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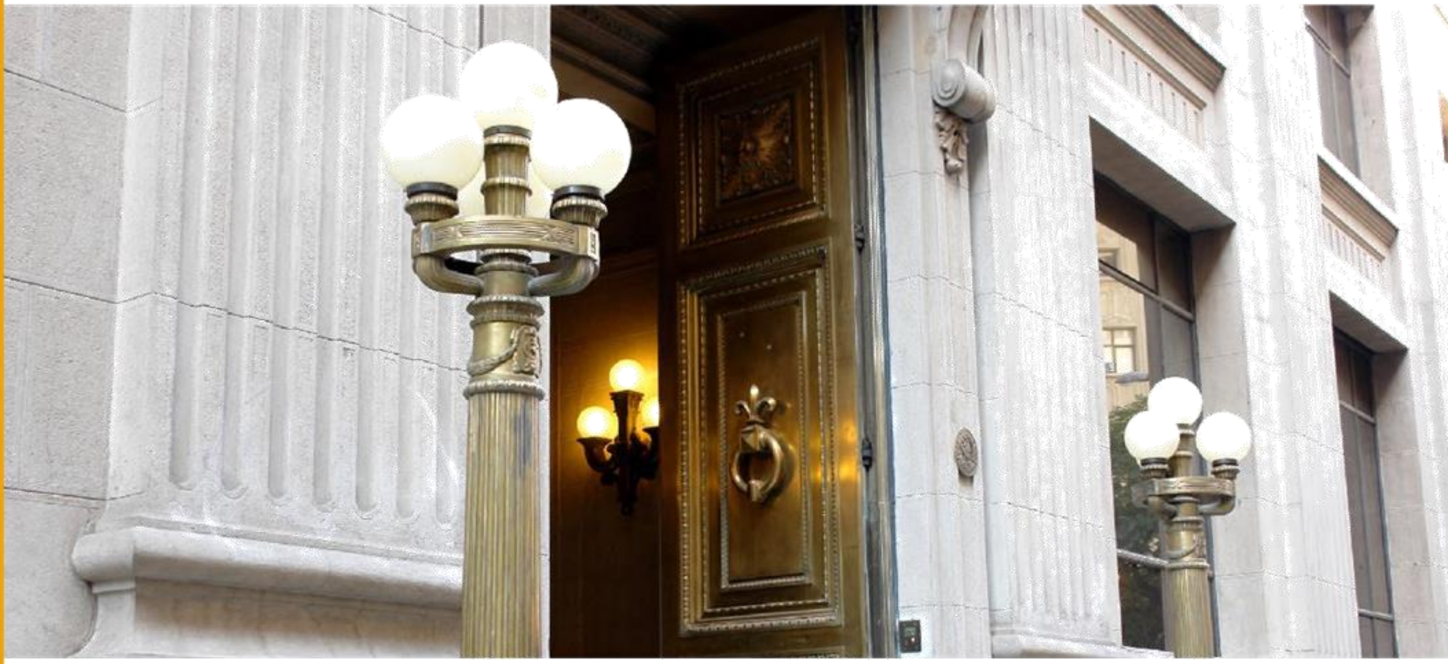

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Anatomy of the Investment Network in a Commodity-Dependent Economy*

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Resumen

Este artículo estudia cómo las redes de inversión transmiten y amplifican los shocks externos en economías dependientes de materias primas. Utilizando datos a nivel de transacción sobre flujos de bienes de capital entre empresas, mapeamos la red de inversión de Chile y evaluamos su rol en la propagación de shocks de precios del cobre a nivel de empresa, sector y agregado. En los datos, encontramos que los proveedores aguas arriba se expanden cuando suben los precios del cobre, pues la minería incrementa la demanda de bienes de capital, mientras que los exportadores no mineros se contraen. Motivados por esta evidencia, desarrollamos y calibramos un modelo multisectorial de una economía pequeña y abierta, con encadenamientos insumo-producto y de inversión, para cuantificar las implicaciones agregadas de un shock de términos de intercambio. Un shock de una desviación estándar en la demanda global de productos mineros aumenta el PIB en un 0,9% y la inversión en un 3,8% en impacto. En ausencia de encadenamientos de inversión, estos efectos se reducen a 0,46% y -0,9%, respectivamente. Consistente con la evidencia empírica, los proveedores aguas arriba del sector minero son los más beneficiados, mientras que los sectores exportadores no mineros se ven perjudicados debido a la apreciación del tipo de cambio real. Por último, una red más densa calibrada con la estructura de redes de la economía de Estados Unidos produce efectos mayores y más persistentes.

Abstract

We study how investment networks transmit and amplify external shocks in commodity-dependent economies. Using transaction-level data on capital-goods flows between firms, we map Chile's investment network and assess its role in the propagation of copper price shocks at the firm, sector, and aggregate level. In the data, we show that upstream suppliers expand when copper prices rise as mining increases demand for capital goods, while non-mining exporters contract. Motivated by this evidence, we build and calibrate a multi-sector small open economy model with input-output and investment linkages to quantify the aggregate implications of a terms-of-trade shock. A one-standard-deviation shock to global demand for mining raises GDP by 0.9%, and investment by 3.8% on impact. Absent investment linkages, the effects drop to 0.46% and -0.9%, respectively. Consistent with the data, upstream suppliers to mining benefit the most, while non-mining export sectors are worse off due to real exchange rate appreciation. A denser U.S.-calibrated network yields larger and more persistent effects.

This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs within its competence. All results have been reviewed to ensure no confidential data is disclosed. The authors would like to thank Luc´ıa Casal, Julieta Caunedo, Xiang Ding, Adriano Fernandes, Alvaro Silva, Christian vom Lehn, Ivan Werning, and participants at several seminars and conferences for their useful comments and suggestions. We also thank Diego Donoso for excellent research assistance. All remaining errors are our own. The views expressed are those of the authors and do not necessarily reflect the views of the Central Bank of Chile or its board members.

1 Introduction

It has long been recognized that an economy's input-output network plays a powerful role in amplifying and propagating sector-specific shocks (Long Jr and Plosser (1983), Horvath (2000), Acemoglu et al. (2012), Baqaee and Farhi (2019)). However, despite the dominant role of investment in business cycle fluctuations and economic development, the analogous role of the "investment network", the flow of capital goods across firms and sectors in the economy, has received far less attention until recently. A fast-growing literature has begun to explore the role of intersectoral investment linkages as a key channel of shock transmission (Foerster et al. (2022), Vom Lehn and Winberry (2022), Ding (2023), Casal and Caunedo (2024), Buera and Trachter (2024)). We contribute to this emerging literature by constructing the investment network of a commodity-dependent economy from granular transaction-level data and assessing its role in the transmission of commodity price shocks, both empirically and quantitatively.

Our paper follows a bottom-up approach to construct the investment network at the *firm-level* using the universe of firm-to-firm transactions in the Chilean economy. Specifically, for each firm, we observe their sales and purchases of all intermediate inputs and capital goods at a daily frequency, thereby allowing us to construct the empirical investment and intermediate networks. Importantly, we show that aggregating our microdata closely replicates the aggregate investment series of the National Accounts. To our knowledge, this is the first paper to construct an investment network using such granular, high-quality administrative data. We leverage this dataset to document heterogeneous firms' responses to a copper price shock and show that firm-level exposure to mining, through investment and IO networks, plays a key role in determining these responses, thereby contributing to the networks literature. Motivated by this evidence, we set up a general equilibrium multi-sector model of a small open economy, calibrate its input-output and investment linkages to microdata, and use it to assess the role of the investment network in the aggregate and sectoral implications of a terms-of-trade shock, thereby contributing to the international macroeconomics literature (see Fernández et al. (2017), Schmitt-Grohé and Uribe (2018), Ayres et al. (2020), Benguria et al. (2024), Di Pace et al. (2025), among others).

We begin by describing our investment and IO networks, and comparing them with those documented for other economies. We show that, as opposed to the IO network, there are only a few "investment hub" sectors supplying capital goods to the rest of the economy, as documented by Vom Lehn and Winberry (2022) for the United States. These investment hubs include the construction sector, machinery and equipment, and wholesale and retail trade sectors; however, there is a lower role for ICT-related sectors relative to the U.S. and other developed economies. These results are consistent with the cross-country analysis in Casal and Caunedo (2024), which shows that the investment network in poorer economies is less diversified than in richer economies.

The empirical firm-level investment network serves as the basis for our econometric analysis to document how exposure to mining through investment and production networks mediates firms' responses to a copper price shock. We treat firms' network exposure to mining as a time-invariant firm characteristic, reflecting persistent relationships shaped by technological complementarities, long-term contracts, and sunk investments, which are plausibly predetermined relative to copper price shocks. We find that firms more exposed to the mining sector through the investment network increase their sales, employment, and value added in response to copper price shocks. We also show that the upstream direct effects on sales are positive for both investment and input-output linkages, but the magnitude is larger for the former. Finally, we show that non-mining exporting firms are adversely affected by increases in copper prices due to an appreciation of the real exchange rate.[1]

Motivated by this evidence, we develop a multi-sector model of a small open economy with input-output and investment networks. Our model economy captures the direct and indirect spillovers of the mining boom as well as the general equilibrium effects through changes in the real exchange rate and factor prices. We calibrate the model to 41 sectors in the Chilean economy, combining transaction-level data with sector-level data from National Accounts to build the investment and input-output networks. The remaining parameters are calibrated to standard values and to match key moments in the economy. We show that the model produces real business cycles that closely match those in the data.

We then use this model as a laboratory to quantify the aggregate effects of a mining boom in response to a global demand shock and to examine its transmission through the networks. In particular, we investigate the economy's response to a one-standard-deviation shock to global demand for Chilean mining, which increases the copper price by 14% and triggers a mining investment boom, as observed in Chile in recent years. In response to this shock, the economy experiences a sizable and persistent expansion: GDP rises by 0.9% and aggregate investment by 3.8%. The increase in output is accompanied by a persistent real appreciation and a significant improvement in the trade balance, as copper accounts for almost half of Chile's exports.

