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 where, following a commodity price boom, commodity exporters increase their deposit holdings in domestic banks. Banks follow with an expansion of their loan supply to non-commodity firms. Then, non-commodity firms increase their hiring. We provide empirical evidence for this mechanism using detailed matched bank-firm-loan microdata from Peru, an SOE that experienced a commodity price boom in the 2000s. We incorporate this mechanism into a SOE model with banks to quantify its aggregate importance. After calibrating the model to match the Peruvian data, our simulations suggest the mechanism explains 16 percentage points of the observed 65% Peruvian GDP growth rate in the boom episode (2003-2011).

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 of small open economies (SOE) is that commodity prices, or more generally, terms of trade, play an important role as originators of business cycles (Fernández et al., 2023; Kose, 2002; Mendoza, 1995; Schmitt-Grohé & Uribe, 2018). Related to how these shocks propagate through the economy, the literature has previously referred to the wealth channel, the lower foreign debt premium channel, the labor reallocation channel, among others. In these same SOEs, there is also evidence of strong financial constraints, which increases the relevance of financial agents. In particular, banks are known for being able to propagate shocks across sectors, firms, and borders.

In this paper, we explore how a commodity price boom interacts with financial constraints 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 posit that after a commodity boom, commodity exporters increase their deposit holdings in domestic banks, which causes banks to increase their loan supply to non-commodity firms. Then, non-commodity firms increase their hiring. Our proposed mechanism complements the previous studies of commodity booms in SOEs, as we focus on the role domestic banks have in locally transmitting the commodity shock from the commodity sector to the non-commodity sector.

We proceed in two parts. In the first part, we show empirical evidence for this mechanism by using granular matched bank-firm-loan microdata from Peru, an SOE that experienced a mining commodity price boom in the 2000s. In the second part, we quantify the aggregate importance of this mechanism by incorporating it into a static SOE model augmented with an endowment commodity sector and banks. We find that our proposed mechanism accounts for 16 percentage points of the observed 65 percent Peruvian GDP growth rate in the booming period of 2003-2011.

On the empirical side, we document three different facts using a detailed matched bank-firm-loan dataset from Peru. First, we report that banks are heterogeneously exposed to the mining commodity sector through their different mining client portfolios. When mining commodity prices rise, banks with greater exposure receive more firm deposits. Second, we exploit the heterogeneity in bank-borrower relationships to find that more exposed banks to mining commodity prices supply more loans to non-mining firms after mining commodity prices increase. Third, we use bank exposure heterogeneity across firms to find that firms more exposed to mining commodity prices through their banks increase their hiring after a hike in mining commodity prices.

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 suggests, banks are heterogeneous in their exposure to the commodity sector. This way, each bank will receive different amounts of deposits from the commodity sector after a commodity price shock.

The model we propose 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. Thus, 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 with the interest rate banks charge for their loans.

The tractability of the model allows us to derive model-based expressions that resemble the regressions estimated in the empirical part. 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 commodity price booming period of 2003-2011.

After simulating the non-linear model using hat algebra, we successfully match the targeted moment and achieve a good fit to untargeted moments.

We then conduct a counterfactual exercise where we turn off the financial propagation mechanism in order to quantify the aggregate importance of the proposed mechanism. More specifically, we turn off the pass-through from commodity prices to firm deposits. We compare the GDP growth of the base and counterfactual economies to find the proposed financial propagation mechanism accounts for 16 percent of the observed GDP growth in Peru within the booming period of 65 percent in 2003-2011.

Section 2 provides details on the Peruvian mining and banking setting. Section 3 introduces the data and the exposure measures we use. Section 4 presents the empirical results. In Section 5 we introduce the theoretical framework. Section 6 presents the simulations with the calibrated theoretical model. Finally, Section 7 concludes.

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 (Corden & Neary, 1982; Fernández et al., 2023; Kose, 2002; Mendoza, 1995; Salter, 1959; Schmitt-Grohé & Uribe, 2018; Swan, 1963) and (ii) the literature that studies how financial frictions interact with commodity shocks (Drechsel & Tenreyro, 2018; Shousha, 2016). We complement the previous research by providing evidence of a new financial propagation mechanism of commodity shocks in SOE that works through the banking system and showing how central banks are in the local propagation of commodity shocks across sectors.

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 proposed financial propagation mechanism using detailed bank-firm-loan matched microdata.

Our empirical strategy is close to Federico et al. (2023); Paravisini (2008); Peek & Rosengren (2005); Schnabl (2012), 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 are not only able to find out how the financial propagation mechanism works in the data, but also to quantify its aggregate importance.

On the theoretical side, we start from the standard textbook SOE model of Uribe & Schmitt-Grohé (2017). Our contribution is to extend it with financial frictions and heterogeneous banks. The extensions are 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). Furthermore, the loans are a CES composite of loans supplied by the different banks, as in Andrés et al. (2013); Gerali et al. (2010); Ulate (2021).

