mechanism. Column 4 shows difference between baseline and counterfactual. All moments are expressed in percentage variations between initial and final states. We report the complete set of results in Appendix Table B.1. For the bank-related variables, the model-based moments are averages computed using loan-based weights of each bank in total loans. These weights are calibrated according to observed data. For these same variables, the empirical untargeted moments are based on the change of the aggregate variable.

the financial propagation mechanism turned on, GDP grows by 20 percent. When we turn off the financial propagation mechanism, GDP grows by 14 percent. Then, the financial propagation mechanism accounts for 6 percentage points or approximately one third of what we observe in the baseline case.

The channels behind this result remain the same as before: the increase in deposits reduces the need of banks to obtain foreign wholesale funding, which results in lower financial outflows and lower interest rates. However, in the absence of the other complementary shocks from the main simulation that helped us match the data, the financial propagation mechanism becomes relatively more significant in driving the baseline GDP growth.

7 Conclusions

This paper proposes a novel financial propagation mechanism in SOEs where commodity price booms affect the non-commodity sector through domestic banks. Following a boom, exporters increase their deposits in domestic banks, enabling banks to expand loans to non-commodity firms. In turn, non-commodity firms increase their output.

Table 7: Commodity price shock-only simulations

	(1)	(2)	(3)
Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.20	1.14	0.06
$\widehat{c_m}$	1.61	1.42	0.19
$\widehat{y_n}$	1.37	1.25	0.11
$\widehat{p_n}$	1.38	1.28	0.10
Ave. $\widehat{L_i}$	1.91	1.60	0.30
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	3.46	5.60	-2.14
Ave. $\widehat{r_b^L}$	-0.03	0.00	-0.03

Note: Column 1 shows moments from baseline simulation with financial propagation mechanism. Column 2 shows moments from counterfactual simulation with no financial propagation mechanism. Column 3 shows difference between baseline and counterfactual. All moments are expressed in percentage variations between initial and final states. We report the complete set of results in Appendix Table B.2. Averages for the bank-related model variables are computed using loan-based weights of each bank in total loans. These weights are calibrated according to observed data.

Using bank-firm-loan microdata from Peru, an SOE that went through a mining commodity price boom in the 2000s, we find empirical support for this mechanism. We document that banks are heterogeneously exposed to the mining sector, as each holds a different mining client composition. After an exogenous rise in mining commodity prices, banks with higher exposure to the mining sector see increased firm deposits and expand their loan supply to non-mining firms. Furthermore, non-mining firms exposed to mining prices through their banks register a boost in output.

We incorporate this mechanism into a static SOE model with banks and an endowment commodity sector to quantify the aggregate importance of this mechanism. We calibrate the model to Peruvian data and replicate key economic moments. A counterfactual analysis suggests the financial propagation mechanism accounts for a ninth of the observed 65 percent GDP growth in Peru during the 2003–2011 boom period.

8 References

Allcott, H. & Keniston, D. (2018). Dutch disease or agglomeration? the local economic effects of natural resource booms in modern america. *The Review of Economic Studies*, 85(2), 695–731.

Andrés, J., Arce, O., & Thomas, C. (2013). Banking competition, collateral constraints, and optimal monetary policy. *Journal of Money, Credit and Banking*, 45(s2), 87–125.

Benguria, F., Saffie, F., & Urzua, S. (2023). Transmission of Commodity Price Super-Cycles. *Review of Economic Studies*, (pp. 1–33).

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies*, 89(1), 181–213.

Bustos, P., Garber, G., & Ponticelli, J. (2016). Capital allocation across regions, sectors and firms: evidence from a commodity boom in Brazil.

Corden, W. M. & Neary, J. P. (1982). Booming sector and de-industrialisation in a small open economy. *Economic Journal*, 92(368), 825–848.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., & Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40, 100813.

Dekle, R., Eaton, J., & Kortum, S. (2008). Global rebalancing with gravity: Measuring the burden of adjustment.

Drechsel, T. & Tenreyro, S. (2018). Commodity booms and busts in emerging economies. *Journal of International Economics*, 112, 200–218.

Federico, S., Hassan, F., & Rappoport, V. (2023). Trade shocks and credit reallocation.

Fernández, A., Schmitt-Grohé, S., & Uribe, M. (2023). How important is the commodity supercycle?

Gerali, A., Neri, S., Sessa, L., & Signoretti, F. M. (2010). Credit and banking in a dsge model of the euro area. *Journal of Money, Credit and Banking*, 42, 107–141.

Greenwood, J., Hercowitz, Z., & Huffman, G. W. (1988). Investment, capacity utilization, and the real business cycle. *The American Economic Review*, (pp. 402–417).

Huo, Z., Levchenko, A., & Pandalai-Nayar, N. (2024). International comovement in the global production network. *Review of Economic Studies*, (pp. rdae033).

Jermann, U. & Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, 102(1), 238–271.

Khwaja, A. I. & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4), 1413–1442.

Kose, M. A. (2002). Explaining business cycles in small open economies: How much do world prices matter? *Journal of International Economics*, 56(2), 299–327.

Mendoza, E. G. (1995). The terms of trade, the real exchange rate, and economic fluctuations. *International Economic Review*, (pp. 101–137).

