The Financial Propagation Mechanism of Commodity Booms*

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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 an SOE model with banks to quantify its aggregate importance. After calibrating the model to the Peruvian data, our simulations suggest that the mechanism explains one tenth 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.

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1 INTRODUCTION

A well-documented fact about small open economies (SOEs) 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 premiums (Shousha, 2016; Drechsel & Tenreyro, 2018), and 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., 2020; 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 paper complements previous studies of commodity booms in SOEs by highlighting the role of domestic banks in the local transmission of shocks from the commodity sector to the non-commodity sector.

We document three 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, exploiting the heterogeneity in bank-borrower relationships, we find that more mining-exposed banks supply more loans to non-mining firms after mining commodity prices increase. After a 100 percent commodity price hike, 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 in our model 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 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. In 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 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 in which 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 one tenth of the observed 65 percent GDP growth in Peru 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 SOEs (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 by providing evidence of a new financial propagation mechanism of commodity shocks in SOEs that works through the banking system.

We also connect with the recent literature that studies 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 that of Peek & Rosengren (2005); Paravisini (2008); Schnabl (2012); Iyer et al. (2014); Gilje et al. (2016); Bustos et al. (2020); Federico et al. (2023), who use detailed bank and loan microdata to study how banks propagate shocks across firms, sectors, and geographies. 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. Firms need to take out loans because they are subject to a working capital constraint, following Neumeyer & Perri (2005); Jermann & Quadrini (2012). Banks are subject to a balance sheet constraint (Gilje et al., 2016; Wang et al., 2022; Whited et al., 2022), as they have to obtain foreign wholesale funding to cover their loans (Shousha, 2016).

Section 2 provides details on the global mining price boom and the Peruvian economy. Section 3 introduces the data and exposure measures. 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 SOE that benefited greatly from the boom. During the boom period, the mining sector represented 70 percent of exported goods and 10 percent of real GDP.

Peru is an ideal setting for examining the financial propagation mechanism of commodity booms in SOE. First, Peru exports a diverse basket of mining commodities: copper, gold, iron, lead, silver, tin, zinc, and aluminum, among others.[1] Thus, we observe variation across different minerals. Second, Peru holds a modest global market share for these commodities, so it is reasonable to assume it is a price taker in these markets[2] Third, despite its aggregate importance, the mining sector is weakly linked to the rest of the economy. For instance, in 2007, it only employed 1 percent of the total labor force, while it only demanded 2 percent of the domestically supplied goods and services. This facilitates the identification of the financial propagation mechanism, as increased labor income or intermediate demand are unlikely to be confounding factors.

In Figure 1 we report a weighted relative mining price index across all minerals that Peru exports. Mining commodity prices increased sharply during the study period. 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. This variable starts growing around the beginning of the boom and keeps increasing throughout the boom. While non-mining GDP is not directly linked to the mining sector, we will argue later that the two are connected through the banking system.

Figure 2 presents the evolution of relevant variables in the banking sector, namely firm deposits and firm loans. The former are the deposits coming from private sector firms to domestic banks, while the latter are the loans going from the domestic banks to the private sector firms. Both series register an increase in the early years of the boom and keep growing during 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

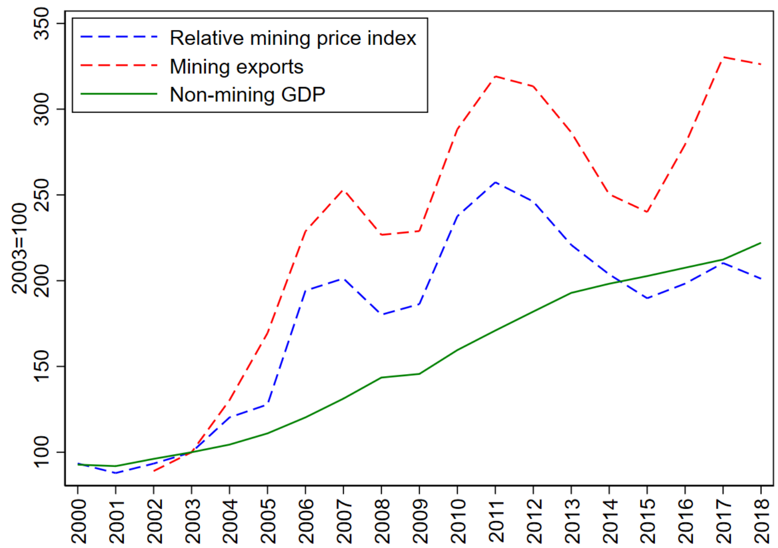
For our empirical analysis, we combine several data sources that result in a matched bank-firm-loan dataset for the Peruvian economy from 2005 to 2018 with annual frequency. First, we use firm-level customs data extracted from ADEX Data Trade. From this dataset, we identify the mining commodity exporters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

[1] Appendix Figure A.1 shows the share of each mining commodity in 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 in the boom from large mining projects entering production.