2 Setting: Mining price boom in Peru

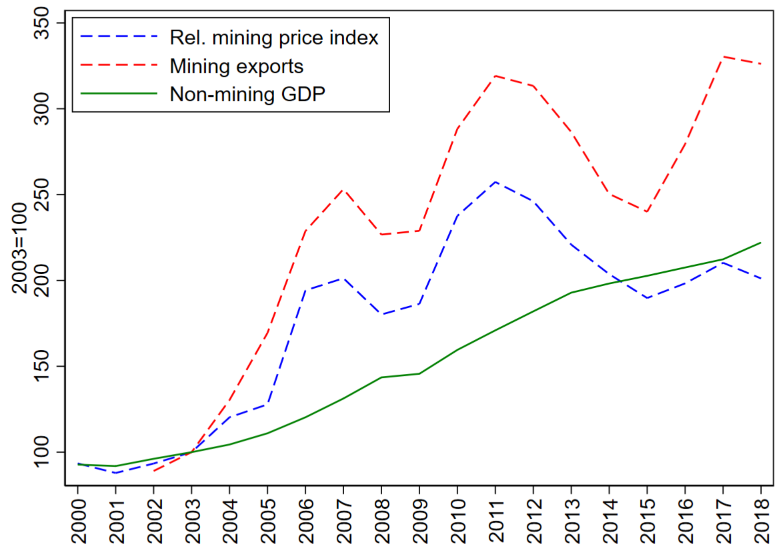
Peru is a SOE in which the mining commodity sector plays an important role. The country exports a diverse basket of mining commodities: copper, gold, iron, lead, silver, tin, zinc, and aluminum, among others. Moreover, it is a price taker in the international markets for each of these minerals.[1]

From the early 2000s to the mid 2010s, Peru experienced a mining commodity price boom, mainly driven by a demand expansion from China (Fernández et al., 2023). Over this period, mining exports represented 60 percent of total exports and 10 percent of real GDP.

In Figure 1 we report a weighted mining relative price index across all minerals that Peru exports. We see the prices increased sharply. For instance, at its peak in 2011, the prices

[1] Appendix Figure A.3 shows the share each mining commodity has over the total mining exports. Additionally, Appendix Table A.1 presents that the share Peru has in the international markets for these minerals is not the largest worldwide.

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.

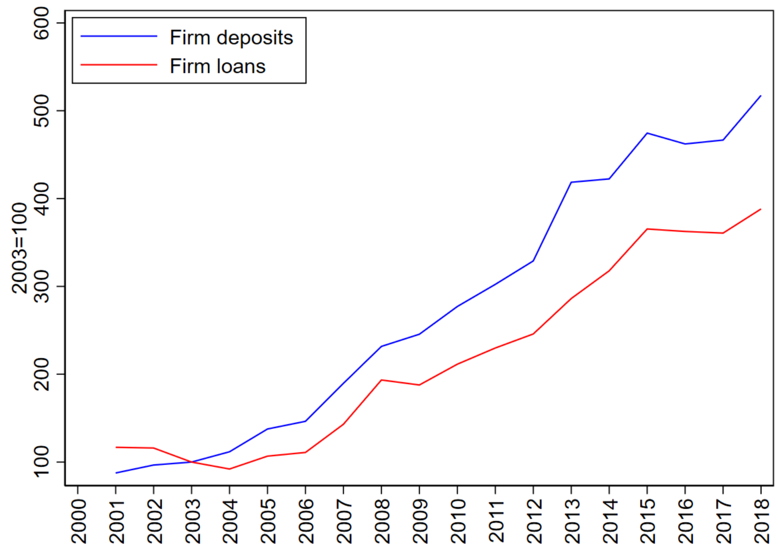
more than doubled in comparison to its value at the start of the boom. Figure 1 also depicts that mining exports increased over this period, closely following the price index.[2]

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 booming 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.

Figure 2 presents the evolution of relevant variables of the banking sector. In particular, we present 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 booming episode. In the next sections,

[2]This boom was mostly price-driven rather than quantity-driven. We show individual mining price and quantity indices in Appendix Figures A.1 and A.2, respectively. Quantities remained relatively flat for most minerals, the only exceptions being copper and iron, which benefited 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.

we will maintain that part of this growth is due to banks being connected to the booming mining sector.

3 Data

For our empirical analysis, we merge 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). Our focus is 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.[3] We show the basic statistics in Appendix Table A.2.

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.[4] 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.3.

Fourth, we work with a subsample of the Peruvian credit registry. We focus on the same sample of firms from the firm survey. 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. 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.4.

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 do not appear 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

[3]The total Peruvian financial system is composed of banks and other non-banking institutions (cajas municipales, cajas rurales, and financieras). With respect to the total financial system, the 9 banks in our sample represent 87 percent of total assets, 87 percent of total firm loans and 88 percent of total firm deposits on average between 2005 and 2018. For those banks that merged during this period, we consider them as one entity and add their accounts. We do not consider banks that are specialized in (i) serving foreign-owned firms only or (ii) credit card and consumer loans only, as both are out of the scope of our analysis. Lastly, we do not consider the cajas municipales, cajas rurales, and financieras, as they could not hold firm deposits due to regulatory reasons over the period of analysis.

[4]While their information is available in the firm survey, we drop non-mining commodity-producing firms from the sample as their activities could be directly correlated with the prices of the mining sector. These sectors are agriculture, electricity, fishing, oil and gas.

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.

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 x in the customs data. We classify a firm as a mining commodity exporter if their average mining exports are larger or equal than 50 percent of their 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.[5] This measure should capture how banks are heterogeneously exposed to the different mining firms. 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] As a summary, we report the total mining weights across banks in Figure 3.