Morelli, J. M., Ottonello, P., & Perez, D. J. (2022). Global banks and systemic debt crises. *Econometrica*, 90(2), 749–798.

Neumeyer, P. A. & Perri, F. (2005). Business cycles in emerging economies: the role of interest rates. *Journal of Monetary Economics*, 52(2), 345–380.

Paravisini, D. (2008). Local bank financial constraints and firm access to external finance. *The Journal of Finance*, 63(5), 2161–2193.

Paravisini, D., Rappoport, V., & Schnabl, P. (2023). Specialization in bank lending: Evidence from exporting firms. *Journal of Finance*, 78(4), 2049–2085.

Peek, J. & Rosengren, E. S. (2005). Unnatural selection: Perverse incentives and the misallocation of credit in japan. *American Economic Review*, 95(4), 1144–1166.

Salter, W. (1959). Internal and external balance: the role of price and expenditure effects. *Economic Record*, 35(71), 226–238.

Schmitt-Grohé, S. & Uribe, M. (2018). How important are terms-of-trade shocks? *International Economic Review*, 59(1), 85–111.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *Journal of Finance*, 67(3), 897–932.

Shousha, S. (2016). Macroeconomic effects of commodity booms and busts: The role of financial frictions.

Silva, A., Caraiani, P., Miranda-Pinto, J., & Olaya-Agudelo, J. (2024). Commodity prices and production networks in small open economies.

Swan, T. W. (1963). Longer-run problems of the balance of payments. *Australian Economy*, (pp. 384–95).

Ulate, M. (2021). Going negative at the zero lower bound: The effects of negative nominal interest rates. *American Economic Review*, 111(1), 1–40.

Uribe, M. & Schmitt-Grohé, S. (2017). *Open economy macroeconomics*. Princeton University Press.

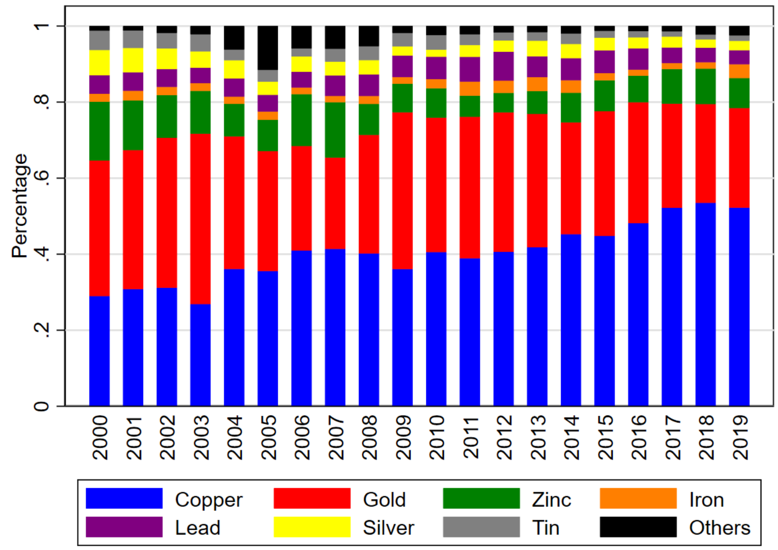
Wang, Y., Whited, T. M., Wu, Y., & Xiao, K. (2022). Bank market power and monetary policy transmission: Evidence from a structural estimation. *Journal of Finance*, 77(4), 2093–2141.

Whited, T. M., Wu, Y., & Xiao, K. (2022). Will central bank digital currency disintermediate banks?