The copper price shock generates powerful upstream effects on firms that supply capital or intermediate goods *directly* to mining companies. These effects are further amplified through the networks that connect these firms to a wide range of *indirect* suppliers. On the other hand, because copper products are mostly exported, the shock has only mild downstream effects, as there are too few domestic customers for copper to generate aggregate effects. Our analysis suggests that sectors with strong linkages to mining, such as construction, utilities, and professional services, experience substantial gains, whereas tradable sectors, such as agriculture and non-durable manufacturing, contract, consistent with Dutch disease dynamics.

To isolate the role of upstream propagation, we explore a counterfactual exercise in which we assume that the mining sector uses only its own output or imported goods as intermediate inputs or in capital goods. In this case, we find that most sectors of the economy would contract in response to the mining boom, highlighting the role of upstream spillovers from the mining sector. In contrast, we show that downstream spillovers have a relatively small aggregate impact, since most mining production is exported. Finally, we explore the role of the real exchange rate in shaping sectoral heterogeneity: in a counterfactual economy in which only the mining sector exports, tradable sectors that reduce their output in the baseline economy now expand and, conversely, the mining sector expands less, highlighting

[1]Filippi et al. (2025) use an earlier vintage of the Chilean firm-level data we use in this paper to study the role of indirect IO exposure to commodity-producing companies. We instead focus on direct and indirect exposure through the investment network, controlling for exposure via the IO network.

the role of the exchange rate appreciation in the reallocation of resources from other tradable sectors to the mining sector in response to a terms of trade shock.

We further demonstrate the importance of the network structure by conducting a series of counterfactual experiments. We find that removing intersectoral investment linkages significantly dampens the aggregate response to a mining boom. For example, absent investment spillovers, the impact on GDP falls from 0.9% in the baseline to 0.46%; analogously, the effect on aggregate investment falls from 3.8% to -0.9%, as RER appreciation crowds out non-commodity exporters, thereby dominating the mining investment boom. However, replacing Chile's networks with denser U.S. counterparts produces stronger and more persistent effects. These findings underscore the critical role of the investment network in shaping macroeconomic outcomes and suggest that richer intersectoral connections could enhance the responsiveness of commodity-dependent economies to foreign shocks.

Related literature. This paper contributes to the literature on investment networks and is closely related to Vom Lehn and Winberry (2022) and Casal and Caunedo (2024).[2] Vom Lehn and Winberry (2022) builds the U.S. investment network for 37 sectors for the period from 1947 to 2018, identifying key "investment hubs" (e.g., construction, machinery, vehicles, professional services) whose shocks significantly affect aggregate employment. Casal and Caunedo (2024) estimate investment networks for 58 countries, showing that forward and backward linkages in capital production explain 28% of cross-country income disparities. We first contribute to this literature by leveraging granular firm-to-firm transaction-level data to construct an investment network for the Chilean economy and to use it to calibrate a multi-sector small open economy model to investigate the role of the network in amplifying commodity price shocks. Moreover, in Buera and Trachter (2024), the investment network plays a central role in propagating the effect of sectoral policies through technology adoption, as the network affects the adoption costs of capital-embedded technologies.

We also contribute to the broader literature on production networks (e.g., Baqaee and Farhi (2018)). Like us, Miranda-Pinto et al. (2023) use firm-level transactions to build Chile's intermediate input network, examining how interconnectedness affects resilience to shocks. They show that more connected firms experienced larger output losses during COVID-19, but they did not examine investment networks or the propagation of sectoral shocks. More broadly, our work relates to research on how production networks transmit idiosyncratic shocks domestically and internationally, from early contributions by Long Jr and Plosser (1983) to modern frameworks by Horvath (2000), Acemoglu et al. (2012),Acemoglu et al. (2016) and Baqaee and Farhi (2019), as surveyed in Carvalho (2014). On the open economy side, Bonadio et al. (2025) and Huo et al. (2025) examine how trade linkages transmit business cycle shocks across borders (see also Di Giovanni et al. (2018), Di Giovanni et al. (2024), and Baqaee and Farhi (2024)).

Finally, our quantitative application focuses on mining investment in a commodity-dependent economy, shedding light on how commodity price shocks propagate through investment spillovers. This is connected with a growing literature investigating the role of terms-of-trade and commodity price shocks on business cycle dynamics (e.g. Mendoza

[2]See also Ding (2023), Foerster et al. (2022) and Quintana (2024).

(1995), Kose et al. (2002), Drechsel and Tenreyro (2018), Fernández et al. (2017), Ben Zeev et al. (2017), Schmitt-Grohé and Uribe (2018), Fernández et al. (2018), Ayres et al. (2020), Kohn et al. (2021), Heresi (2023), Benguria et al. (2024), and Di Pace et al. (2025)). Recent work by Silva et al. (2024), Romero (2025), and Filippi et al. (2025) emphasizes the input-output linkages in the domestic transmission of commodity price shocks.

In summary, the contributions of our paper lie at the intersection of three areas of the literature. First, we advance the empirical mapping of capital purchases across firms and sectors by constructing an investment network using transaction-level microdata. Second, we shed light on the macroeconomic propagation mechanisms by quantifying how investment networks amplify sectoral shocks, thus enriching the understanding of sectoral comovement. Third, we contribute to the literature on real business cycles in emerging economies by demonstrating the critical role of investment linkages in transmitting terms-of-trade shocks, an aspect that traditional open-economy models often overlook. Together, these contributions underscore the importance of accounting for capital-goods linkages between firms and sectors to fully understand how domestic and external shocks affect the economy.

The remainder of the paper is structured as follows. Section 2 introduces the data sources and describes the construction of the Chilean investment network from transaction-level data. Section 3 presents our empirical results focusing on the granular spillovers of an exogenous mining price shock on non-mining firms economy-wide. Section 4 presents the quantitative framework used to rationalize our empirical findings, which consists of a multi-sector real business cycle model of a small, open, commodity-exporting economy. Section 5 presents our quantitative results, including macroeconomic and sectoral responses to a commodity price boom, and counterfactual analyses to uncover the main economic mechanisms. Section 6 concludes.

2 The investment network

In this section, we describe the data sources used to construct the investment network from transaction-level data and describe its main properties.

2.1 Data

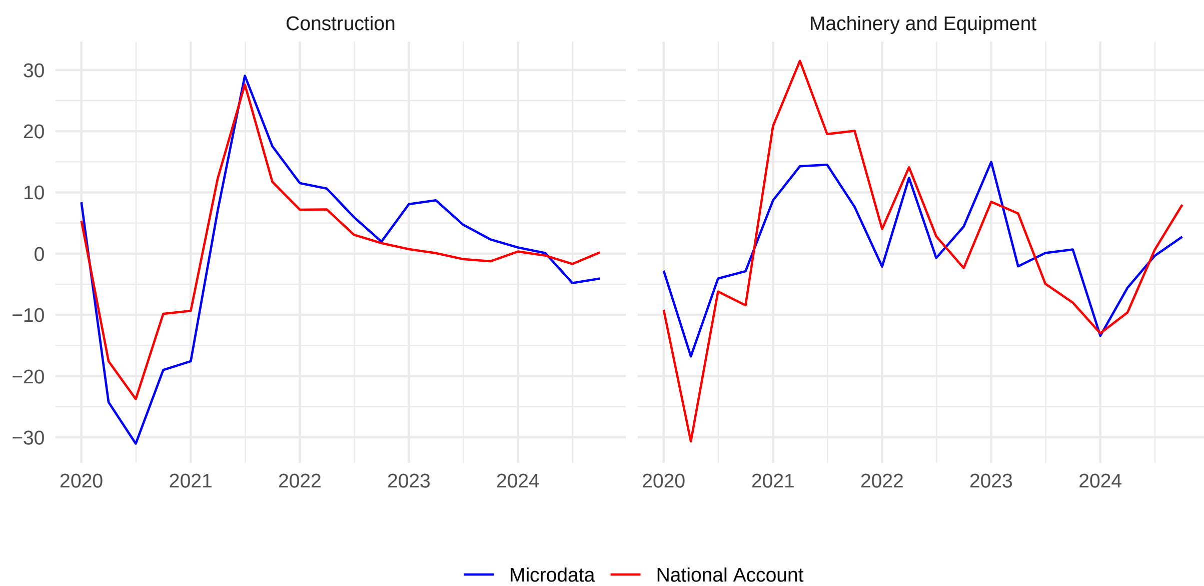
We use firm-to-firm transaction-level data for the universe of Chilean firms, sourced from the Chilean Tax Authority and the National Customs Service.[3] First, we use Electronic Invoice documents (EI), which report the buyer and seller identifiers, prices, and quantities for each individual item, and a free-text description of the products. Second, we use Declarations of

[3]The Central Bank of Chile (CBC) has access to anonymized data from various public and private entities through collaboration agreements with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction, and publication of the results must not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. The authors implemented all the analyses and did not involve or compromise the institutions involved. The information contained in the databases of the Chilean IRS is of a tax nature and originates in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

Entry and Exit covering the universe of imports and exports. These records include product classification according to Harmonized System codes at the 6-digit level (HS6), the CIF value for imports, the FOB value for exports, and the quantities transacted. We focus on the period from 2014 to 2024. We further limit the sample to firms that are listed in the National Accounts Firm Directory, have positive sales and purchases, and have an average of at least 5 employees.[4]

To ensure comparability across products, we classify all transacted goods into intermediate inputs or capital goods. We begin by using the product-classification algorithm proposed in Acevedo et al. (2025) to map domestic transactions issued in EI to the standardized Central Product Classification (CPC). Then we apply a CPC–HS6 concordance to map CPC categories to HS6 product codes. Finally, we classify all transacted goods as either intermediate inputs or capital goods using the National Accounts classification of broad economic categories, mapped to products through their HS6 codes.