For each bank b, we construct the weighted mining commodity price exposure index E_{bt} defined as

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

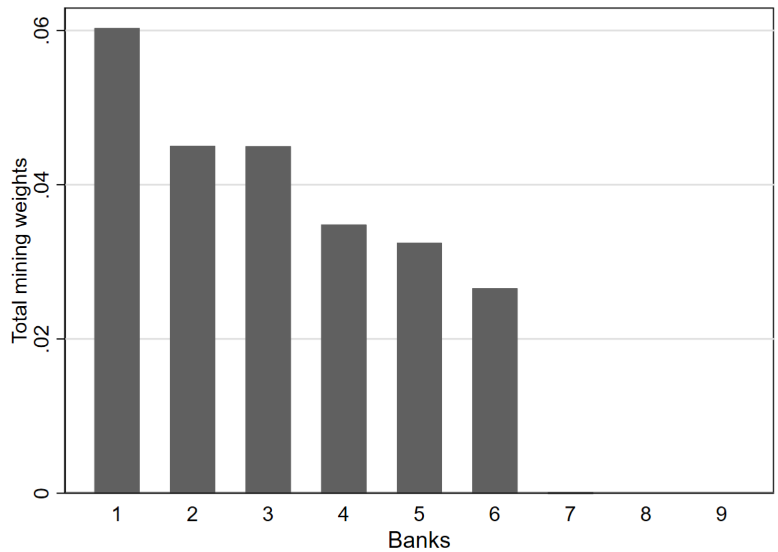
where ω_{bx} is the aforementioned weight of mining firm x in total loan portfolio of bank b and p_{xt} is the relevant mineral price for mining firm x (i.e. copper price for a copper exporter, gold price for a gold exporter). Importantly, we take the commodity prices as exogenous to Peruvian firms, following the SOE assumption.

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

[5]As our goal is to measure how many deposits the banks received from mining exporters, ideally, the exposure weights should correspond to the deposit portfolio. However, because detailed micro-level deposit data is not available, we use the loan portfolio weights from the credit registry as a proxy.

[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.

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.

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.[7]

4 Estimations

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 microdata 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)

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

non-firms related to exposed banks increased their hiring.

Fact 1: More exposed banks receive more firm deposits

We first analyze if banks that 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 exposure to such prices across banks to estimate

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

where D_{bt} are the firm deposits, α_b is a bank fixed effect and α_t is a period fixed effect.[8]

Table 1: Bank-level estimation

E_{bt}	23.598***
	(5.000)
Obs.	121
Adj. R2	0.965

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

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, a 100 percent increase in mining commodity prices would result in an increase of 65 percent in firm deposits within exposed banks ($E_{bt} > 0$) with respect to non-exposed banks ($E_{bt} = 0$).[9] Then, more exposed banks receive more firm deposits after mining commodity prices increase.

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

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

[9]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.

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.[10]

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 different banks. More specifically, we estimate

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

where L_{ibt} are the outstanding loans from bank b to non-mining firm i, α_b is a bank fixed effect, α_t is a period fixed effect, 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 demand shocks.

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 supply shock coming from the banks.

Table 2: Loan-level estimation

E_{bt}	8.855***
	(2.799)
Obs.	75,011
Adj. R2	0.532

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm and bank-period in parentheses.

[10] 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.

Table 2 presents the result. We find a positive elasticity between the loans a bank gives to its 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 25 percent in loans supplied from exposed banks ($E_{bt} > 0$) when compared to non-exposed banks ($E_{bt} = 0$).[11] Therefore, after a hike in mining commodity prices, we find that more exposed banks supply more loans to their non-mining clients.

Fact 3: More exposed non-mining firms hire more

We now ask about what occurs with non-mining firms related to exposed banks. Here, we maintain the exogeneity assumption for the mining commodity prices and leverage the heterogeneity in loan portfolios across non-mining firms to estimate

$$\ln\left(w_t h_{it}\right) = \alpha_i + \alpha_t + \kappa e_{it} + \varepsilon_{it}, \tag{5}$$

where $w_t h_{it}$ is the wage bill of non-mining firm i, α_i is a firm fixed effect and α_t is a period fixed effect.

Table 3: Firm-level estimation

e_{it}	1.026***
	(0.301)
Obs.	38,163
Adj. R2	0.929

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

Table 3 shows the result. There is a positive elasticity between the wage bill 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 wage bill of exposed firms ($e_{it} > 0$)

[11] The calculation we perform is $\zeta \times \overline{\omega_{bx}} \times [\ln(2)] \approx 25\%$.

with respect to non-exposed firms ($e_{it} = 0$).[12] Thus, we encounter that more exposed non-mining firms increase their hiring after mining commodity prices go up.

Additional estimations

In Appendix A.3 we report additional specifications for the bank-level regression. We first find that there is no difference in the effect of mining commodity prices over firm deposits when we take the currency of the firm deposits into account. We also note that there is no statistical effect of mining commodity prices on household deposits. Finally, we find that total firm loans supplied by banks at the aggregate level increase when there is a positive mining commodity price shock.

Appendix A.4 presents additional exercises for the loan-level regression. We find that the main result remains even when we change fixed effects to also consider firms that maintain loans with only one bank. Then, we find there is no statistically significant effect of mining commodity prices on consumer loans and on the extensive margin of firm loans.

Appendix A.5 extends the firm-level regression results. We obtain that firm-level sales increase for exposed firms when mining commodity prices increase. Furthermore, we find that the main result remains when we consider an alternative set of fixed effects that also account for sector and geographic region.

5 Model

In this section, we introduce a static SOE model to show the theoretical underpinnings of the financial propagation mechanism of commodity booms and quantify its aggregate importance. The basic structure of the model is composed of a representative household, a discrete

[12]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.

number of non-tradable intermediate goods producers, a loan aggregator, a discrete number of banks, and a representative commodity producer. The household owns all the firms and banks. The economy is subject to a fixed commodity endowment. 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. In first place, non-commodity firms produce using a linear production technology that uses only labor. However, they face a working capital constraint. This means these firms have to pay for a certain part 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.