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 of each mining commodity across the sample in total mining commodity exports. For mining exports we first normalize the dollar value and then divide it by the Peruvian imports price index. The non-mining GDP is expressed in real domestic currency units and normalized.

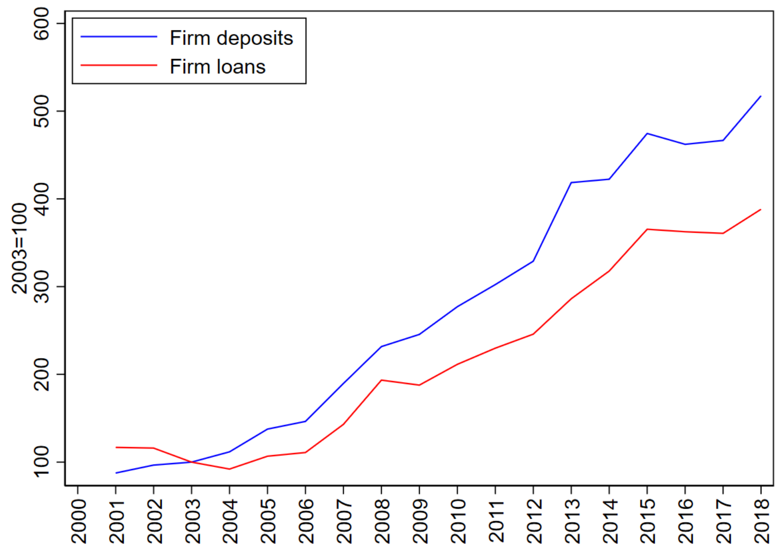
Second, we retrieve end-of-year bank balance sheet data from the Peruvian banking regulator (SBS). We focus on firm deposits—the total amount of deposits from private sector firms held in the banks under consideration. We have information for 9 domestic banks, whose firm deposits represented 7 percent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

Third, we use the Peruvian firm survey (EEA) to recover firm-level balance sheet information. We have information on 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 statistics on the firms in Appendix Table A.4.

[4]The total Peruvian financial system is composed of banks and other non-banking institutions (*cajas municipales*, *cajas rurales*, and *financieras*). 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 because of 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 2: Firm deposits and firm loans



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

Fourth, we exploit 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.

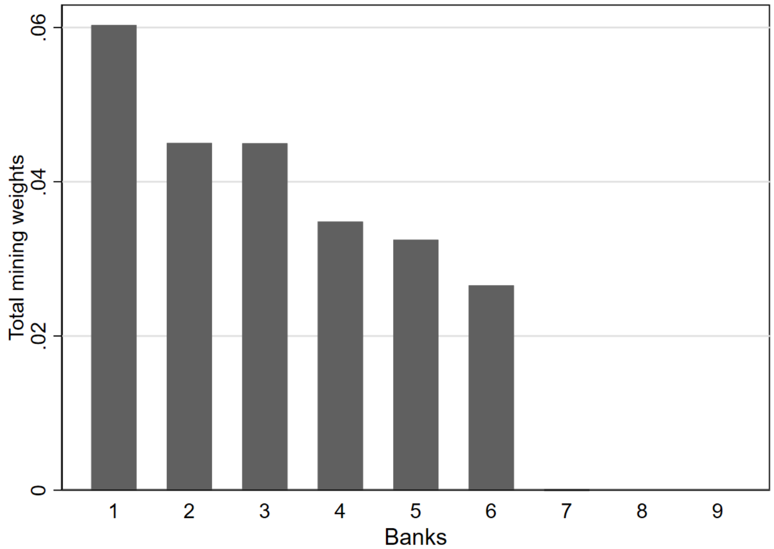
Last, we retrieve international commodity prices from the IMF commodity price database. We have information on aluminum, copper, gold, iron, lead, silver, tin, and zinc prices. Metals that are not found in the commodity price database are assigned the all-metals average price index. Per the usual SOE 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 the Mining Sector

The key variable in the empirical analysis is the exposure of banks and firms to 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

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.

greater than or equal to 50 percent of its total exports.