A Empirical appendix

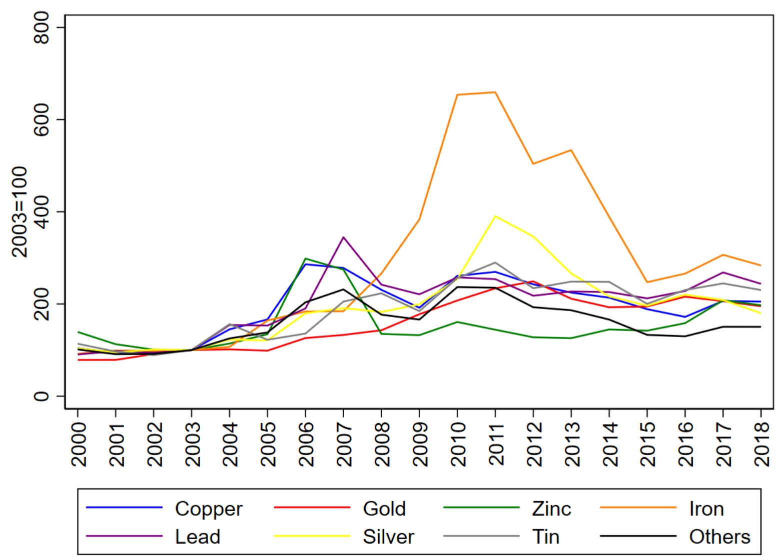
A.1 Mining sector

Figure A.1: Mining exports by mineral



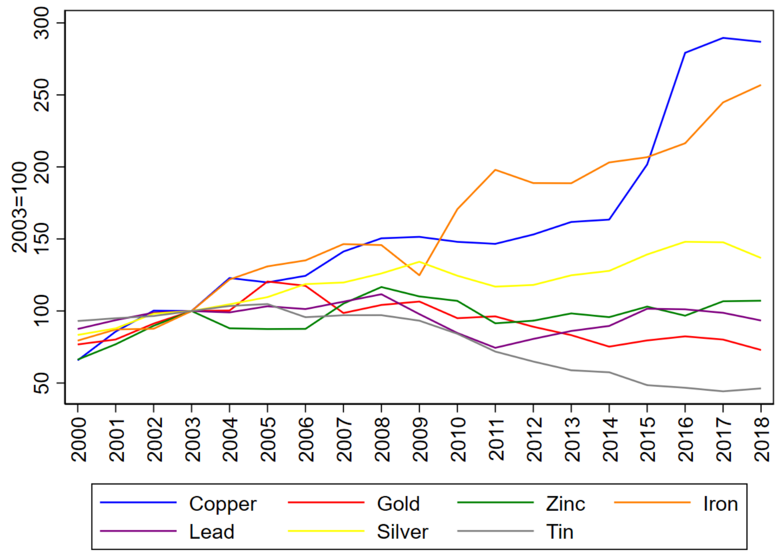
Note: Figure shows evolution of the shares of each mining commodity over total mining commodity exports.

Figure A.2: Mining prices



Note: Figure shows evolution of mining commodity relative prices. We normalize the dollar prices for the commodities and then divide them by the Peruvian imports price index.

Figure A.3: Mining output



Note: Figure shows evolution of mining physical output by commodity.

Table A.1: Mining production ranking of Peru, 2011

Mineral	World ranking	Share of total world output	Largest competitors
Copper	3	8%	CHL: 33%, CHN: 8%, USA: 7%
Gold	6	6%	CHN: 14%, AUS: 10%, USA: 9%
Zinc	3	10%	CHN: 34%, AUS: 12%, USA: 10%
Lead	4	5%	CHN: 50%, AUS: 13%, USA: 7%
Tin	3	12%	CHN: 49%, IDN: 17%, BOL: 8%
Silver	3	15%	MEX: 18%, CHN: 16%, AUS: 7%
Iron	17	<1%	CHN: 45%, AUS: 17%, BRA: 13%

Note: Figure shows share of Peruvian output over total world output for each of the listed mining commodities.
Source: United States Geological Survey.

A.2 Sample statistics

Table A.2: Bank statistics

	Mean	Std. dev.	Min.	Max.
Assets (bill. USD)	6.89	8.24	0.20	32.00
Firm deposits (bill. USD)	1.22	1.61	0.01	5.92
Foreign wholesale funding (bill. USD)	0.81	1.11	-0.04	5.37
E_{bt}	0.13	0.10	0.00	0.30

Note: Table shows information for the 9 banks considered in the analysis. For those banks that merged during this period, we consider them one entity and add their accounts. Additionally, we do not consider banks that are specialized in (i) serving foreign-owned firms only or (ii) credit card and consumer loans only. Foreign wholesale funding is defined as liabilities minus total deposits and equity. E_{bt} is the bank-level weighted commodity price exposure index from Equation 1.

Table A.3: Loan statistics

	Mean	Std. dev.	Min.	Max.
Loans (thousands USD)	279.92	589.72	0.00	6134.41
Number of bank relationships per firm	2.67	0.98	2.00	9.00

Note: Table shows information the on outstanding loan amounts and number of bank relationships per firm.

Table A.4: Firm statistics

	Mean	Std. dev.	Min.	Max.
Wage bill (thousands USD)	1992.81	3545.70	2.85	43208.87
Sales (thousands USD)	14903.33	25005.45	49.44	306591.20
e_{it}	0.02	0.07	0.00	0.30

Note: Table shows information for approximately 5,600 firms we consider in the analysis. e_{it} is the firm-level weighted commodity price exposure index from Equation 2.

B Model appendix

B.1 Model summary

Labor supply

$$h^{\psi} = \frac{w}{p}$$

Final consumption bundle

$$c = \left[(1-\Lambda_n)^{\frac{1}{\gamma}} c_m^{\frac{\gamma-1}{\gamma}} + \Lambda_n^{\frac{1}{\gamma}} y_n^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}$$

Relative demand

$$\left(\frac{1}{p_n}\right) = \left(\frac{1-\Lambda_n}{\Lambda_n}\right)^{\frac{1}{\gamma}} \left(\frac{y_n}{c_m}\right)^{\frac{1}{\gamma}}$$

Final consumption price index

$$p = \left[(1-\Lambda_n) + \Lambda_n p_n^{1-\gamma}\right]^{\frac{1}{1-\gamma}}$$

Non-tradable good price index

$$p_n = \left(\sum_i \Lambda_n p_i^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

Real GDP ($\overline{p_n}$ and $\overline{p_x}$ are constant relative prices)

$$GDP = \overline{p_n} y_n + \overline{p_x} y_x + X_{nm} - c_m$$

Imports

$$c_m = p_x y_x + X_{nm} + \sum_i L_i - \sum_b D_b - \sum_b \left[1 + r + \phi \ln\left(\frac{\mathcal{B}_b}{D_b}\right)\right] N_b,$$