In second place, 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. We present the equilibrium conditions in Appendix B.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.[13] It solves the problem

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

subject to

$$pc = wh + \pi,$$

[13]The representative household also funds the banks with equity and receives it back at the end of the period when banks are liquidated. In the simulations, we exogenously set the change in equity to match the change observed in the data.

where υ is the constant 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 by 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. The relative price of this bundle is p_n.

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 perfect competition and are owned by the household. They use labor h_i to produce y_i with productivity A_i and charge relative price p_i.

Moreover, these firms are subject to a working capital constraint, which means they must pay a proportion θ percent of the wage bill wh_i in advance, before production takes place (Neumeyer & Perri, 2005; Jermann & Quadrini, 2012). Then, 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 and r_i^L is the loan interest rate each firm faces.

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

$$L_i = \theta w h_i.$$

Commodity exporter

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

Disciplined by the data, we assume that the commodity exporter holds deposits in the domestic banks. Additionally, the amount of deposits held is sensitive to the commodity prices. 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 wholly transfers the export revenue to households.

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 (Andrés et al., 2013; Gerali et al., 2010; Ulate, 2021) and charge an interest rate r_i^L. The loan bundle is

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

where s_{ib} are fixed weights and ε is the elasticity of substitution.[14]

Banks

There is a discrete number of banks indexed by $b \in [1,\ldots,B]$. Each sells 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. We assume that 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 $\phi \ln\left(\frac{\mathscr{B}_b}{D_b}\right)$, where ϕ is a cost function parameter and $\mathscr{B}_b$ is a constant that serves as a benchmark.[15]

The problem banks solve is

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

[14] Appendix Table A.11 shows there is no effect of the mining commodity price shock over the extensive margin. Thus, we do not consider it within the model.

[15] We may think of constant benchmark $\mathscr{B}_b$ as capturing the reputation of the domestic bank has in foreign markets or the relationships the domestic bank may have with foreign lenders. The functional form $\ln\left(\frac{\mathscr{B}_b}{D_b}\right)$ 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.

subject to

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

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

After solving their problem, the interest rate r_b^L charged is

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

where we see that the introduction of the balance sheet friction and the premium banks pay connects the interest rate banks charge with the amount of firm deposits they hold.

Based on Equation 3, we define the relationship between deposits D_b and commodity prices p_x as

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

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.

Labor market clearing condition

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

$$h = \sum_i h_i.$$

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 $1 + \widehat{i} = \frac{1+i'}{1+i}$. 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.[16] We present the equilibrium conditions expressed in terms of hat algebra in Appendix B.2.

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 $\left\{r_i^L\right\}_i, \left\{r_b^L\right\}_b$; 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.

Parameters

We divide the parameters into the non-bank block, the bank block and ratios. We present the complete parametrization in Appendix B.3. 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. In the rest of this section we provide detail on how we obtain the values for the bank block parameters based on the data and the regressions of Section 4.

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

[16] 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.

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 $r^L = 0.11$.[17] With this, we recover a firm-level value for θ. 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. We have $\beta = 23.598$.

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 resemble Equations 4 and 5. We show the detailed steps in Appendix B.4. 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 $\kappa = \sigma\theta\phi\beta$. Given we know the numerical values of estimated coefficients β, ζ and κ, as well as calibrated parameters σ and θ, we find $\varepsilon = 12.273$ and $\phi = 0.031$.

6 Simulations

In this section, we perform simulations of the hat algebra version of the model to quantify the aggregate importance of the financial propagation mechanism of commodity booms. After calibrating the model to match the Peruvian economy, 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 $\widehat{A}_i = 1.09$ for all i. Within the model, we also have additional shocks that

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

help us match the data. We set these shocks to match their observed changes in the data in the period of analysis. We set the market foreign interest rate $\widehat{r} = -0.05$, the equity $\widehat{K_b} = 2.21$ for all b, and the non-mining exports $\widehat{X_{nm}} = 2.10$.

Table 4 reports the results of the simulations.[18] Columns 1 and 2 show the moments coming from the data and the model, respectively. First, we see that our baseline simulation hits the targeted moment. Second, related to the untargeted moments, our baseline simulation gets fairly close to the data.

Within our model, when there is a commodity price boom that increases the firm deposits, banks require less foreign wholesale funding. In first place, this reduces the premiums banks pay for their foreign wholesale funding, so they end up charging 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 is an interest rate channel effect that drives GDP upward.

In second place, 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. Then, imports are larger. Because imports are complements with the domestic non-tradable goods, this also increases the demand for domestic non-tradable goods. Then, there is a wealth channel effect that also drives GDP upward.

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 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.

[18] In Appendix B.6 we present the results of the model under alternative parametrizations for the bank block of the model.

The difference between both cases is 16 percentage points. Thus, measured in terms of GDP growth, the financial propagation mechanism of commodity price booms is 16 percentage points.

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.

Table 4: Simulations

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	1.49	0.16
Untargeted moments				
$\widehat{c_m}$	2.24	2.13	1.62	0.51
$\widehat{y_n}$	1.71	1.83	1.53	0.30
$\widehat{p_n}$	1.29	1.36	1.13	0.23
Ave. $\widehat{L_i}$	2.34	2.53	1.75	0.78
Ave. $\widehat{D_b}$	3.02	2.64	1.00	1.64
Ave. $\widehat{N_b}$	8.56	4.12	6.81	-2.69
Ave. $\widehat{r_i^L}$	-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.4.