Figure 1: Real Investment: Microdata vs. National Accounts



Notes: The blue Microdata lines result from aggregating our transaction-level data. The red National Accounts lines are sourced from the Central Bank of Chile's public database.

We then combine firms' purchases of domestic machinery and equipment with their imports of capital goods to construct daily firm-to-firm flows of machinery and equipment.[5] For

[4]The Firm Directory ensures that each firm corresponds to a legally recognized entity and is assigned to a sector in a consistent and standardized way. Its composition is also stable over time, which enhances the coherence of our analysis. In addition, we apply a 5-employee threshold to exclude very small or minimally active entities with irregular reporting and to focus on firms with aggregate relevance.

[5]We exclude: (i) capital goods not classified as Machinery & Equipment, such as nuts, olives, poultry, pigs, and other live animals; (ii) purchases made by certain retailers and wholesalers in the trade sector, due to their intermediary role (resellers), to avoid double counting; and (iii) sales conducted by firms in the construction sector (excluding real estate companies), which are classified as construction.

construction investment, we instead take all sales from the construction sector as recorded in the electronic invoices. The resulting firm-level network of capital-goods flows is the basis for the econometric analysis in Section 3. Finally, we aggregate these flows to the 41-sector level and to an annual frequency to construct the sectoral input networks used to calibrate the general equilibrium model in Section 4. This sector-level representation also provides a tractable way to illustrate the anatomy of the Chilean investment network. Figure 1 shows that our aggregation of granular data closely replicates the aggregate investment series from the National Accounts.

We combine the transaction-level data described above with sector-level information from Chile's National Accounts. In particular, we use the input–output matrix, the shares of imported intermediates, labor, and value added, and the final-use shares of production (consumption and exports) for sectors in 2022, the most recent year available.[6]

2.2 Properties of the Chilean Investment Network

Figure 2 presents the Chilean empirical investment network (labeled $\Lambda = [\lambda_{ij}]$ henceforth) constructed from firm-to-firm transaction-level data and aggregated to $N = 41$ economic sectors. Each entry λ_{ij} of the matrix represents the share of total capital expenditures (investment) by firm j that is purchased from firm i, such that $\sum_i \lambda_{ij} = 1$. Figure 3 presents the analogous intermediates or input-output network (labeled $\Gamma = [\gamma_{ij}]$ henceforth).[7]

The properties of the investment network and the input-output network are substantially different. To see this, consider the following two measures: (i) the degree of homophily of each matrix, given by the diagonal weights;[8] and (ii) the sectors' outdegrees, given by the row sums of the weight coefficients in the network, which measure the relevance of a given sector as capital provider of other sectors in the economy. To benchmark our network data, Appendix C compares the outdegrees of Chilean networks with those of the United States, as reported in Vom Lehn and Winberry (2022); we also contrast our investment network against the one estimated for Chile by Casal and Caunedo (2024).

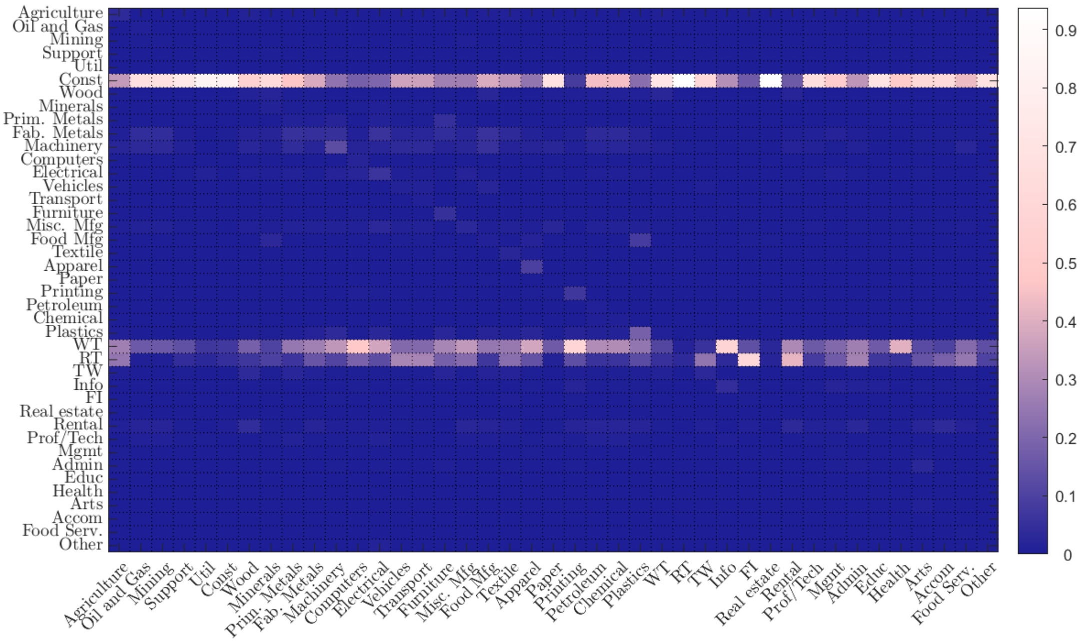
The contrast between the input-output and the investment networks shows that (i) there is much stronger homophily in the input-output network than in the investment network, implying that firms tend to supply intermediate goods to firms in the same sectors; whereas, for investment goods, there are only a few "investment hub" sectors supplying capital goods to the rest of the economy, as in Vom Lehn and Winberry (2022) for the U.S. economy.

[6]In the empirical Section 3, we also use the microdata to construct the input-output matrix at the firm-level. In the quantitative Sections 4 and 5, we instead prefer to use the sector-level input-output matrix from the National Accounts to ensure consistency with Chilean macroeconomic aggregates. However, recall National Accounts do not provide information on the sector-to-sector allocation of investment flows, so we rely on transaction-level data to construct the investment network.

[7]To ensure data anonymization, each cell of the matrix must contain at least 25 firms. Since this is not the case in the raw investment data for sector "Oil and gas extraction", we imputed the same coefficients of purchases (column coefficients) of sector "mining, except oil and gas". Analogously, for "Other transport equipment" and "Petroleum and coal products", we imputed the coefficients of sectors "Model vehicles, bodies and trailers, and parts" and "Chemical products", respectively. Finally, we normalized each column to add-up to 1.

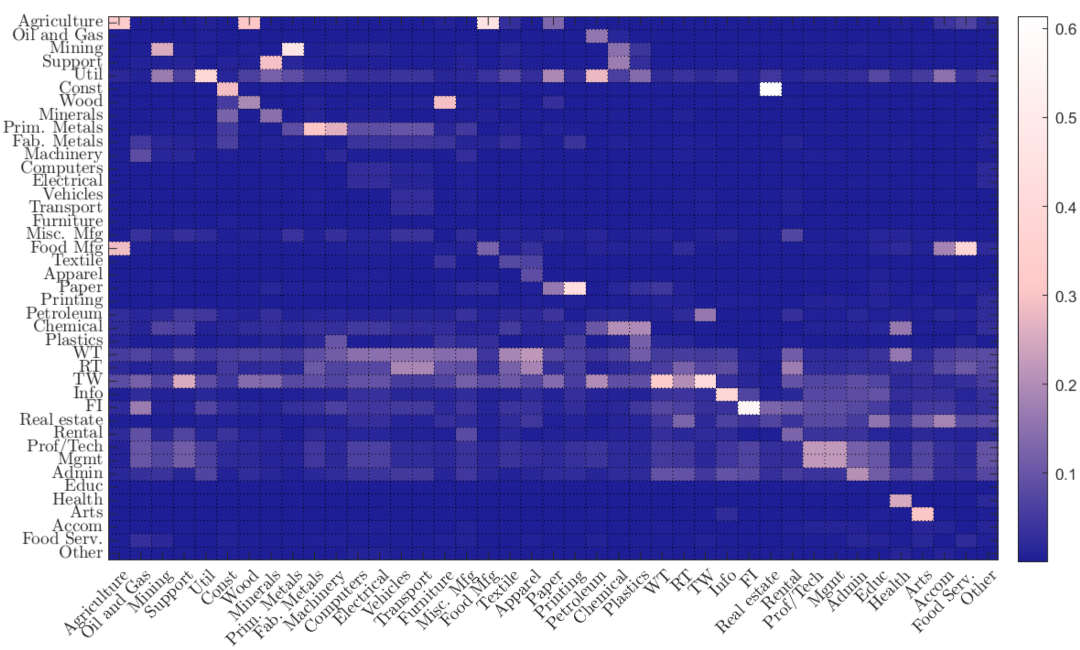
[8]The degree of homophily in a network characterizes the tendency of similar nodes to form connections, which can have significant implications for the structure and dynamics of the network.

Figure 2: Chilean Investment Network



Notes: Heatmap of the Chilean Investment Network at $N = 41$ sectors. Entry (i, j) represents the share of investment expenditures in sector j purchased from sector i. Average over the sample 2014-2024.

Figure 3: Chilean Input-Output Network



Notes: Heatmap of the Chilean Input-Output Network at $N = 41$ sectors. Entry (i, j) represents the share of intermediate expenditures in sector j purchased from sector i. Year 2022.

This is consistent with (ii) sectoral outdegree is higher for construction and commerce in the investment network, although construction is not a major provider of intermediate goods (except for real estate, business services, and personal services); manufacturing is also an essential provider of both investment and intermediate goods. These results are consistent with the findings of Casal and Caunedo (2024), who show that the investment network in richer economies is more diversified than that of poorer economies. For example, the outdegree of construction is much larger than in other sectors in poorer economies, whereas in richer economies it is more evenly distributed across sectors. This is particularly relevant because, as emphasized by Acemoglu et al. (2012) in the context of the IO network, the greater the asymmetry in outdegrees across sectors, the greater the possibility of "cascade effects", that is, idiosyncratic shocks having significant aggregate impact.