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 do 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 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 the 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, in which 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

[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.

index E_{bt} as

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

where ω_{bx} is the weight of mining firm x in the total loan portfolio of bank b and p_{xt} is the relevant mineral price for mining firm x (e.g., 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, 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 of this section is to empirically demonstrate the existence of the financial propagation mechanism that connects the commodity price boom to the rest of the economy. We use detailed microdata from Peru to establish three 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-commodity firms related to exposed banks increased their output. Together, these 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 exposed to mining exporters experienced an increase in their deposits. We rely on the exogeneity

[7]For 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.	$\ln\left(D_{bt}\right)$	$\ln\left(D_{bt}^{dom}\right)$	$\ln\left(D_{bt}^{usd}\right)$	$\ln\left(D_{bt}\right)$	$\ln\left(L_{bt}\right)$	$\ln\left(D_{bt}^{hh}\right)$
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 to deposits in domestic currency. Column 3 changes the dependent variable to deposits in US dollars. Column 4 adds a lag of the independent variable to the estimation. Column 5 changes the dependent variable to total firm loans. Column 6 changes the dependent variable to household deposits.

assumption for mining commodity prices in an SOE and exploit the heterogeneous exposure to such prices across banks to estimate

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

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, in which we do not account for the effect that the non-mining clients have on 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]

[9] Firm deposits refer to deposits that originate from firms. Therefore, this measure 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.

While we only have information on total firm deposits across all sectors and not mining-specific firm deposits, we argue that the positive effect we find occurs mostly because the mining sector increases its 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 analyze 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} is a firm-bank fixed effect that controls for the special relationship a firm-bank pair could have, and α_{it} is a firm-period fixed effect that controls for any firm-period-specific 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, in which the sample consists of only 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 by exposed banks ($E_{bt} > 0$) compared to non-exposed

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

Table 2: Loan-level results

	(1)	(2)	(3)	(4)
Dep. var.	$\ln\left(L_{ibt}\right)$	$\ln\left(L_{ibt}\right)$	$\ln\left(L_{ibt}\right)$	$\mathbb{I}_{ibt}^{entry}$
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.

banks ($E_{bt} = 0$).[12]

Taken together, Facts 1 and 2 suggest that banks face financial liquidity frictions that are relieved by the deposit inflow after the commodity price shock. If there were no financial frictions (i.e., if banks had costless access to liquidity), then we would not see an increase in loan supply after the shock, as banks would have already exploited all profitable lending opportunities (Gilje et al., 2016; Gilje, 2019; Bustos et al., 2020).

Fact 3: More exposed non-mining firms produce more. We now ask what occurs to the production by 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 mining commodity prices and leverage the heterogeneity in loan portfolios across non-mining firms to estimate

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

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

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

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 to the wage bill.

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]

Fact 3 also suggests non-mining firms face financial frictions. As with the banks, if firms were not exposed to such frictions (i.e., if they had costless access to financing), they would have already taken all the borrowing opportunities and we would not see the increase in output after the shock.

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 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 lag of the weighted mining commodity price exposure index. Because of the lag, we shorten our sample

[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.

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 shows 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^{hh}_{bt}. 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 from more than one bank. This excludes 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 two-digit ISIC sector and r denotes geographic region. The assumption is that all firms within the same region and sector face the same loan demand shock in any given period. 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 whether 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. We do not find a statistically significant effect of mining commodity prices on 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 two-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. Including the lag also requires us to shorten the sample to 2006-2018. We present the results in Column 3 of Table 3, in which 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. We explore the relationship between non-mining firm wage bill $w_t h_{it}$ and 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 mining commodity prices through banks. This suggests that mining-exposed firms not only produce more when mining commodity prices go up but 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 of the non-commodity firms 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 that 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. Each bank will receive different amounts of deposits from the commodity sector according to its exposure after a shock to commodity prices.

Motivated by our empirical results, we introduce 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 production takes place (Neumeyer & Perri, 2005; Jermann & Quadrini, 2012). 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 (Shousha, 2016). Because foreign lenders are concerned that domestic banks might default, domestic banks must pay a premium. This premium is decreasing in the amount of deposits held. Importantly, this friction connects the interest rates that banks charge on loans to the amount of deposits held.

The frictions we introduce in the model have several effects. After a commodity price boom that increases 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 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. 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. Moreover, the household provides equity K_b to fund the banks. Because our focus is not on equity, we will define it exogenously in our simulations.

Following the 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

$$pc + \sum_b K_b = wh + \pi,$$

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. We calibrate the elasticity of substitution so that the importable good and the non-tradable good are complements.

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

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

where σ is the elasticity of substitution and Λ_i denotes the weights, with $\Lambda_i \geq 0$ and $\sum_i \Lambda_i = 1$. We calibrate this bundle such that non-tradable intermediate goods are substitutes. Also, the relative price of the non-tradable consumption bundle is p_n.

5.2 Non-Tradable Intermediate Good 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 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

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

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, r_i^L is the loan interest rate each firm faces, and p_n is the relative price of the non-tradable consumption bundle.