7 Conclusions

In this paper, we propose a novel financial propagation mechanism in SOEs by which commodity price booms influence the non-commodity sector via the domestic banking system. Our proposed mechanism suggests that, following a commodity price boom, commodity exporters increase their deposit holdings in domestic banks, leading banks to expand their loan supply to non-commodity firms, which in turn stimulates increased hiring within these non-commodity firms.

We use detailed matched bank-firm-loan microdata from Peru, an SOE that went through a mining commodity price boom in the 2000s, and 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 increase in mining commodity prices, we find that (i) banks more exposed to the mining commodity prices experience an increase in their firm deposit holdings, (ii) banks more exposed to the mining commodity prices increase their loan supply to non-mining firms, and (iii) firms more exposed to the mining commodity prices through their banks increase their hiring.

We then turn to quantifying the aggregate importance of this mechanism by introducing this mechanism into a static SOE model with banks and an endowment commodity sector. We assume that commodity exporters hold part of their export revenue as deposits in banks, with each bank being heterogeneous in its exposure to the commodity sector. Furthermore, there are two key financial frictions: (i) firms need to take loans from banks because they are subject to a working capital constraint, and (ii) banks face a balance sheet constraint, which means they must obtain foreign wholesale funding to cover the loans if deposits and equity are not enough.

We recover the bank-related parameters of the model from the regressions of the first part of the paper and calibrate the model to match the Peruvian economy in the booming period. Next, we solve the non-linear model using hat algebra and find that our model fits targeted and untargeted moments. We then perform a counterfactual exercise where we turn off the proposed financial propagation mechanism. By comparing the GDP growth of the baseline and counterfactual economies, we obtain that the proposed financial propagation mechanism accounts for 16 percentage points of the observed GDP growth rate in Peru during the booming period (65 percent in 2003-2011).

Our findings indicate that the proposed financial propagation mechanism exists and highlight the critical role that banks play in transmitting commodity booms to the non-commodity sector in SOEs. Far from being passive during booming periods, banks facilitate the propagation of shocks across sectors and amplify their impact.

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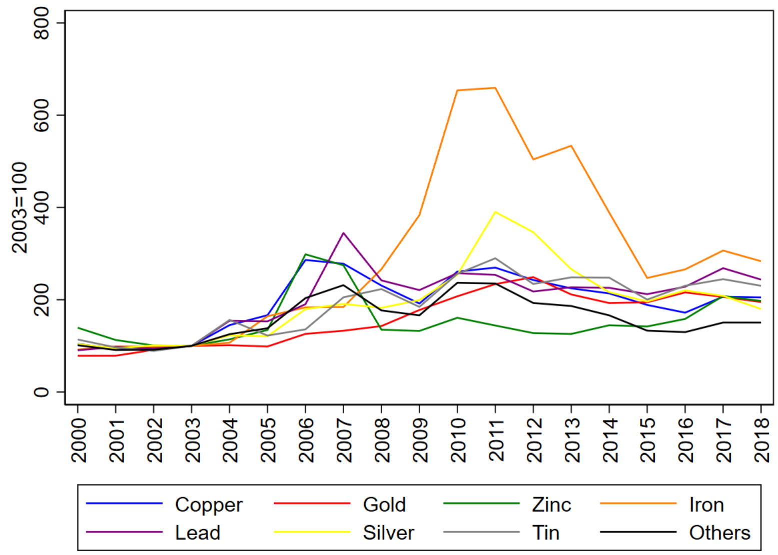
A Empirical appendix