To examine the transmission of an aggregate shock through the investment network, we need to account for both the input-output structure and the investment network. When a shock induces a spurt in capital expenditures in a given sector (say, mining), some firms providing capital goods to this sector are directly affected, while other firms that sell intermediate inputs to the capital goods producers are indirectly affected. The direct effect is captured by the investment network Λ, and the indirect effect is captured by the Leontief-inverse intermediates network $\mathcal{L} = (I - \Gamma)^{-1}$ (see Carvalho and Tahbaz-Salehi (2019)). As shown in Vom Lehn and Winberry (2022), Foerster et al. (2022) and Casal and Caunedo (2024), the critical matrix that captures the role of each sector in providing capital goods directly or indirectly (that is, by providing intermediate inputs to capital producers) is the Leontief-adjusted investment network $\Omega = \mathcal{L}\Lambda = (I - \Gamma)^{-1}\Lambda$. In Section 3, we use firm-level exposure to the mining sector, either directly through Λ or indirectly through Ω, to study the propagation effects of a mining investment boom to the rest of the economy.

3 Empirical analysis

This section describes the construction of our key firm-level measures of network linkages with the mining sector and presents the empirical strategy to identify heterogeneous firm responses to a copper price shock. As noted above, the commodity boom generates direct and indirect network effects: on the one hand, non-commodity firms that supply capital and/or intermediate inputs to mining companies benefit directly from higher demand, on the other, large intermediate suppliers of "investment hub" companies also benefit indirectly, activating upstream cascade effects.

We follow a similar strategy to Acemoglu et al. (2016) by creating time-invariant, firm-level network exposure metrics and interacting them with shocks. Unlike Acemoglu et al. (2016), we focus on a specific type of demand shock, namely foreign demand for commodities, which translates into copper price shocks. Silva et al. (2024) and Romero (2025) study the same type of shock but focus on IO rather than investment linkages, and apply it to a set of commodity-exporting countries.

The identification assumption is that copper prices, determined in international markets, are exogenous to non-commodity firms in a small open economy such as Chile. We further assume that the (HP-filtered) real copper price (P_t^*) follows a first-order autoregressive process and extract its i.i.d. shocks ($\hat{P}_t^*$) accordingly. We treat network exposure as a time-invariant firm characteristic reflecting long-term relationships among firms, making exposure plausibly predetermined relative to contemporaneous copper-price shocks.

Our main estimating specification takes the form:

$$\log Y_{it} = \psi Upstream_i^{\Omega} \cdot \log \hat{P}_t^* + \delta Exporter_i \cdot \log \hat{P}_t^* + \varphi_i + \varphi_{st} + \varphi_{et} + \varepsilon_{it}, \qquad (1)$$

where Y_{it} denotes sales, value added, or employment of firm i in sector s, firm-size category e, and year t, and $\hat{P}_t^*$ denotes the real copper price in year t. Coefficients capture contemporaneous, within-year responses to copper price shocks. The variable $Upstream_i^{\Omega}$ measures firm i's exposure to the mining sector through the Leontief-adjusted investment network, capturing both direct and indirect linkages. Specifically,

$$Upstream_i^{\Omega} = \sum_{j \in Mining} \omega_{ij},$$

where ω_{ij} denotes the (i,j) entry of the Leontief-adjusted investment network introduced above ($\Omega = (I - \Gamma)^{-1}\Lambda$). Since the underlying exposure measures are highly non-linear and right-skewed, we transform all exposure variables into indicator variables that take the value one if the firm exhibits any positive exposure to the mining sector[9]. This approach avoids imposing linearity in exposure intensity and allows the estimated coefficients to capture average differences in outcomes between exposed and non-exposed firms in response to copper price shocks. $Exporter_i$ is a time-invariant dummy equal to one if firm i exported more than 10% of its sales on average over the period 2018-2023 (exports-to-sales ratio).

All specifications include firm fixed effects, φ_i, as well as sector-by-year fixed effects[10], φ_{st}, and size-by-year fixed effects, φ_{et}.[11] Firm size and economic sector are assigned based on firms' modal classification during the sample. These absorb time-invariant firm characteristics and common shocks at the sector and firm-size levels. For example, if a particular industry (e.g., manufacturing) is affected by a new tax, the sector-by-year fixed effects ensure that the estimated copper price effect is not confounded by that policy change. Similarly, if credit conditions tighten in year t, small firms may be disproportionately affected relative to large firms. Without the size-by-year fixed effect, the copper price shock could inadvertently capture size-dependent financial constraints. Standard errors are clustered at the firm level to address serial correlation and unobserved firm-level heterogeneity over time.

We use specification 1 to evaluate two hypotheses. First, firms with upstream exposure to investment in the mining sector are expected to benefit from increases in international

[9]Our results are robust to defining this binary variable to equal one when the upstream and downstream measures exceed the 10th and 25th percentiles of the distribution of positive values for the relationship.

[10]The regression accounts for the 41 economic sectors used in the model section of the paper.

[11]Firm size is defined based on firms' annual sales in the previous year. Firms are initially classified into five sales-based size categories: size 0 includes firms with no sales; size 1 (micro) includes firms with annual sales between 0 and 2,400 UF; size 2 (small) includes firms with annual sales between 2,400 and 25,000 UF; size 3 (medium) includes firms with annual sales between 25,000 and 100,000 UF; and size 4 (large) includes firms with annual sales above 100,000 UF. To obtain a time-invariant measure, firm size is constructed as the most frequently observed size category for each firm over the period 2018–2023. In the event of a tie in modal frequency, the lower category in the fixed ordering, micro (1) $<$ small (2) $<$ medium (3) $<$ large (4), is selected.

copper prices, implying a positive interaction between upstream exposure and the price of copper ($H_0: \ \psi > 0$). Second, (non-mining) exporting firms are predicted to be negatively affected by copper price increases due to appreciation of the real exchange rate, leading to a negative interaction between the exporter status and the copper price ($H_0: \ \delta < 0$).

To disentangle the direct and indirect channels of the Leontief-adjusted investment network and account for the downstream exposure to the provision of intermediate inputs by the mining sector, we estimate the following alternative specification:

$$\begin{aligned}\log Y_{it} =& \alpha Upstream_i^{\Lambda} \cdot \log \hat{P}_t^* + \beta Upstream_i^{\Gamma} \cdot \log \hat{P}_t^* + \gamma Downstream_i^{\Gamma} \cdot \log \hat{P}_t^* \\ &+ \delta Exporter_i \cdot \log \hat{P}_t^* + \varphi_i + \varphi_{st} + \varphi_{et} + \varepsilon_{it}. \end{aligned} \tag{2}$$

The IO network exposure (Γ) captures firms' input-output linkages to the mining sector, measuring the extent to which they supply intermediate inputs to mining firms. In contrast, the investment-network exposure (Λ) reflects capital-formation linkages, capturing firms' involvement in providing capital goods and investment services used by mining firms averaged between 2018 and 2023. Finally, the downstream exposure measure captures firms' dependence on the mining sector as an input supplier, reflecting the extent to which mining sector shocks affect firms through input-cost channels rather than through demand for their own output. Formally, we define:

$$Upstream_i^{\Lambda} = \sum_{j \in Mining} \lambda_{ij}, \qquad Upstream_i^{\Gamma} = \sum_{j \in Mining} \gamma_{ij}, \qquad Downstream_i^{\Gamma} = \sum_{j \in Mining} \gamma_{ji}.$$

We use the specification 2 to evaluate the following hypotheses. First, firms that are upstream from mining through the investment network are expected to benefit from increases in copper prices, implying $\alpha > 0$. Second, firms that are upstream through production linkages are also expected to experience positive demand spillovers, implying $\beta > 0$. Finally, downstream exposure through input-output linkages is not expected to generate systematic gains, as opposing input-cost and demand effects may offset each other, implying $\gamma \approx 0$.

Table 1 reports estimates of the effect of copper price shocks on firm-level sales, employment, and value added, interacting the price of copper with different measures of exposure to the mining sector.

The first set of columns, (1) to (3), decompose upstream exposure into investment and production linkages. Firms upstream of mining in the investment network experience positive, precisely estimated effects of copper price increases. The coefficient on $Upstream_i^{\Lambda} \times \log \hat{P}_t^*$ is 0.097 in column (1) and increases to 0.17 when estimated separately, indicating that firms supplying capital goods to the mining sector benefit significantly from higher copper prices. This pattern is consistent with the idea that higher prices stimulate mining investment, thereby increasing demand for capital inputs. Upstream exposure through production linkages also generates positive and statistically significant effects. The coefficients on $Upstream_i^{\Gamma} \times \log \hat{P}_t^*$ range from 0.1 to 0.14, suggesting that firms supplying intermediate inputs to mining benefit from increased mining activity through input–output channels.