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

$$L_i = \theta w h_i.$$

5.3 Commodity Exporter

We assume there is a representative commodity exporter, fully owned by the household.[14] It receives an endowment $y_x = 1$ and exports it at exogenous price p_x. This firm does not hire labor to operate or use intermediate inputs.[15]

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 an SOE, they do not encompass all export activity. Thus, we introduce a representative non-commodity exporter that is owned by the household. Similarly to its commodity-exporting counterpart, the non-commodity exporter receives an exogenous endowment X_{nm} that it exports at relative 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 into loan bundle L_i using CES technology (Gerali et al.,

[14] In Appendix B.7 we explore the possibility of the domestic household not wholly owning the commodity exporting firm.

[15] This is based on the observation that, in the Peruvian setting, the mining sector employs few workers and demands few domestically supplied goods and services.

2010; Andrés et al., 2013; Ulate, 2021) and charge interest rate r_i^L. The CES assumption reflects two facts from firm and bank relationships. First, firms may obtain loans from more than one bank. Second, there is imperfect substitutability across different banks as they may be specialized in certain sectors or may have special relationships with specific firms (Chodorow-Reich, 2014; Cong et al., 2019; Paravisini et al., 2023).

The problem of the loan aggregator is

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

subject to loan bundle

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

where s_{ib} are fixed weights and ε is the elasticity of substitution across banks.[16] The calibration we follow for the simulations sets the bank-level loans that compose the bundle as substitutes. 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 $b \in [1, \ldots, B]$, with each offering a differentiated variety of loans. Banks operate in a monopolistically competitive fashion and are owned by 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 (Gilje et al., 2016; 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, and foreign wholesale funding N_b.[17] 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 (Shousha, 2016).

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

[16] 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.

[17] As stated above, because our focus is not on equity, in our simulations we set equity K_b exogenously to match its observed change in the data.

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

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

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 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, 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 their income increases.

[18] We may think of constant benchmark $\mathcal{B}_b$ as capturing the reputation of the domestic bank 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.4).

5.7 Market Clearing Conditions, Balance of Payments, and Real GDP

The markets for the final consumption good c, 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

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

where $p_x y_x + X_{nm} - c_m$ is the trade balance and $\sum_b \left[r + \phi \ln \left(\frac{\mathcal{B}_b}{D_b} \right) \right] N_b$ is the financial account. Last, 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, loan, 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, weights, ratios, and shocks. We present the non-bank block parameters, the bank block parameters, weights and shocks in Table 4, while we relegate the ratios to Appendix Table B.1. Based on the matched bank-firm-loan dataset from Peru, we calibrate the model for 3 representative non-tradable firms, 9 banks and a representative commodity exporter.[19] For the non-bank block, we calibrate the intratemporal parameters using standard values in the SOE literature (Uribe & Schmitt-Grohé, 2017), while we set the elasticity of substitution in the non-tradable basket so firms have a markup of 25 percent. For the ratios, we calibrate them to match the averages in Peruvian data in the period 2005-2018.

Table 4: Parameters

	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	5
	Bank block	
β	Commodity price to deposit elasticity	23.598
ε	Elasticity of substitution across banks in loan bundle	4.927
ϕ	Bank cost function parameter	0.045
θ	Working capital financed by loans	0.236
	Firm weights in total labor and price index	
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
	Shocks	
$\widehat{p_x}$	Commodity price shock	2.57
$\widehat{A_i}$	TFP	1.04
$\widehat{r}$	Foreign interest rate	-0.03
$\widehat{K_b}$	Bank equity	2.21
$\widehat{X_{nm}}$	Non-mining exports	2.37

Note: All ratios calculated using deflated data and expressed in domestic currency. Imports and exports consider traded goods only. Because foreign wholesale funding N_b is not properly measured in the data, we calculate $N_b = L_b - D_b - K_b$ as a proxy. We provide details on the data underlying the shocks in Appendix B.5.

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

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 financial expenses. Let $\theta r^L Z$ be the financial expenses 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.4.

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 that we know the numerical values of estimated coefficients β, ζ, and κ, as well as calibrated parameters σ and θ, we find $\varepsilon = 4.927$ and $\phi = 0.045$.

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 relative mining 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 because it is when 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 $\widehat{A_i} = 1.04$ for all i. Within the model, we also have additional shocks that help us 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 $\widehat{r} = -0.03$, the equity $\widehat{K_b} = 2.21$ for all b, and the

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

non-mining exports $\widehat{X_{nm}} = 2.37$.[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 5 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. 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.

Second, because the amount of foreign wholesale funding decreases, there are fewer 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 domestic non-tradable goods, the

[21] We provide details on the data underlying the shocks in Appendix B.5.
[22] We provide details on the data-based moments in Appendix B.5.