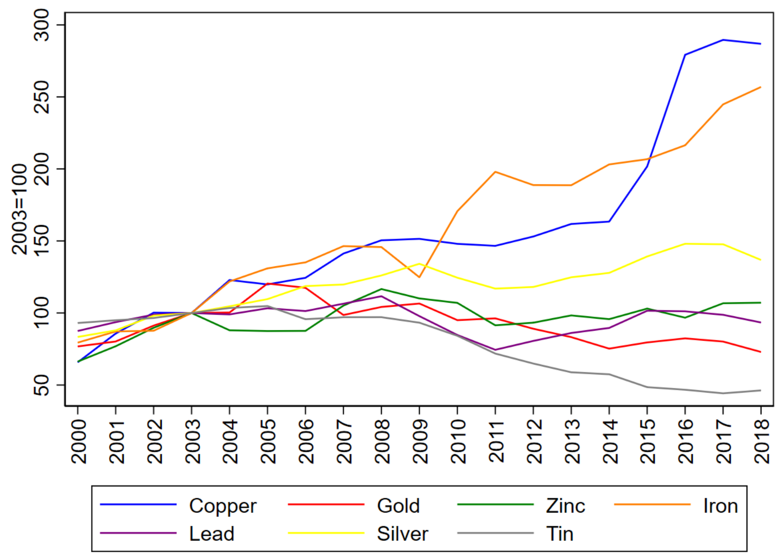
A.1 Mining sector

Figure A.1: Mining prices



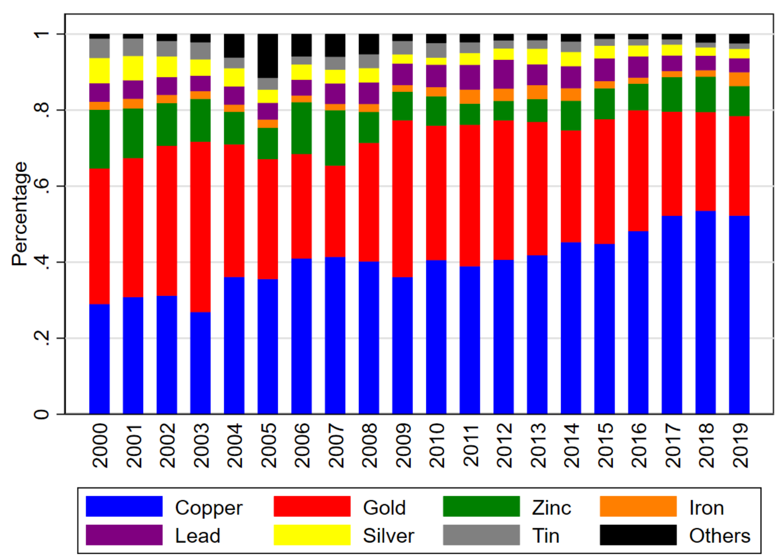
Note: Figure shows evolution of mining commodity relative prices. We normalize the dollar prices for the commodities and then divide them by the Peruvian imports price index.

Figure A.2: Mining output



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

Figure A.3: Mining exports by mineral



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

Table A.1: Mining production ranking of Peru, 2018

Mineral	World ranking	Share of total world output	Largest competitors
Copper	2	12%	CHL: 29%, CHN: 8%, COD: 6%
Gold	6	4%	CHN: 12%, AUS: 10%, RUS: 9%
Zinc	2	12%	CHN: 33%, AUS: 9%, USA: 7%
Lead	3	6%	CHN: 46%, AUS: 9%, USA: 6%
Tin	4	6%	CHN: 28%, IDN: 27%, MMR: 17%
Silver	2	15%	MEX: 22%, CHN: 13%, RUS: 8%
Iron	14	1%	AUS: 37%, BRA: 19%, CHN: 14%

Note: Figure shows share of Peruvian output over total world output for each of the listed mining commodities.

A.2 Sample statistics

Table A.2: Bank statistics

	Mean	Std. dev.	Min.	Max.
Assets (bill. USD)	6.79	8.12	0.20	31.50
Firm deposits (bill. USD)	1.20	1.58	0.01	5.91
Foreign wholesale funding (bill. USD)	0.80	1.09	-0.04	5.20
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: 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.

Table A.4: Loan statistics

	Mean	Std. dev.	Min.	Max.
Loans (thousands USD)	275.88	581.34	0.00	6038.63
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.

A.3 Additional bank-level regressions

Firm deposits by currency. In Peru, firms may hold deposits in domestic currency or in dollars. The average of firm deposits in domestic currency over total firm deposits is 48 percent for the 2005-2018 period. To see whether there is a difference in how firm deposits respond according to the currency, we estimate

$$\ln\left(D_{bt}^{curr}\right) = \alpha_b + \alpha_t + \beta E_{bt} + \varepsilon_{bt},$$

where we differentiate deposits D_{bt}^{curr} by currency.

In the estimations, dollar-denominated deposits are converted to domestic currency beforehand. Table A.5 shows that different currencies do not imply significantly different elasticities with respect to the mining commodity prices, as the estimated coefficients are similar between them and are also close to the original estimate of Table 1.

Table A.5: Bank-level estimation, deposits by currency

	Domestic currency	Dollars
E_{bt}	23.488***	22.790***
	(5.234)	(7.083)
Obs.	121	121
Adj. R2	0.948	0.943

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022). Dollar-denominated deposits are converted to domestic currency for the estimations.

Household deposits. While our main focus is on firm deposits, we can also analyze the response of household deposits to the changes in mining commodity prices. Thus, we estimate

$$\ln\left(D_{bt}^{hh}\right) = \alpha_b + \alpha_t + \beta E_{bt} + \varepsilon_{bt},$$

where D_{bt}^{hh} represents the deposits made by households in the different banks. Table A.6

shows there is not a statistically significant effect of mining commodity prices over the deposits made by households.

Table A.6: Bank-level estimation, household deposits

E_{bt}	-0.957
	(3.520)
Obs.	121
Adj. R2	0.980

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

Total firm loans. In the main estimations we showed how individual loans in our sample respond to the mining commodity prices (Table 2). Here, we perform a bank-level estimation using the total of firm loans L_{bt} given by each bank to private sector firms. We estimate

$$\ln(L_{bt}) = \alpha_b + \alpha_t + \beta E_{bt} + \varepsilon_{bt}.$$

Table A.7 displays that total firm loans also increase after a commodity price shock. This suggests the loan-level result we found in the main text also holds at the aggregate bank-level.

Table A.7: Bank-level estimation, aggregate loans

E_{bt}	6.478***
	(2.363)
Obs.	120
Adj. R2	0.982

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

A.4 Additional loan-level regressions

Alternative fixed effects. The 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 replace α_{it} with α_{srt}, where s denotes 2-digit ISIC sector and r denotes geographic region. Then, we estimate

$$\ln(L_{ibt}) = \alpha_{ib} + \alpha_{srt} + \zeta E_{bt} + \varepsilon_{ibt}.$$

We present the results in Table A.8. There are two differences with respect to the main estimations (Table 2). First, the number of observations increases. Second, the magnitude of the coefficient is larger. Then, we may interpret the main estimations as a lower bound for the effect of mining commodity prices on loan supply.

Table A.8: Loan-level estimation, alternative fixed effects

E_{bt}	12.134***
	(2.268)
Obs.	105,806
Adj. R2	0.127

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm and bank-period in parentheses.