Interestingly, downstream exposure also yields positive and statistically significant effects. While the benchmark model predicts offsetting forces for downstream firms, the positive es-

Table 1: Effects of Copper Price Shocks on Firm-Level Outcomes

	log (Sales)				log (Empl.)	log (VA)
	(1)	(2)	(3)	(4)	(5)	(6)
$Upstream_i^{\Lambda} \cdot \log \hat{P}_t^*$	0.097***		0.166***			
	(0.030)		(0.027)			
$Upstream_i^{\Gamma} \cdot \log \hat{P}_t^*$	0.104***	0.137***				
	(0.025)	(0.022)				
$Downstream_i^{\Gamma} \cdot \log \hat{P}_t^*$	0.099***	0.102***				
	(0.024)	(0.0247)				
$Upstream_i^{\Omega} \cdot \log \hat{P}_t^*$				0.312***	0.152***	0.066**
				(0.035)	(0.017)	(0.030)
$Exporter_i \cdot \log \hat{P}_t^*$	-0.289***	-0.292***	-0.291***	-0.290***	-0.099***	-0.278***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.025)	(0.061)
Observations	738,320	738,320	738,320	738,320	709,996	640,467
R^2	0.799	0.799	0.799	0.799	0.817	0.791

Notes: Columns (1)-(3) reports variants of specification 1, while Columns (4)-(6) report results for specification 2 for alternative firm outcomes. The variable $\log \hat{P}_t^*$ denotes the sequence of shocks obtained by running an AR(1) model on the Hodrick-Prescott cycle time series of the real (US PPI deflated) copper price. All specifications include firm fixed effects (φ_i), sector-by-year (φ_{st}) fixed effects, and size-by-year (φ_{et}) fixed effects. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

timates suggest that general-equilibrium demand spillovers dominate input-cost effects for sales, a pattern consistent with broader network amplification mechanisms. The estimated coefficients on $Downstream_i^{\Gamma} \times \log \hat{P}_t^*$ lie around 0.1, indicating that, for sales, positive demand spillovers or broader general-equilibrium effects may outweigh any potential increases in input costs for downstream firms.

Columns (4) to (6) report the findings when using instead the Leontief-adjusted investment network as a measure of exposure, which combines both the direct and indirect upstream linkages. The estimated coefficient for sales of 0.31 is large and precisely estimated (Column 4), highlighting the importance of indirect network effects in amplifying the impact of copper price shocks on firms' sales. This is also the case for employment and value added, as captured by Columns (5) and (6), respectively.

Exporting firms consistently show negative responses to higher copper prices, as shown by the highly significant and negative coefficients on $Exporter_i \times \log \hat{P}_t^*$. This result implies that higher copper prices reduce the competitiveness of non-mining exporters, consistent with conventional wisdom on the impact of a real exchange rate appreciation (see Heresi (2023)).

Taken together, the evidence presented above suggests that: (i) upstream firms benefit from increases in copper prices –particularly, once indirect linkages captured by the Leontief-adjusted network are incorporated–; (ii) non-mining exporting firms experience adverse effects consistent with a real exchange rate appreciation channel; and (iii) downstream firms are positively impacted, perhaps due to broader general-equilibrium spillovers. In the following sections, we build, calibrate, and simulate a general equilibrium, multi-sector model economy with input-output and investment linkages that can account for the stylized facts presented in this section and that we use to assess their aggregate implications.

4 Model

We now develop a multi-sector real business cycle model of a small open economy with input-output and investment networks to interpret our cross-sectional empirical results and examine its aggregate implications. In the following section, we calibrate the model and use it as a laboratory to investigate the role of the investment network in transmitting a shock to the foreign demand for mining, the main export in this economy. Time is discrete and indexed by t, with an infinite horizon. There are N sectors of production that use capital, labor, and intermediate inputs, and a representative household that consumes a bundle of the economy's output, supplies the factors of production, and owns all firms. Consumption, investment, and intermediate inputs can also be imported, while sectoral production can be sold to other sectors as intermediates, used for final consumption or investment, or sold abroad.

4.1 Network production structure

There is a finite number N of sectors indexed by j producing with a constant returns-to-scale (CRS) technology:

$$Q_{jt} = A_{jt}\Big(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}\Big)^{\theta_j} M_{jt}^{1-\theta_j} \tag{3}$$

where, for each sector j, Q_{jt} is gross output, A_{jt} is total factor productivity, K_{jt} is capital, L_{jt} is labor, and M_{jt} is a bundle of intermediate goods. The coefficients α_j and θ_j determine the sector-specific capital and value-added shares. The bundle of intermediate goods is produced with the following CRS technology:

$$M_{jt} = (M_{jt}^H)^{\phi_j}(M_{jt}^F)^{(1-\phi_j)}, \quad M_{jt}^H = \prod_{i=1}^{N}\big(M_{ijt}\big)^{\gamma_{ij}}, \quad \sum_{i=1}^{N}\gamma_{ij} = 1, \quad \gamma_{ij} \geq 0 \tag{4}$$

where M_{jt}^H and M_{jt}^F are home-produced and foreign-imported intermediate goods, respectively, with shares governed by ϕ_j. In turn, M_{ijt} is the quantity of sector i's output used as intermediate input in the production of sector j, with share γ_{ij}. We denote by Γ the domestic input-output (intermediates) network with typical element γ_{ij}.

We also assume a network structure for the investment bundle, which is produced by an analogous CRS technology:

$$I_{jt} = (I_{jt}^H)^{\kappa_j}(I_{jt}^F)^{(1-\kappa_j)}, \quad I_{jt}^H = \prod_{i=1}^{N}\big(I_{ijt}\big)^{\lambda_{ij}}, \quad \sum_{i=1}^{N}\lambda_{ij} = 1, \quad \lambda_{ij} \geq 0 \tag{5}$$

where I_{jt}^H and I_{jt}^F are home-produced and imported investment goods, respectively, with shares governed by κ_j, and I_{ijt} is the quantity of sector's i output used to produce the investment bundle of sector j. We denote by Λ the investment network with typical element λ_{ij}. The columns of Λ (Γ) add up to the degree of returns-to-scale in the investment (intermediates) technology, which here is unity. The row sums of Λ (Γ) indicate the importance of each sector as a supplier of new capital (intermediates) to all other sectors.

4.2 Representative household

The household has preferences over consumption C_t and hours worked L_t, given by:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{L_t^{1+\eta}}{1+\eta} \right), \quad C_t = \prod_{j=1}^{N} (C_{jt})^{\xi_j} (C_t^F)^{\xi_F}, \quad \sum_{j=1}^{N} \xi_j + \xi_F = 1, \quad \xi_j, \xi_F \geq 0,$$

where C_{jt} is the consumption of the goods produced in sector j and C_t^F is the consumption of imported foreign products. The parameters β, η, ξ_F and ξ_j are the discount factor, the inverse Frisch elasticity of the labor supply, the weight of imported goods in the consumption basket, and the share of household expenditure on the good produced by sector j. The household budget constraint is given by:

$$p_t C_t + \sum_{j=1}^{N} p_{jt}^I I_{jt} + \mathcal{E}_t B_t \leq w_t L_t + \sum_{j=1}^{N} r_{jt} K_{jt} + \mathcal{E}_t R_{t-1} B_{t-1} + \Pi_t$$

where B_t is the stock of foreign bonds, $\mathcal{E}_t$ is the exchange rate, $R_t = (1 + r_t)$ is the gross interest rate, p_{jt}^I is the price of the sector j's investment bundle, r_{jt} is the rental rate on the sector j's capital, w_t is the wage, and Π_t are profits from firms.

The technology to accumulate sector j's specific capital is

$$K_{jt+1} = (1 - \delta_j) K_{jt} + \left[1 - \Phi \left(\frac{I_{jt}}{I_{jt-1}} \right) \right] I_{jt}$$

where $\delta_j \in [0, 1]$ is the depreciation rate, I_{jt} is the bundle of investment goods, and the function $\Phi(.) = (\zeta_j/2) \left(I_{jt}/I_{jt-1} - 1 \right)^2$ induces convex investment adjustment costs, with $\zeta_j = \Phi''(1)$, and satisfying $\Phi(1) = \Phi'(1) = 0$ in steady state. We also impose a static cross-sectoral investment friction to avoid excessive reallocation across sectors, following Huffman and Wynne (1999) and described in detail in Appendix A.

4.3 Rest of the world

Export quantities. We assume a reduced form schedule for the sector-specific foreign demand for domestic goods:

$$X_{jt} = \xi_j^X \left(p_{jt}^X \right)^{-\varphi} y_{jt}^*, \quad \sum_{j=1}^{N} \xi_j^X = 1, \quad \xi_j^X \geq 0,$$

where ξ_j^X governs foreign preferences for domestic good j (and hence export shares), φ is the price elasticity of demand (common to all sectors), p_{jt}^X is the price paid for sector j's output abroad, and y_{jt}^* is a sector-specific foreign demand shifter. Our focus in this paper is to understand the macroeconomic effects of a shock to the demand shifter of the mining sector; therefore, we set $y_{jt}^* = 1$ for all j's different from mining.

Terms of trade. We assume the Law of One Price holds for import and export prices. That is, for export prices, $p_{jt} = \mathcal{E}_t p_{jt}^X$ for each sector $j = 1, ..., N$. Regarding import prices, for simplicity, we assume $p_t^{I^F} = p_t^{M^F} = p_t^F = \mathcal{E}_t p_t^*$. Without loss of generality, we assume $p_t^* = 1$, and set p_t^F as the numeraire. In sum, $p_t^F = 1$ $\forall t$, and $p_{jt} = p_{jt}^X$ $\forall j, t$. Hence, the real exchange rate is given by $1/p_t$, where an increase denotes a real depreciation.

Interest rate. The interest rate paid on foreign debt is composed by an exogenous risk-free rate (r_t^*) and an endogenous spread, raising the cost of capital when the net foreign assets-to-GDP ratio $\left(\frac{\mathcal{E}_t B_t}{p_t^Y Y_t}\right)$ is below its steady state value ($\bar{b}$):

$$r_t = r_t^* + \psi \left[\exp\left(\bar{b} - \frac{\mathcal{E}_t B_t}{p_t^Y Y_t} \right) - 1 \right],$$

where $\psi > 0$ governs the spread elasticity. As shown by Schmitt-Grohé and Uribe (2003), this debt-elastic spread induces stationarity and pins down a well-defined steady state for the net foreign assets-to-GDP ratio.