Labor market clearing condition

$$h = \sum_i h_i$$

Non-tradable intermediate good production function, for all i

$$y_i = A_i h_i$$

Non-tradable intermediate good demand, for all i

$$y_i = \left(\frac{p_i}{p_n}\right)^{-\sigma} \Lambda_n y_n$$

Non-tradable intermediate good price index, for all i

$$p_i = \frac{\sigma}{\sigma - 1} \frac{w}{A_i} \left(1 + \theta r_i^L\right)$$

Loan demand, for all i

$$L_i = \theta w h_i$$

Bank loan demand, for all i, b

$$L_{ib} = \left(\frac{1 + r_b^L}{1 + r_i^L}\right)^{-\varepsilon} s_{ib} L_i$$

Firm average interest rate, for all i

$$1 + r_i^L = \left[\sum_b s_{ib} \left(1 + r_b^L\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$$

Deposits, for all b

$$\ln\left(D_b\right) = \alpha_b + \beta \omega_{bx} \ln\left(p_x\right)$$

Bank interest rate, for all b

$$1 + r_b^L = \frac{\varepsilon}{\varepsilon - 1} \left[1 + r + \phi \ln\left(\frac{\mathcal{B}_b}{D_b}\right)\right]$$

Bank balance sheet, for all b

$$\sum_i L_{ib} = D_b + K_b + N_b$$

B.2 Hat algebra model summary

Labor supply

$$\widehat{h}^{\psi} = \frac{\widehat{w}}{\widehat{p}}$$

Final consumption bundle

$$\widehat{c} = \left[(1-\Lambda_n)\,\widehat{c_m}^{\frac{\gamma-1}{\gamma}} + (\Lambda_n)\,\widehat{y_n}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}$$

Relative demand

$$\left(\frac{1}{\widehat{p_n}}\right) = \left(\frac{\widehat{y_n}}{\widehat{c_m}}\right)^{\frac{1}{\gamma}}$$

Final consumption price index

$$\widehat{p} = \left[(1-\Lambda_n) + \Lambda_n \widehat{p_n}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}$$

Non-tradable good price index

$$\widehat{p_n} = \left(\sum_i \Lambda_i \widehat{p}_i^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

Real GDP

$$\widehat{GDP} = \Omega_n \widehat{y_n} + \Omega_x \eta_x + \Omega_x (1-\eta_x)\,\widehat{X_{nm}} - \Omega_m \widehat{c_m}$$

Imports

$$\begin{aligned}\widehat{c_m} =& \chi_x (1-\eta_x)\,\widehat{X_{nm}} + \chi_x \eta_x \sum_x \omega_x \widehat{p_x} + \chi_L \sum_i \omega_{Li} \widehat{L_i} - \chi_D \sum_b \omega_{Db} \widehat{D_b} \\ & - \chi_N (1+\bar{r}) \sum_b \omega_{Nb} (1+\widehat{r})\,\widehat{N_b} + \phi \Omega_N \nu \sum_b \omega_{Nb} \ln\left(\widehat{D_b}\right) \widehat{N_b}\end{aligned}$$

Labor market clearing condition

$$\widehat{h} = \sum_i \Lambda_i^h \widehat{h}_i$$

Non-tradable intermediate good production function, for all i

$$\widehat{y_i} = \widehat{A_i}\widehat{h}_i$$

Non-tradable intermediate good demand, for all i

$$\widehat{y_i} = \left(\frac{\widehat{p_i}}{\widehat{p_n}}\right)^{-\sigma} \widehat{y_n}$$

Non-tradable intermediate good price index, for all i

$$\widehat{p_i} = \frac{\widehat{w}}{\widehat{A_i}} \left(1 + \theta \widehat{r_i^L}\right)$$

Loan demand, for all i

$$\widehat{L_i} = \widehat{w}\widehat{h_i}$$

Bank loan demand, for all i, b

$$\widehat{L_{ib}} = \left(\frac{1+\widehat{r_b^L}}{1+\widehat{r_i^L}}\right)^{-\varepsilon} \widehat{L_i}$$

Firm average interest rate, for all i

$$1 + \widehat{r_i^L} = \left[\sum_b s_{ib} \left(1 + \widehat{r_{ib}^L}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$$

Deposits, for all b

$$\ln\left(\widehat{D_b}\right) = \beta\omega_{bx} \ln\left(\widehat{p_x}\right)$$

Bank interest rate, for all b

$$1 + \widehat{r_b^L} = 1 + \widehat{r} - \phi \ln\left(\widehat{D_b}\right)$$

Bank balance sheet, for all b

$$\sum_i \omega_{ib}^L \widehat{L_{ib}} = \Omega_b^D \widehat{D_b} + \Omega_b^K \widehat{K_b} + \Omega_b^N \widehat{N_b}$$

B.3 From model to regressions

Loan-level regression. We start from the equilibrium conditions for loans expressed in natural logarithms. We have the loan demand

$$\ln\left(L_{ib}\right) = -\varepsilon r_b^L + \varepsilon r_i^L + \ln\left(s_{ib}\right) + \ln\left(L_i\right),$$

and the interest rate set by banks

$$r_b^L = \ln\left(\frac{\varepsilon}{\varepsilon-1}\right) + r + \phi\ln\left(\mathcal{B}_b\right) - \phi\ln\left(D_b\right),$$

where we require $\frac{\mathcal{B}_b}{D_b} > 1$ and $\phi\ln\left(\frac{\mathcal{B}_b}{D_b}\right) \approx 0$ for this approximation to hold and to obtain a positive interest rate.