Consumer loans. Our main analysis focuses on how mining commodity prices affect non-mining firm loans. In this section, we explore whether we can find the same relation using household consumer loans L^c_{ibt}.[19] We now estimate

$$\ln(L^c_{ibt}) = \alpha_b + \alpha_t + \alpha_{ib} + \alpha_{it} + \zeta E_{bt} + \varepsilon_{ibt},$$

where we use a random sample of consumption loans. Table A.9 shows the statistics of the sample, while Table A.10 shows the results. We find no statistically significant effect of mining commodity prices on consumption loans.

[19]This also includes credit cards.

Table A.9: Loan statistics, consumer loans

	Mean	Std. dev.	Min.	Max.
Loans (thousands USD)	1.98	2.97	0.00	21.39
Number of bank relationships per firm	2.25	0.51	2.00	7.00

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

Table A.10: Loan-level estimation, consumer loans

E_{bt}	-2.517
	(1.658)
Obs.	448,675
Adj. R2	0.239

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm and bank-period in parentheses.

Extensive margin. The focus of the proposed financial propagation mechanism is on the intensive margin. Here, we explore if there is also an effect on the extensive margin. We define indicator variable $\mathbb{I}_{ibt}$, which is equal to 1 if a new relationship is formed between firm i and bank b in period t. We estimate

$$\mathbb{I}_{ibt} = \alpha_b + \alpha_{it} + \zeta E_{bt} + \varepsilon_{ibt}.$$

We present the results in Table A.11. We do not find a statistically significant effect of mining commodity prices in the extensive margin. We argue this could be due to our sample consisting of mostly medium to large firms, who are more likely to be already connected to banks by the period the sample starts.

Table A.11: Loan-level estimation, extensive margin

E_{bt}	-0.569
	(0.735)
Obs.	144,572
Adj. R2	0.106

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm and bank-period in parentheses.

A.5 Additional firm-level regressions

Sales. We explore the relationship between non-mining firm-level sales $p_{it}y_{it}$ and the exposure to mining commodity prices. We estimate

$$\ln(p_{it}y_{it}) = \alpha_i + \alpha_t + \kappa e_{it} + \varepsilon_{it}.$$

Table A.12 shows the results. We find a positive elasticity between the sales of a non-mining firm and its exposure to the mining commodity prices through banks.

Table A.12: Firm-level estimation, sales

e_{it}	1.006***
	(0.321)
Obs.	38,163
Adj. R2	0.901

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

Alternative fixed effects. In the main estimation (Table 3) we did not account sector-related and geographic region-related non-observables. Here, we control for these by replacing fixed effect α_t with α_{srt}, where s denotes 2-digit ISIC sector and r denotes region. We now estimate

$$\ln(w_t h_{it}) = \alpha_i + \alpha_{srt} + \kappa e_{it} + \varepsilon_{it}.$$

Table A.13 presents the results. We find a similar coefficient to that of the main estimations, which suggests sector-related and geographic region-related non-observables do not play a large role in the determination of the sensitivity of the wage bill to the mining commodity prices.

Table A.13: Firm-level estimation, alternative fixed effects

e_{it}	1.136***
	(0.354)
Obs.	34,275
Adj. R2	0.929

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by firm in parentheses. Estimation also considers the shift-share correction suggested by Borusyak et al. (2022).

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

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

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

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

Imports

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

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

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

Bank interest rate, for all b

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

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

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

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

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

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

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

Bank interest rate, for all b

$$1+\widehat{r_b^L} = 1+\widehat{r}+\phi\frac{1}{\widehat{D_b}}$$

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 Parametrization

Table B.1: 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	12.273
ϕ	Bank cost function parameter	0.031
θ	Working capital financed by loans	0.236

Table B.2: Parameters (2)

	Trade balance	
χ_x	Exports / Imports	1.108
η_x	Mining exports / Exports	0.569
χ_L	Total firm loans / Imports	0.916
χ_D	Total firm deposits / Imports	0.338
χ_N	Total wholesale funding / Imports	0.302
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

Table B.3: Parameters (3)

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

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

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

and the interest rate set by banks

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

Replace to obtain

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

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

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

Add a residual to obtain

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

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

This expression is Equation 4.

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

$$\ln(y_i) = \ln(A_i) + \ln(h_i),$$

the loan demand

$$\ln(L_i) = \ln(\theta) + \ln(wh_i),$$

the demand faced by non-tradable intermediate firms

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

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

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

Replace to obtain

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

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

$$\ln(w_t h_{it}) = \underbrace{-\sigma \ln\left(\frac{\sigma}{\sigma - 1}\right) - \sigma\theta \ln\left(\frac{\varepsilon}{\varepsilon - 1}\right)}_{\text{constant}} \underbrace{- \sigma\theta\phi \sum_b s_{ib}\left(\alpha_b + \ln\left(\overline{N_b}\right)\right)}_{\alpha_i} + \underbrace{(\sigma - 1)\ln(A_{it})}_{\text{residual}}$$
$$+ \underbrace{\sigma \ln(p_{nt}) + \ln(y_{nt}) - (\sigma - 1)\ln(w_t) - \sigma\theta r_t}_{\alpha_t} + \underbrace{\sigma\theta\phi\beta}_{\kappa} \sum_b s_{ib} \sum_x \omega_{bx} \ln(p_{xt}),$$

such that

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

$$\kappa = \sigma\theta\phi\beta.$$

This expression is Equation 5.