4.4 Market clearing

The market-clearing condition for each sector j requires that sectoral output Q_{jt} equals the amount of good j demanded for domestic consumption, investment, intermediate goods, and foreign consumption (i.e., exports):

$$Q_{jt} = C_{jt} + \sum_{i=1}^{N} I_{jit} + \sum_{i=1}^{N} M_{jit} + X_{jt}.$$

Labor market clearing requires that labor supplied by households equals the sum of labor demanded by firms, $L_t = \sum_{i=1}^{N} L_{it}$.

Appendix B shows how the balance of payments can be written as:

$$B_t = (1 + r_{t-1}) B_{t-1} + TB_t$$
$$TB_t \equiv \sum_{j=1}^{N} p_{jt} X_{jt} - p_t^F \left(C_t^F + \sum_{j=1}^{N} I_{jt}^F + \sum_{j=1}^{N} M_{jt}^F \right)$$

where the second equality defines the trade balance.

4.5 Exogenous processes

We assume that (log) sectoral productivities, $\ln A_j$, follow autoregressive processes:

$$\ln A_{j,t} = \rho_j \ln A_{j,t-1} + \epsilon^A_{j,t}, \qquad \epsilon^A_{j,t} \sim (0, \sigma_j^2), \quad \forall j = 1, ..., N.$$

Analogously, we also assume exogenous AR(1) processes in logs for the foreign demand for Chilean mining (Y_t^*), the foreign currency price of imported goods (p_t^*), and the international risk-free interest rate (r_t^*), as follows:

$$\begin{aligned}
\ln p_t^* =& \rho_p \ln p_{t-1}^* + \epsilon_t^p, \qquad && \epsilon_t^p \sim (0, \sigma_p^2) \\
\ln y_t^* =& \rho_Y \ln y_{t-1}^* + \epsilon_t^Y, \qquad && \epsilon_t^Y \sim (0, \sigma_y^2) \\
\ln r_t^* =& (1-\rho_r)\ln(1/\beta) + \rho_r \ln r_{t-1}^* + \epsilon_t^r, \qquad && \epsilon_t^r \sim (0, \sigma_r^2)
\end{aligned}$$

Note that we are implicitly normalizing the steady states of A_j, p^*, and y^* to one, while $r^* = 1/\beta$.

5 Quantitative analysis

We now calibrate the model and show that its business cycle moments are consistent with key features of the microdata. We then quantitatively analyze the effect of a foreign demand shock for copper on macroeconomic and sectoral aggregates, disentangling the transmission mechanisms identified in Section 3.

5.1 Calibration

Table 2 lists the key sector-level parameters in the model that we calibrate to Chilean data.[12] The investment network is calibrated to the microdata using the average shares from 2014 to 2024, as reported in Section 2 and illustrated in Figure 2. Instead, for the IO network and other sectoral parameters, we use the latest available version of the National Accounts (2022) and the Input-Output network, which is illustrated in Figure 3.

[12]The only exception is the sector-level depreciation rates, for which we use U.S. values as reported in Vom Lehn and Winberry (2022).

Table 2: Calibration for $N = 41$ sectors

Parameter	Definition	Data
λ_{ij}	Sector i share in sector j investment bundle	Microdata (Section 2)
γ_{ij}	Sector i share in sector j intermediate bundle	National Accounts
θ_j	Value added over sales	National Accounts
$1 - \alpha_j$	Wage bill over value added	National Accounts
ξ_j	Good j share in total consumption	National Accounts
ξ_j^X	Good j share in total exports	National Accounts
κ_j	Domestic investment share	Microdata (Section 2)
ϕ_j	Domestic intermediates share	National Accounts
δ_j	Depreciation rate	Vom Lehn and Winberry (2022)

Table 3 presents the calibration for the remaining parameters. We set $\beta = 0.96$ to get a 4% interest rate in steady state. We use canonical values for $\sigma = 1$ (log utility), $\eta = 0$ (infinite Frisch elasticity of labor supply), and $\varphi = 1$ (unitary elasticity of foreign demand). The parameter governing intertemporal capital adjustment costs ζ (*common* to all sectors) is set to match the volatility of *aggregate* investment observed in the data (see Table 5 below). The Huffman-Wynne intratemporal investment friction is set to $\nu = -1.04$ following Vom Lehn and Winberry (2022). The debt-elasticity of the spread ψ is set to a small value, to induce stationarity while not affecting aggregate dynamics. We also target a trade surplus of 2.7% of GDP, which implies a steady-state net foreign assets-to-GDP ratio $\bar{b} = -0.65$. The share of imported consumption is set at $\xi^F = 0.1$ as observed in the data.

Table 3: Calibration of structural parameters

	Definition	Value
β	Discount factor	0.96
σ	CRRA parameter	1
η	Frisch elast. (inv.)	0
ν	HW friction	-1.04
φ	Elast. foreign demand	1
ψ	Elast. spread	0.0001
$\bar{b}$	SS NFA to GDP ratio	-0.65
ξ^F	Imported cons. share	0.1
ζ	Investment adj. costs	0.41

	Definition	Value
ρ_y	Persist. foreign demand	0.9
σ_y	Std. Dev. foreign demand	0.26
ρ_p	Persist. import price	0.61
σ_p	Std. Dev. import price	0.038
ρ_r	Persist. interest rate	0.88
σ_r	Std. Dev. interest rate	0.12

The persistence and volatility of sectoral productivities, A_{jt}, are estimated using the TFP time series from the National Commission of Productivity (CNEP), which are available for 8 sectors (see Table 4) and we map into our 41 industries. Finally, the autocorrelation and standard deviation of the AR(1) processes for y_t^*, p_t^*, and r_t^* are calibrated to match the persistence and volatility of real copper prices (the LME price series deflated by an index of external prices), real import prices (proxied by the U.S. PPI), and the risk-free foreign interest rate (LIBOR) (see Table 3).

Table 4: Estimated AR(1) for sectoral productivities

	Agric	**Mining**	**Industry**	**Utilities**	**Constr**	**Trade**	**Transp**	**Services**
ρ_j	0.75	0.90	0.46	0.71	0.85	0.68	0.73	0.79
σ_j	0.047	0.079	0.029	0.105	0.051	0.049	0.036	0.019

Notes: Estimates for $\ln A_{j,t} = \rho_j \ln A_{j,t-1} + \epsilon^A_{j,t}$, $\epsilon^A_{j,t} \sim (0, \sigma_j^2)$ using quadratic detrended sector-level TFP from CNEP, sample 1990-2023.

5.1.1 Model fit

Table 5 compares the model simulated moments with the data, both for steady state shares (left-hand panel) and volatilities (right-hand panel). We display in bold the values matched by construction due to our calibration strategy.

Table 5: Model vs. Data moments

Steady State Shares, %	Data	Model
Consumption-to-GDP	66.5	63.2
Investment-to-GDP	29.7	34.1
Exports-to-GDP	35.4	40.1
Imports-to-GDP	32.7	37.4
Trade Balance-to-GDP	**2.7**	**2.7**
Mining Exports-to-Exports	**55.4**	**55.4**
Labor Share in GDP	44.0	42.8

Volatilities, %	Data	Model
GDP growth	3.5	3.7
Consumption growth	4.2	2.2
Investment growth	**9.6**	**9.6**
Employment growth	3.0	2.9
TFP growth	2.2	3.2
Mining Price growth	**19.3**	**19.3**

As shown in Table 5 the model matches the data reasonably well, featuring realistic macroeconomic ratios and volatilities. The model also implies a good fit for the sectoral Domar weights and value-added shares, as shown in Appendix C.

5.2 Mining boom through the lens of the model

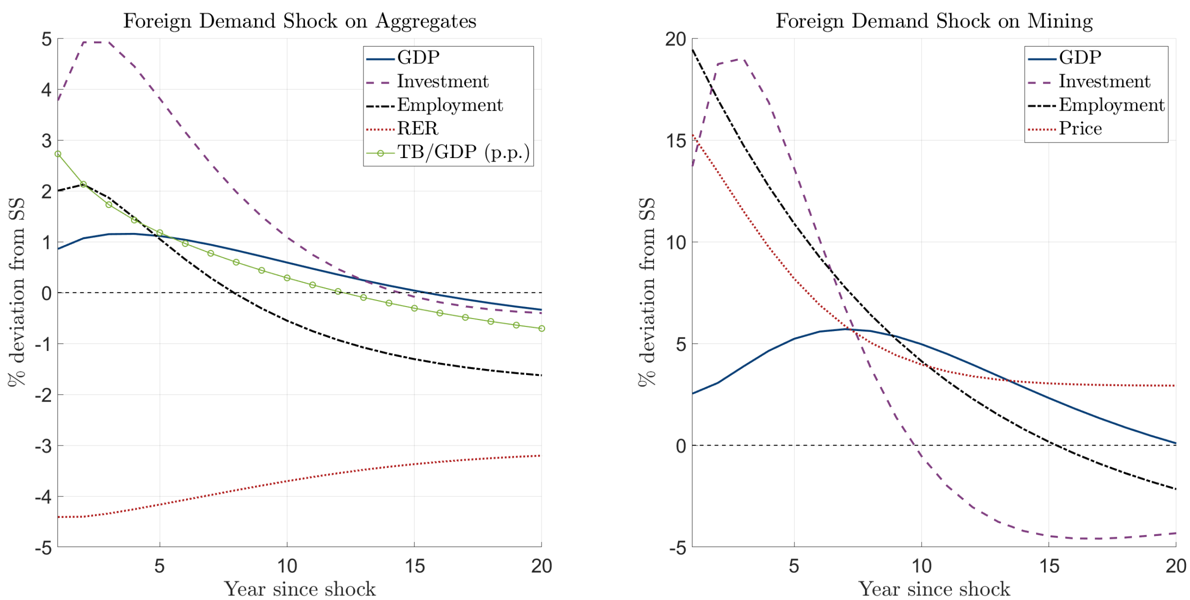
We showed above that our multi-sector small open economy yields simulated aggregate moments that closely match those in the data when calibrated to standard values in the literature and to the Chilean investment and input-output networks. In this section, we use the model as a laboratory to investigate the role of the investment network as an amplifier of sectoral shocks. In particular, we focus our analysis on the response of the economy to a shock to foreign demand for mining that increases the copper price and triggers a mining investment boom, as observed in Chile in recent years.