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 in which 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 one tenth of the observed GDP growth in 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 banks now require more foreign wholesale funding. First, this drives up their premiums and interest rates charged. Thus, 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 lower demand for non-tradable goods. These two channels reduce the GDP growth rate.[23]

We interpret this result as a lower bound of the aggregate importance of the financial propagation mechanism of commodity booms. First, the model is calibrated using data from medium to large firms coming from the firm survey. This excludes small firms, who presumably are more financially constrained than their larger counterparts and would react more strongly to an increased loan supply. Second, our simulation includes other shocks, which decreases the relative importance of the financial propagation mechanism.

6.2 Simulation with Only a Commodity Price Shock

In this section, we isolate the effects of a commodity price shock by simulating the model with only this shock, excluding any other disturbances. Thus, the model economy is subject to a pure wealth increase coming from the commodity price shock, more in line with the standard SOE

[23] In Appendix B.7 we explore the sensitivity of the model results under alternative parameterizations.

Table 5: 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	2.37	2.15	0.21
$\widehat{y_n}$	1.71	1.84	1.72	0.12
$\widehat{p_n}$	1.29	1.65	1.56	0.09
Ave. $\widehat{L_i}$	2.34	3.09	2.71	0.38
Ave. $\widehat{D_b}$	3.02	2.64	1.00	1.64
Ave. $\widehat{N_b}$	8.56	6.27	8.62	-2.35
Ave. $\widehat{r_b^L}$	-0.05	-0.07	-0.03	-0.04

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 the 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. 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.

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 6 presents the results after the commodity price shock. Under the baseline case, with the financial propagation mechanism turned on, GDP grows by 34 percent. When we turn off the financial propagation mechanism, GDP grows by 27 percent. Thus, the financial propagation mechanism accounts for 7 percentage points or approximately one fifth 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 more important in driving the baseline GDP growth.

Table 6: Commodity price shock-only simulations

	(1)	(2)	(3)
Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.34	1.27	0.07
$\widehat{c_m}$	1.93	1.73	0.20
$\widehat{y_n}$	1.54	1.43	0.11
$\widehat{p_n}$	1.58	1.48	0.10
Ave. $\widehat{L_i}$	2.45	2.11	0.34
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	5.32	7.69	-2.37
Ave. $\widehat{r_b^L}$	-0.04	0.00	-0.04

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 the 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.3. 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.

7 Conclusions

This paper proposes a novel financial propagation mechanism in SOEs in which 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.

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 one tenth of the observed 65 percent GDP growth in Peru during the 2003–2011 boom.

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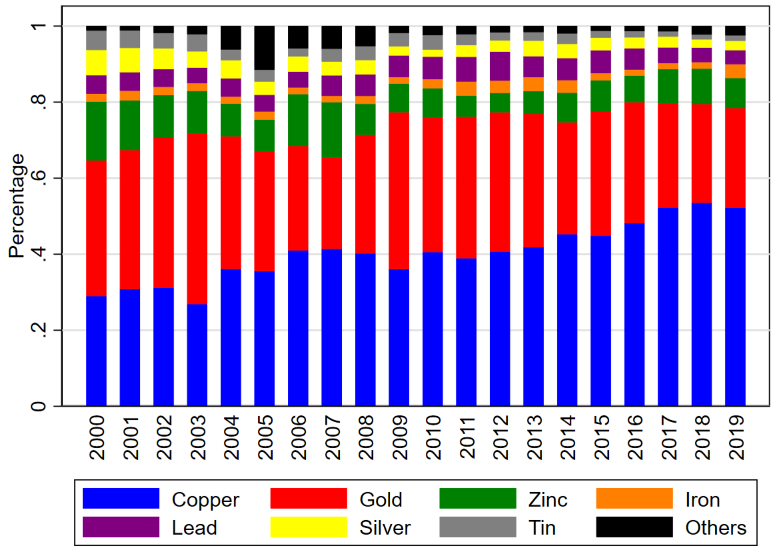
A Empirical Appendix