Replace to obtain

$$\ln\left(L_{ib}\right) = -\varepsilon\ln\left(\frac{\varepsilon}{\varepsilon-1}\right) - \varepsilon r + \varepsilon r_i^L + \ln\left(s_{ib}\right) + \ln\left(L_i\right) - \varepsilon\phi\ln\left(\mathcal{B}_b\right) + \varepsilon\phi\ln\left(D_b\right).$$

Replace $\ln\left(D_b\right) = \alpha_b + \beta\sum_x \omega_{bx}\ln\left(p_x\right)$, add time subindices and collect terms to find

$$\ln\left(L_{ibt}\right) = \underbrace{-\varepsilon\ln\left(\frac{\varepsilon}{\varepsilon-1}\right)}_{\text{constant}} + \underbrace{\ln\left(s_{ib}\right) - \varepsilon\phi\alpha_b - \varepsilon\phi\ln\left(\mathcal{B}_b\right)}_{\alpha_{ib}} + \underbrace{\varepsilon r_{it}^L + \ln\left(\mathcal{B}_b\right) - \varepsilon r_t}_{\alpha_{it}} + \underbrace{\varepsilon\phi\beta}_{\zeta}\sum_x \omega_{bx}\ln\left(p_{xt}\right).$$

Add a residual, where we can interpret it as a measurement error, to obtain

$$\ln\left(L_{ibt}\right) = \alpha_{ib} + \alpha_{it} + \zeta\sum_x \omega_{bx}\ln\left(p_{xt}\right) + u_{ibt},$$

$$\zeta = \varepsilon\phi\beta.$$

This expression corresponds with Equation 4. Note that in this derivation we assumed there is more than one commodity exporter, so we obtain the case we have in the data.

Firm-level regression. We begin with the equilibrium conditions of the non-tradable intermediate firms expressed in natural logarithms. We have the demand faced by non-tradable intermediate firms

$$\ln\left(y_i\right) = -\sigma\ln\left(p_i\right) + \sigma\ln\left(p_n\right) + \ln\left(y_n\right),$$

the price set by non-tradable intermediate firms

$$\ln(p_i) = \ln\left(\frac{\sigma}{\sigma-1}\right) + \ln(w) - \ln(A_i) + \theta r_i^L.$$

the interest rate faced by non-tradable intermediate firms

$$r_i^L = \sum_b s_{ib} r_{ib}^L,$$

and the interest rate set by banks

$$r_b^L = \ln\left(\frac{\varepsilon}{\varepsilon-1}\right) + r + \phi\ln(\mathcal{B}_b) - \phi\ln(D_b).$$

Replace to obtain

$$\ln(p_i y_i) = \sigma\ln(p_n) + \ln(y_n) - (\sigma-1)\ln\left(\frac{\sigma}{\sigma-1}\right) - (\sigma-1)\ln(w) + (\sigma-1)\ln(A_i) - (\sigma-1)\theta r_i^L.$$

Replace interest rate, $\ln(D_b) = \alpha_b + \beta\sum_x \omega_{bx}\ln(p_x)$, add time subindices and collect terms to find

$$\begin{aligned}\ln(p_{it}y_{it}) = & \underbrace{-(\sigma-1)\ln\left(\frac{\sigma}{\sigma-1}\right) - (\sigma-1)\theta\ln\left(\frac{\varepsilon}{\varepsilon-1}\right)}_{\text{constant}} \underbrace{-(\sigma-1)\theta\phi\sum_b s_{ib}\ln(\mathcal{B}_b)}_{\alpha_i} + \underbrace{(\sigma-1)\ln(A_{it})}_{\text{residual}} \\ & + \underbrace{\sigma\ln(p_{nt}) + \ln(y_{nt}) - (\sigma-1)\ln(w_t) - (\sigma-1)\theta r_t}_{\alpha_t} + \underbrace{(\sigma-1)\theta\phi\beta}_{\kappa}\sum_b s_{ib}\sum_x \omega_{bx}\ln(p_{xt}),\end{aligned}$$

such that

$$\ln(p_{it}y_{it}) = \alpha_i + \alpha_t + \kappa\sum_b s_{ib}\sum_x \omega_{bx}\ln(p_{xt}) + u_{it},$$

$$\kappa = (\sigma-1)\theta\phi\beta.$$

This expression corresponds with Equation 5. As in the previous case, for this derivation we assumed there is more than one commodity exporter, so we recover the case we have in the data.

B.4 Data-based moments and shocks

Targeted and untargeted moments. We set the moments to match their observed changes in the data between 2003 and 2011.