B.5 Complete results

Table B.4: Simulations

Variable	Baseline: Fin. mech.	CF: No fin. mech. ($\beta = 0$)	Baseline minus CF
$\widehat{GDP}$	1.65	1.49	0.16
$\widehat{h}$	1.67	1.40	0.27
$\widehat{w}$	1.51	1.25	0.26
$\widehat{p}$	1.20	1.07	0.12
$\widehat{c}$	1.95	1.57	0.38
$\widehat{c_m}$	2.13	1.62	0.51
$\widehat{y_n}$	1.83	1.53	0.30
$\widehat{p_n}$	1.36	1.13	0.23
Ave. $\widehat{L_i}$	2.53	1.75	0.78
Ave. $\widehat{D_b}$	2.64	1.00	1.64
Ave. $\widehat{N_b}$	4.12	6.81	-2.69
Ave. $\widehat{r_i^L}$	-0.07	-0.04	-0.03

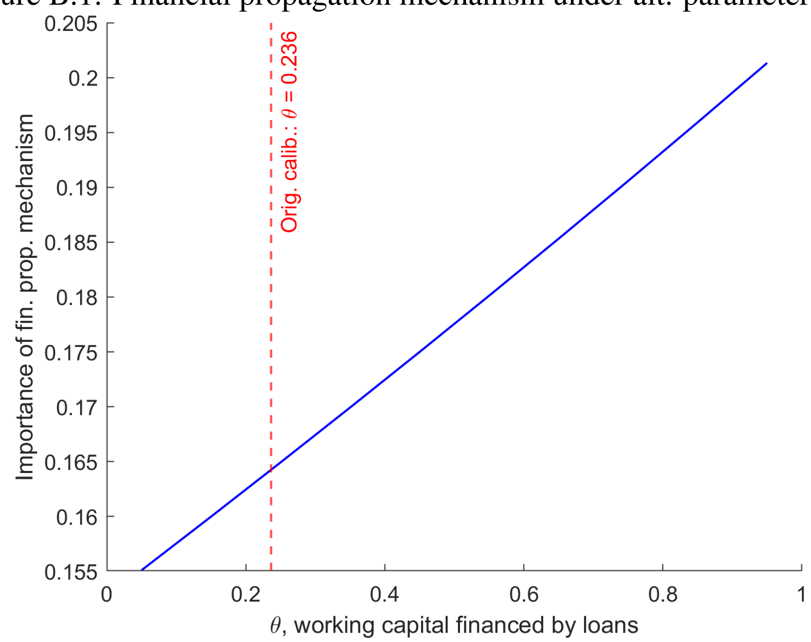
Note: Column 1 shows moments from baseline simulation with financial propagation mechanism. Column 2 shows moments from counterfactual simulation with no financial propagation mechanism. Column 3 shows difference between baseline and counterfactual. All moments are expressed in percentage variations between initial and final states.

B.6 Alternative parametrizations

In this section, we analyze how the model changes when we choose different bank block parameters. In each of the exercises, we maintain the original calibration and only change the numerical values of selected parameters. As in the main analysis, we focus on comparing the importance of the financial propagation mechanism in terms of GDP growth between the baseline and counterfactual scenarios.

θ, working capital financed by loans. Figure B.1 shows how the importance of the financial propagation mechanism varies with θ, the parameter that captures how much working capital of the non-tradable intermediate firms is financed by loans. As θ increases, the importance of the proposed mechanism grows. This is because a higher θ means firms require to take higher loans and, thus, the mechanism becomes more important overall.

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

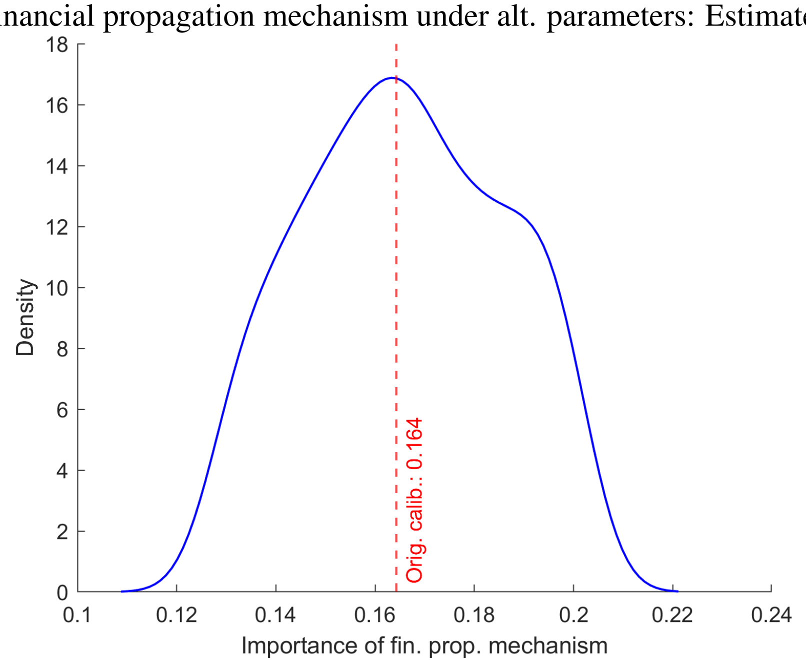


Note: Figure shows the importance of the financial mechanism in the theoretical model under different values for θ. The importance is defined as the difference in GDP growth between the baseline case and the counterfactual case with no financial propagation mechanism. Vertical line denotes original calibration.

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.2 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 0.128 to 0.202, our result under the original calibration is close to the mean (0.166) and median (0.165) of the distribution. Therefore, our main result is a central value within the range and not an extreme one.

Figure B.2: 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.