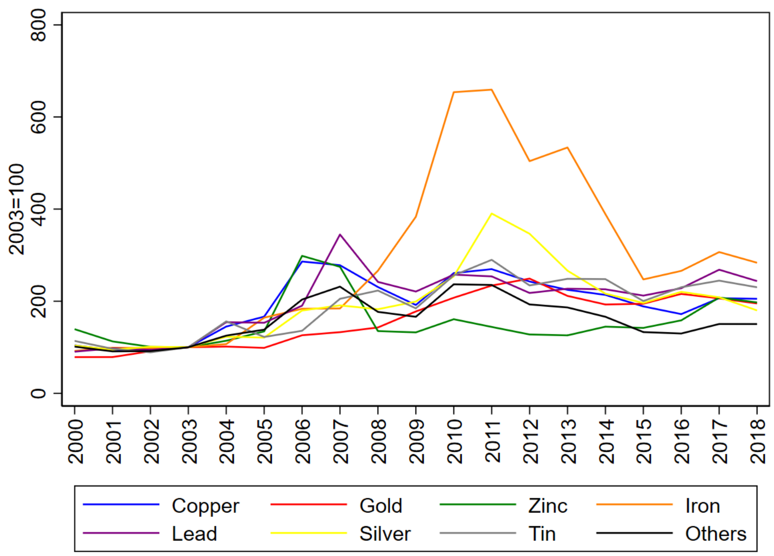
A.1 Mining Sector

Figure A.1: Mining exports by mineral



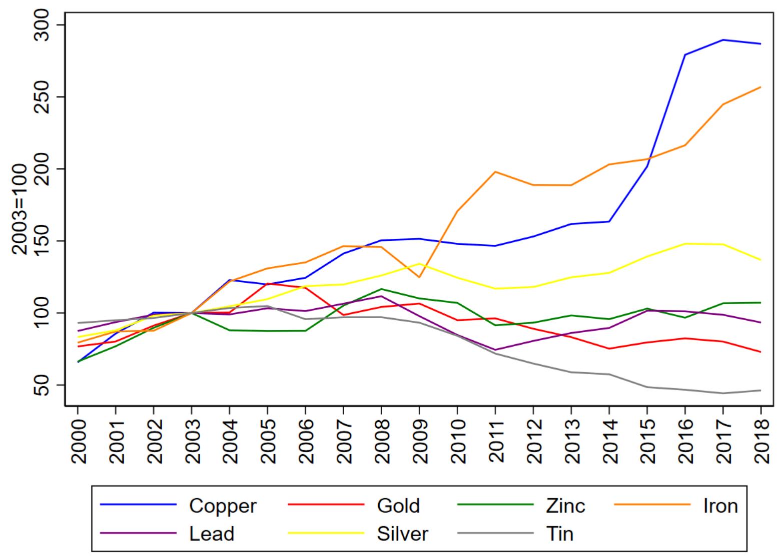
Note: Figure shows evolution of the shares of each mining commodity over total mining commodity exports.

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

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

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

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

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 Ratios

Table B.1: Ratios

	Trade balance ratios	
χ_x	Exports / Imports	1.006
η_x	Mining exports / Exports	0.692
χ_L	Total firm loans / Imports	0.823
χ_D	Total firm deposits / Imports	0.327
χ_N	Total wholesale funding / Imports	0.224
χ_K	Total equity / Imports	0.308
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	0.0137
ν	Country spread	0.0190
	GDP ratios	
Ω_n	(Consumption + Investment + Gov. exp.) / GDP	0.967
Ω_x	Exports / GDP	0.229
Ω_m	Imports / GDP	0.193
	Firm weights in total labor and price index	
Λ_i^h	Wage bill / Total wage bill	By firm
	Bank balance sheet ratios	
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. Imports and exports consider traded goods only.

B.4 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, which we interpret as the classical 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

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

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

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

Replace to obtain

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

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

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

such that

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

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

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.5 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 imported goods series.
- $\widehat{y_n}$: 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 $N_b = L_b - D_b - K_b$ as a proxy for foreign wholesale funding. 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 exported goods, converted to domestic currency and deflated by the GDP deflator.
- $\widehat{r}$: We calculate the change in the sum of US federal funds rate and change in Peruvian EMBI minus Peruvian inflation rate.

B.6 Complete Simulation Results

Table B.2: 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
$\widehat{h}$	1.77	1.66	0.11
$\widehat{w}$	1.75	1.64	0.11
$\widehat{p}$	1.35	1.30	0.04
$\widehat{c}$	2.04	1.89	0.15
$\widehat{c_m}$	2.37	2.15	0.21
$\widehat{y_n}$	1.84	1.72	0.12
$\widehat{p_n}$	1.65	1.56	0.09
Ave. $\widehat{L_i}$	3.09	2.71	0.38
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	6.27	8.62	-2.35
Ave. $\widehat{r_b^L}$	-0.07	-0.03	-0.04

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 the 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.3: Commodity price shock-only simulations, complete results

	(1)	(2)	(3)
Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.34	1.27	0.07
$\widehat{h}$	1.54	1.43	0.11
$\widehat{w}$	1.59	1.48	0.11
$\widehat{p}$	1.31	1.26	0.05
$\widehat{c}$	1.69	1.55	0.14
$\widehat{c_m}$	1.93	1.73	0.20
$\widehat{y_n}$	1.54	1.43	0.11
$\widehat{p_n}$	1.58	1.48	0.10
Ave. $\widehat{L_i}$	2.45	2.11	0.34
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	5.32	7.69	-2.37
Ave. $\widehat{r_b^L}$	-0.04	0.00	-0.04