- $\widehat{GDP}$: We use the real GDP series.
- $\widehat{c_m}$: We use the real imports series. Includes imported goods and services.
- $\widehat{y_n}$: We use the real non-mining GDP series.
- $\widehat{p_n}$: We use the real exchange rate series. We use the bilateral series with respect to the US. We do not use the multilateral real exchange rate (i.e., an average real exchange rate with respect to different trade partners) as it considers weights that shift over time.
- $\widehat{L_i}$: We use the aggregate firm loans issued by banks, deflated by the GDP deflator.
- $\widehat{D_b}$: We use the aggregate firm deposits held in banks, deflated by the GDP deflator.
- $\widehat{N_b}$: We consider a simplified bank balance sheet. On the asset side we have firm loans L_b. On the liabilities side we have firm deposits D_b, equity K_b and foreign wholesale funding N_b. However, N_b is not properly measured in the data. We calculate a proxy for foreign wholesale funding as $N_b = L_b - D_b - K_b$. All involved series are deflated by the GDP deflator.
- $\widehat{r_i^L}$: We use the average loan interest rate series for both domestic currency and US dollars. Then, we calculate a weighted interest rate using the respective weights of domestic currency-denominated and US dollar-denominated loans over total loans.

Shocks. We set the shocks to match their observed changes in the data between 2003 and 2011.

- $\widehat{K_b}$: We use the aggregate bank equity series, deflated by the GDP deflator.
- $\widehat{X_{nm}}$: We use the total non-mining exports, converted to domestic currency and deflated by the GDP deflator. Includes exported goods and services.
- $\widehat{r}$: We calculate the change in the sum of US federal funds rate and change in Peruvian EMBI minus Peruvian inflation rate.

B.5 Complete simulation results

Table B.1: Main simulation, complete results

	(1)	(2)	(3)
Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.65	1.58	0.07
$\widehat{h}$	1.70	1.58	0.11
$\widehat{w}$	1.56	1.46	0.10
$\widehat{p}$	1.22	1.18	0.04
$\widehat{c}$	1.98	1.82	0.16
$\widehat{c_m}$	2.19	1.98	0.21
$\widehat{y_n}$	1.84	1.72	0.12
$\widehat{p_n}$	1.41	1.33	0.08
Ave. $\widehat{L_i}$	2.65	2.30	0.34
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	6.06	8.23	-2.17
Ave. $\widehat{r_b^L}$	-0.07	-0.04	-0.03

Note: Column 1 shows moments from baseline simulation with financial propagation mechanism. Column 2 shows moments from counterfactual simulation with no financial propagation mechanism. Column 3 shows difference between baseline and counterfactual. All moments are expressed in percentage variations between initial and final states. Averages for the bank-related model variables are computed using loan-based weights of each bank in total loans. These weights are calibrated according to observed data.

Table B.2: Commodity price shock-only simulations, complete results

	(1)	(2)	(3)
Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.20	1.14	0.06
$\widehat{h}$	1.37	1.25	0.11
$\widehat{w}$	1.39	1.28	0.11
$\widehat{p}$	1.21	1.15	0.06
$\widehat{c}$	1.46	1.32	0.14
$\widehat{c_m}$	1.61	1.42	0.19
$\widehat{y_n}$	1.37	1.25	0.11
$\widehat{p_n}$	1.38	1.28	0.10
Ave. $\widehat{L_i}$	1.91	1.60	0.30
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	3.46	5.60	-2.14
Ave. $\widehat{r_b^L}$	-0.03	0.00	-0.03

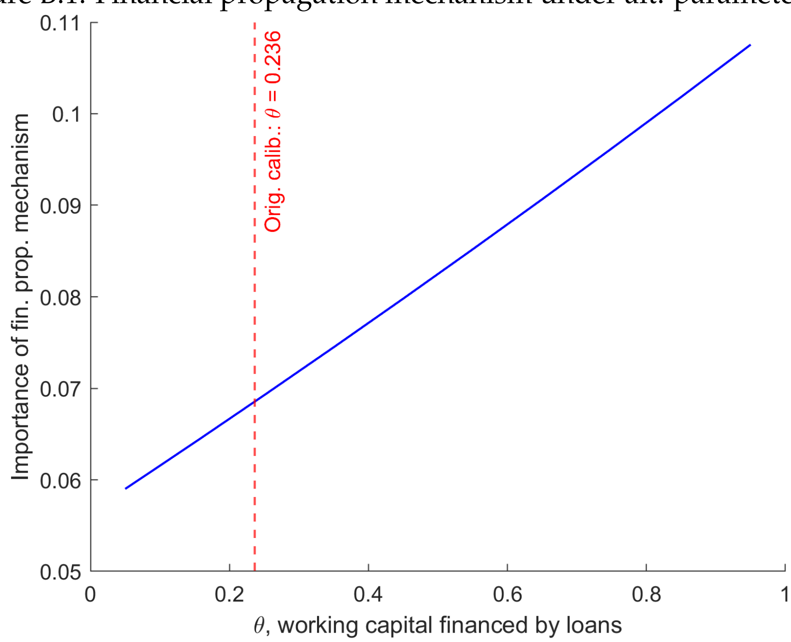
Note: Column 1 shows moments from baseline simulation with financial propagation mechanism. Column 2 shows moments from counterfactual simulation with no financial propagation mechanism. Column 3 shows difference between baseline and counterfactual. All moments are expressed in percentage variations between initial and final states. Averages for the bank-related model variables are computed using loan-based weights of each bank in total loans. These weights are calibrated according to observed data.