Figure 4 presents the dynamic responses of key macroeconomic variables to a one-standard-deviation shock to the foreign demand for mining (Y^*_{jt}). The shock increases the relative price of mining (copper) by 14% and leads to a prolonged mining investment boom.

The left panel shows the aggregate effects of the shock, while the right panel shows the impact on the mining sector. In the next subsection, we examine the spillovers to the remaining sectors of the economy with a focus on the role of the investment network.

As shown in the left panel of Figure 4, the aggregate economy experiences a sizable and persistent expansion: GDP rises by 0.9% on impact, reaching its peak at 1.2% four years after shock. In turn, investment jumps by 3.8% on impact and peaks at 4.9% two years after the shock. As we show below, these effects are driven by the shock's propagation through the investment network, which links mining production with capital-goods providers and their input providers throughout the rest of the economy. This amplification operates through both direct and indirect channels, as captured by the Leontief-adjusted investment network, which accounts for the full cascade of intermediate and investment linkages across sectors.

Figure 4: A typical mining investment boom (1 s.d. $= \sigma_y = 26\%$, $\rho_y = 0.9$)



Notes: Responses to a one standard deviation shock ($\sigma_y = 26\%$ with $\rho_y = 0.9$) to the foreign demand for Chilean mining (Y_t^*). The left panel illustrates aggregate responses, while the right panel displays responses specific to the mining sector. All figures are in percent log-deviations from steady state, except for the trade balance-to-GDP ratio, which is expressed in percentage points of GDP.

The right panel of Figure 4 zooms in on the mining sector. Mining investment jumps by 14% on impact, peaking at 19% three years after the shock, closely mirroring the behavior of mining investment in Chile during 2022 to 2025.[13] The mining GDP response is hump-shaped, reflecting the gradual build-up of productive capacity, peaking roughly seven to eight years after the initial shock, mirroring the long gestation periods typically observed in large-scale mining projects. The real exchange rate (RER), depicted by the red dotted line, appreciates by 4% on impact and remains persistently low throughout the simulation horizon. Despite sustained real appreciation, the trade balance improves significantly because Chile exports almost all of the copper it produces, which accounts for approximately half of its

[13]See Box I.1 in the Monetary Policy Report of September 2024 of the Central Bank of Chile for details.

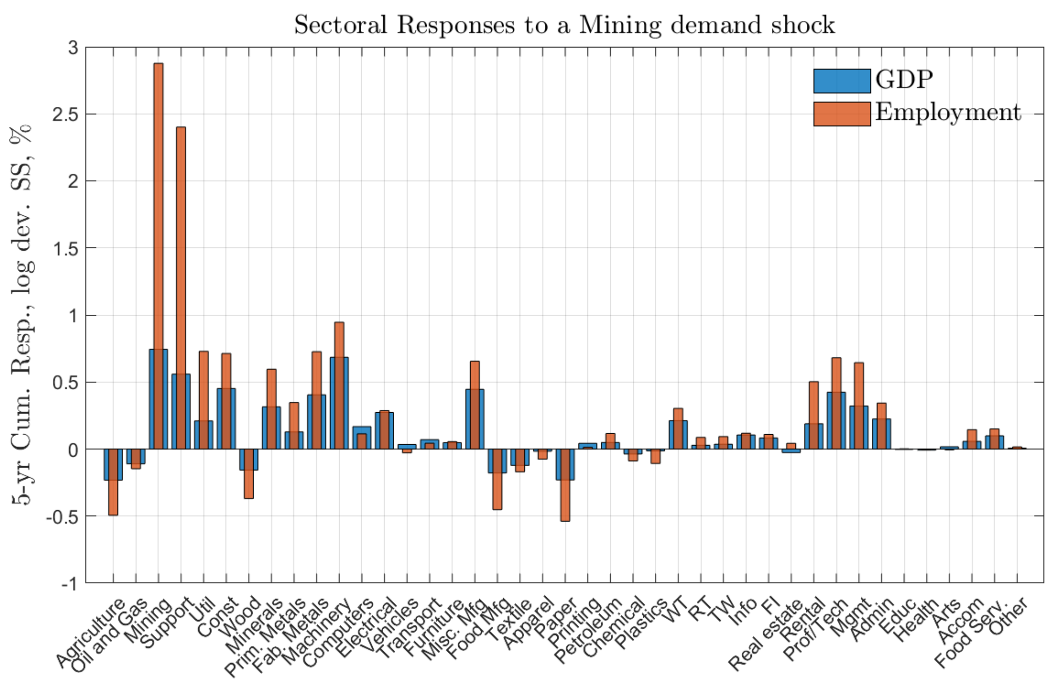
total exports. As the mining sector expands in response to the shock, exports rise sharply, both in terms of quantities and value, more than offset the higher imports in response to the real appreciation, which turns imports relatively cheaper.

The aggregate expansion following a mining boom is driven not only by the direct increase in mining activity but also by the propagation of the shock through the investment network. To understand the distributional consequences of this propagation, we now turn to the sectoral response to the mining boom.

5.3 Heterogeneous impact of the mining boom

As shown above, a positive shock to global mining demand induces a sizable expansion in both the mining sector and the aggregate economy. We now turn to the heterogeneous effects across non-mining sectors and examine the channels through which the investment network amplifies the shock.

Figure 5: Heterogeneous effects of a mining investment boom



Notes: Bars represent the five-year cumulative responses of GDP and employment (in log-deviation from steady state, %) to a 1% shock in global demand for mining.

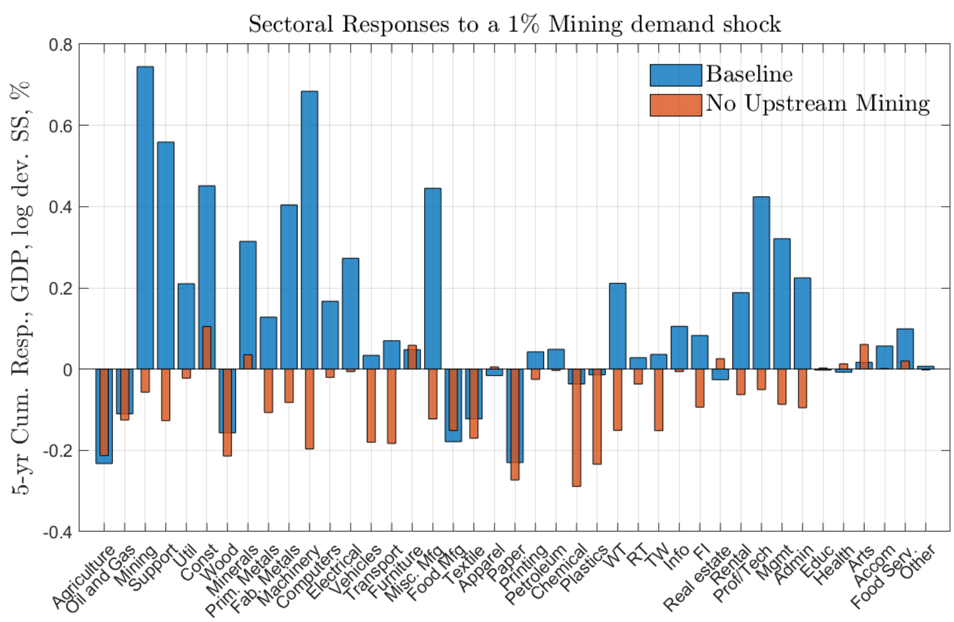
Figure 5 shows that the sectoral responses in GDP and employment to a one percent shock in global demand for mining are highly uneven. Sectors with strong upstream investment or intermediate links to mining, such as construction, utilities, professional services, and management, experience the largest gains in value added. These sectors are either direct suppliers of capital goods or providers of inputs to mining investment hubs. For example, utilities play a central role in powering mining operations, while professional services and management support design and coordination for mining projects. Their prominent position in the Leontief-adjusted investment network ensures they benefit from both direct and indirect spillovers.

In contrast, several tradable sectors, such as non-durable manufacturing sectors (including food, paper, wood, among others), are negatively affected. This pattern is consistent with Dutch disease-like dynamics: the mining boom leads to real exchange rate appreciation, which reduces the international competitiveness of tradable goods and reallocates resources toward non-tradable sectors. The model thus captures both the expansion of some sectors driven by network spillovers and the negative general equilibrium impact on the remaining sectors, offering a nuanced view of the heterogeneous effects of commodity shocks.

5.3.1 The network channel driving heterogeneity across sectors

To isolate the role of upstream propagation, Figure 6 presents a counterfactual in which the mining sector does not source capital or intermediate goods domestically. More specifically, in this counterfactual, we assume that the mining sector sources its intermediate and capital goods either from imports or from its own resources.[14] This counterfactual shows that the higher demand for intermediate and capital goods due to the mining boom is a key driving force behind the positive impact of the higher foreign demand for mining in different sectors of the domestic economy: most sectors in the economy would instead contract in response to the mining boom absent the upstream spillovers of the mining sector. Thus, the upstreamness of the mining sector is key to understanding its positive impact on the economy.