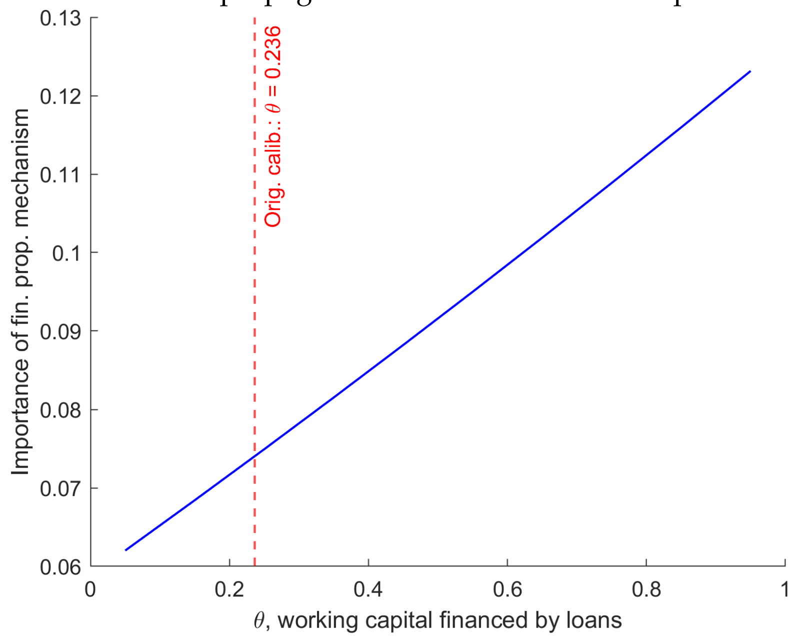
Note: Column 1 shows moments from baseline simulation with financial propagation mechanism. Column 2 shows moments from counterfactual simulation with no financial propagation mechanism. Column 3 shows the difference between baseline and counterfactual. All moments are expressed in percentage variations 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.7 Model Sensitivity to Different Parameterizations

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.

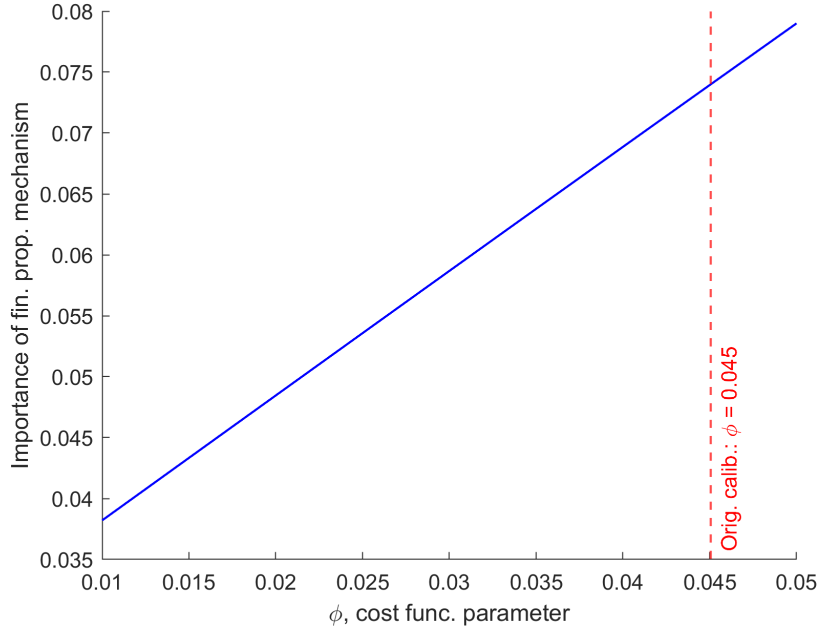
Figure B.1: Financial propagation mechanism under alt. parameters: θ



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.