B.6 Model sensitivity to different parametrizations

In this section, we explore the sensitivity of the model results to variations in key bank-related and commodity-related parameters. We keep the original calibration and shocks, only changing the numerical values of selected parameters. We focus on examining the importance of the financial propagation mechanism, that is, the difference in GDP growth when the mechanism is turned on and off.

θ**, working capital financed by loans.** In Figure B.1 we see that the importance of the financial propagation mechanism grows as θ increases. This is because a higher θ means firms require to take higher loans, making the financial propagation mechanism becomes more important overall.

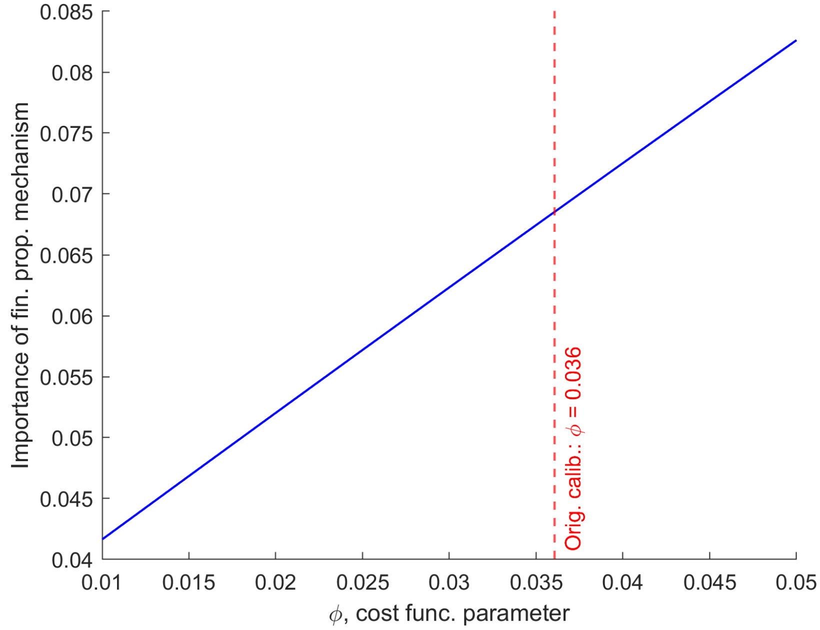
Figure B.1: Financial propagation mechanism under alt. parameters: θ



Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for θ. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

ϕ, bank cost function parameter. Figure B.2 shows that the importance of the importance of the financial propagation mechanism grows as ϕ increases. With a larger ϕ, bank costs become more responsive to the amount of deposits held, intensifying the role of the financial propagation mechanism in the economy.

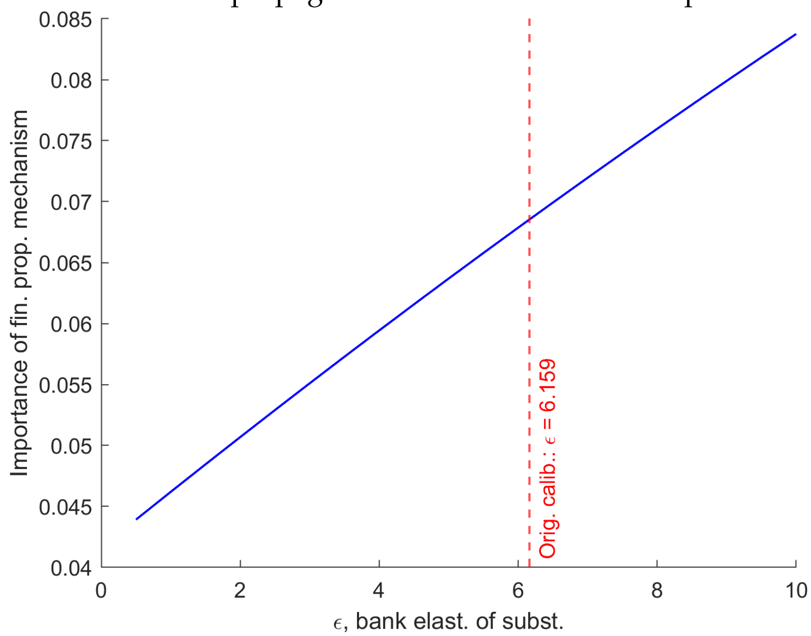
Figure B.2: Financial propagation mechanism under alt. parameters: ϕ



Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for ϕ. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

ε, **bank elasticity of substitution.** Figure B.3 displays that the importance of the importance of the financial propagation mechanism grows as ε increases. A larger ε implies the demand for loans becomes more sensitive to interest rate changes. This way, the role the financial propagation mechanism plays in the model economy expands.

Figure B.3: Financial propagation mechanism under alt. parameters: ε

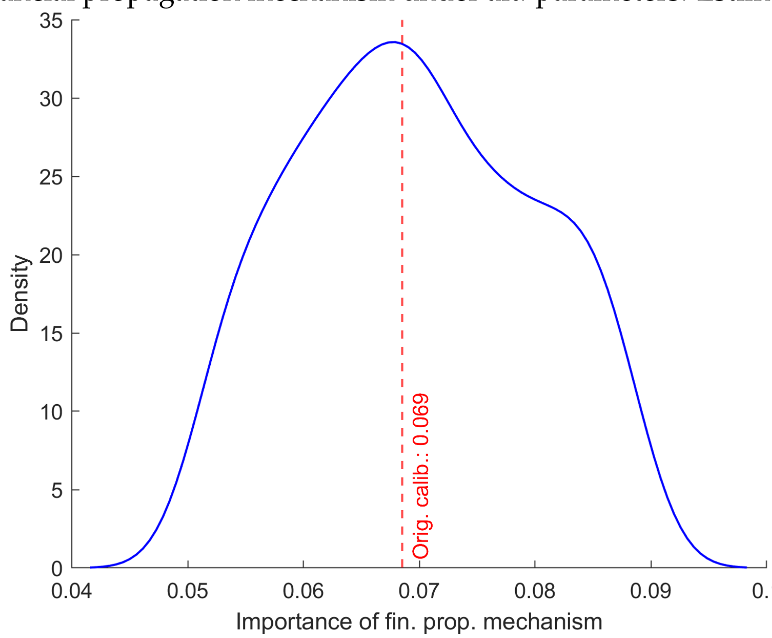


Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for ε. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

Estimated coefficients. The bank block calibration relies on estimated coefficients β, ζ, and κ. To account for the uncertainty around their estimation, we perform the following exercise based on Huo et al. (2024). We draw random values of β, ζ, and κ from a ± 1 standard deviation normally distributed range around their point estimates. We further assume these distributions are independent of each other. Then, we simulate the model and calculate the importance of the financial propagation mechanism.

Figure B.4 presents the density of the importance of the financial propagation mechanism after repeating the exercise 1000 times. While the range of results can vary from 0.051 to 0.089, our result under the original calibration is close to the mean (0.07) and median (0.069) of the distribution. Therefore, we find our main result is a central value within the range.

Figure B.4: Financial propagation mechanism under alt. parameters: Estimated coefficients



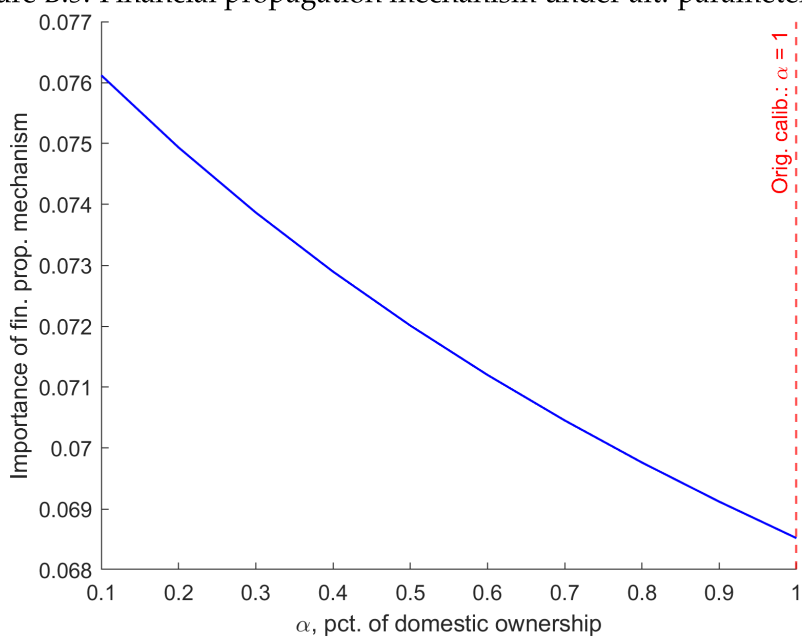
Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for of estimated coefficients β, ζ, and κ. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

α, percentage of domestic ownership of mining commodity firm. In this section we assume a more general form of the balance of payments equation

$$c_m = \alpha p_x y_x + X_{nm} + \sum_i L_i - \sum_b D_b - \sum_b \left[1 + r + \phi \ln\left(\frac{\mathcal{B}_b}{D_b}\right)\right] N_b,$$

where parameter α governs the strength of the wealth channel. In the main simulations, we assume $\alpha = 1$, which means that the mining commodity firm is wholly owned by the domestic household. Figure B.5 shows how the importance of the financial propagation mechanism changes when we vary this parameter. $0 \leq \alpha < 1$ implies $1 - \alpha$ percent of the commodity firm revenue flows out of the domestic economy to a foreign owner. As α decreases, outflows increase, weakening the wealth channel for the domestic economy. Consequently, as the role of the wealth channel diminishes, the financial propagation mechanism becomes relatively more important to overall GDP growth.

Figure B.5: Financial propagation mechanism under alt. parameters: α



Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for α. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.