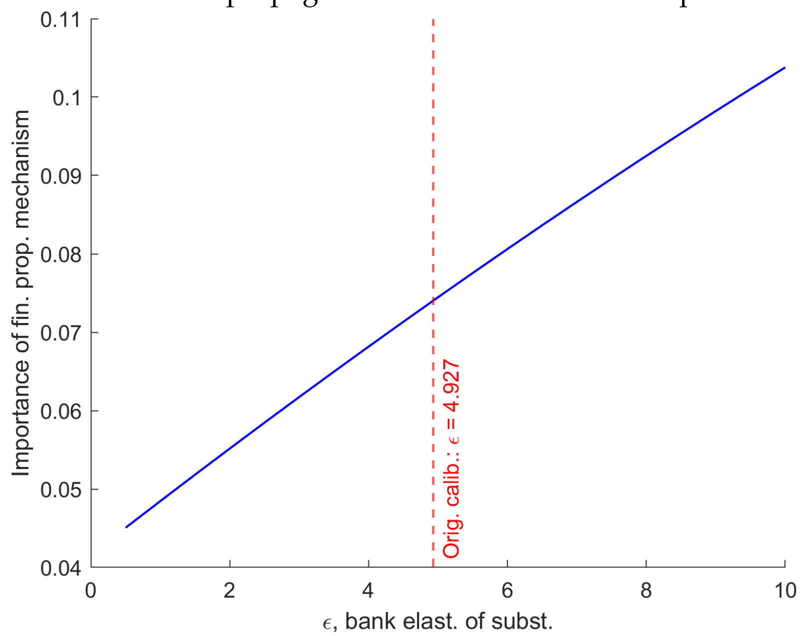
Figure B.2: Financial propagation mechanism under alt. parameters: ϕ



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

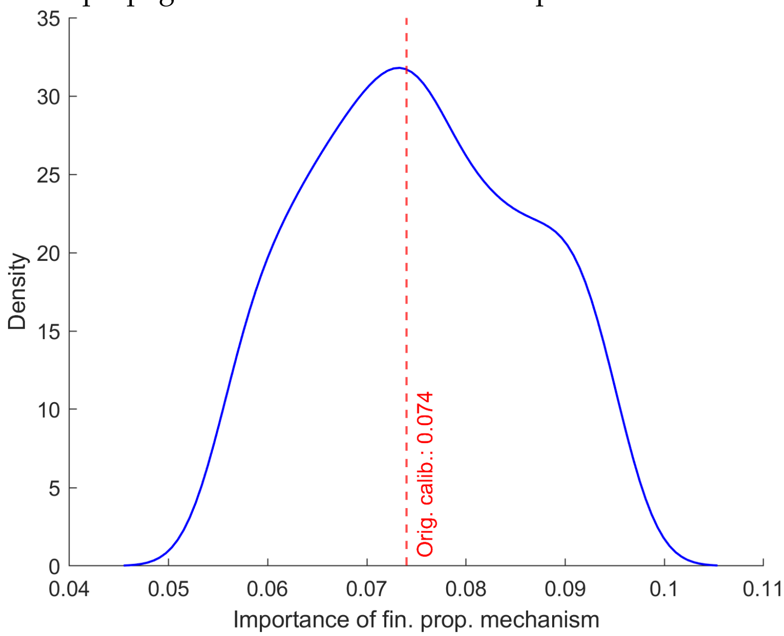


Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for ε. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

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 0.088, our result under the original calibration is close to the mean (0.075) and median (0.075) 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



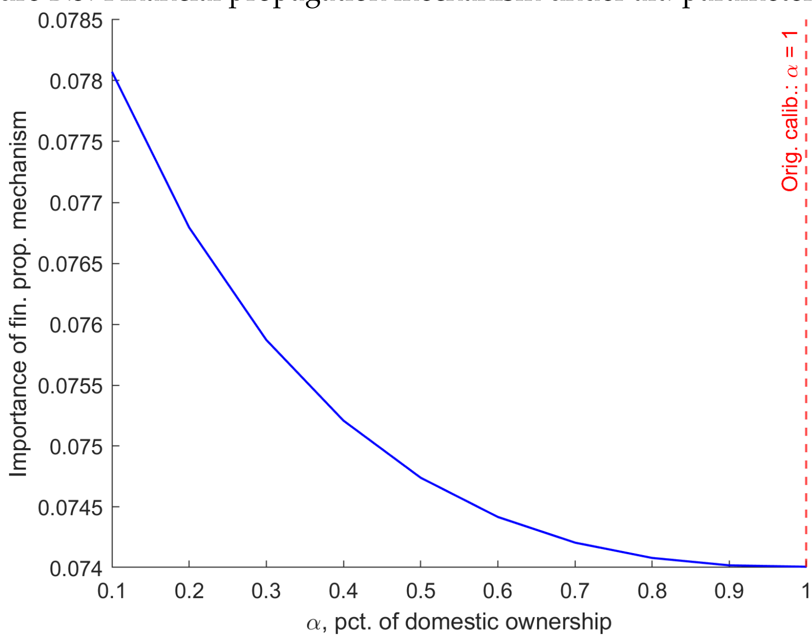
Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for of estimated coefficients β, ζ, and κ. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism.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

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

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.