Figure 6: No Upstream linkages in the Mining Sector

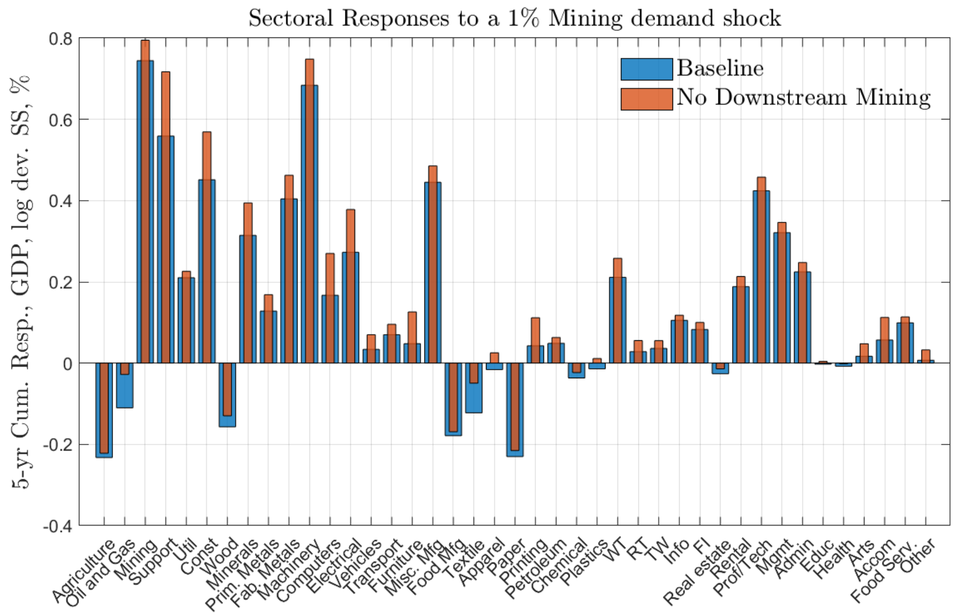


Notes: Bars represent the five-year cumulative response of GDP (in log-deviation from steady state, %) to a 1% shock in global demand for mining. In the "No Upstream Mining" counterfactual, the mining **column** in both networks is set to zero (except the diagonal, which is set to 1).

[14]In practice, we zero-out the column that represents demand for inputs from the mining sector in both the investment and input-output networks, except for the diagonal element which is set to 1.

In contrast, Figure 7 shows that removing downstream links, i.e., assuming that no other sector uses mining output, has a much smaller effect on aggregate dynamics because most of the mining production (90%) is exported in the baseline economy (as in the data).[15]

Figure 7: No Downstream linkages in the Mining Sector



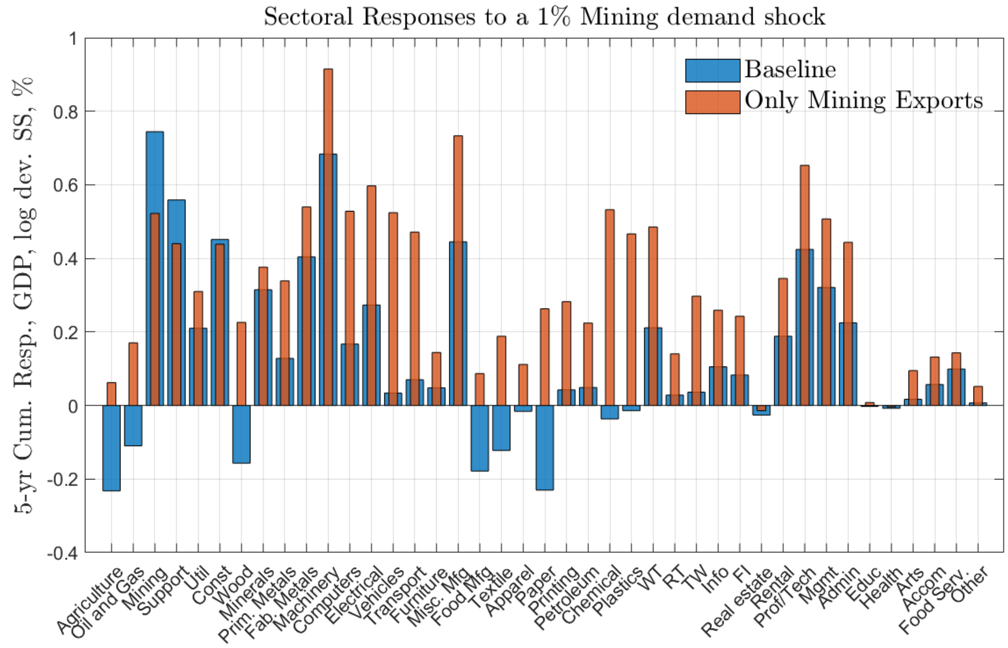
Notes: Bars represent the five-year cumulative response of GDP (in log-deviation from steady state, %) to a 1% shock in global demand for mining. In the "No Downstream Mining" counterfactual, the mining **row** in both networks is zeroed out (except the diagonal).

5.3.2 The real exchange rate channel

Figure 8 explores the role of the real exchange rate in shaping sectoral heterogeneity. We simulate a counterfactual in which only the mining sector exports, setting export shares to zero ($\xi_j^X = 0$) for all other sectors. In this scenario, sectors such as agriculture and food manufacturing, which reduce output in the baseline economy, actually expand. The reason is that the commodity boom generates a positive income effect, boosting domestic demand (wealth effect) without the negative impact of the real appreciation (substitution effect). In the baseline economy, real appreciation reduces the competitiveness of the export sector, thus reallocating resources to the mining sector. Notice that in this counterfactual the mining sector increases less than in the baseline, given the lower reallocation of resources from other sectors.

[15]For this counterfactual, we set to zero the row corresponding to mining in the investment and input-output network matrices, except for the element in the diagonal, which is kept at its baseline value.

Figure 8: Only Mining Exports



Notes: Export shares (ξ_j^X) are set to zero for all sectors except mining. Tradable sectors benefit from the income effect in the absence of real exchange rate pressures.

These exercises underscore two key insights. First, the upstream propagation of mining investment, through demand for capital and intermediate goods, is the dominant channel driving economy-wide spillovers. Second, appreciation of the real exchange rate induced by the boom exerts contractionary pressures on tradable sectors, consistent with the dynamics of Dutch disease. Together, these mechanisms explain the observed heterogeneity in sectoral outcomes and highlight the importance of network structure and macroeconomic context in shaping the transmission of commodity shocks.

These results are consistent with the empirical evidence presented in Section 3. In particular, in that section, we used firm-level data to show that: (i) upstream firms benefit from increases in copper prices, in particular once indirect linkages are taken into account, both through the input-output table and, especially, through the investment network; and (ii) non-mining exporting firms experience adverse effects consistent with a real exchange rate appreciation channel. These two findings are consistent with the quantitative results presented here. However, we also found that (iii) downstream firms are positively impacted, perhaps due to broader general-equilibrium spillovers, while in the model we do not find strong downstream effects.

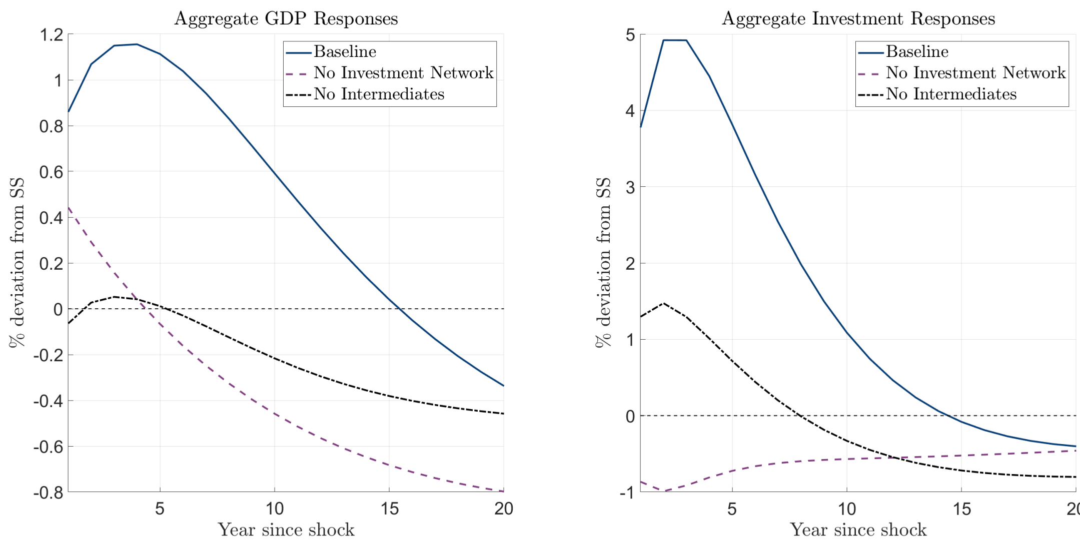
5.4 The role of the investment network as shock amplifier

In this section, we use the model as a laboratory to investigate the role of the investment network in the propagation of shocks to the foreign demand for mining.

5.4.1 An economy with no networks

Figure 9 presents a counterfactual analysis that isolates the role of intersectoral links in propagating a mining investment shock. The figure contains two panels: the left-hand panel displays the dynamic response of aggregate GDP, while the right-hand panel shows the response of aggregate investment. In each panel, the solid blue line represents the baseline model with the investment and intermediate input networks.

Figure 9: Model with no investment network



Notes: Responses to a one standard deviation shock ($\sigma_y = 26\%$ with $\rho_y = 0.9$) to the global demand for Chilean mining (Y_t^*), under the baseline versus counterfactuals. The "No Investment Counterfactual" removes the investment linkages in the economy ($\Lambda = I$), while the "No Intermediates" model removes intermediate usage ($\theta = 1$). The left panel illustrates aggregate GDP responses, while the right panel displays aggregate investment. All figures are in percent log-deviations from steady state.

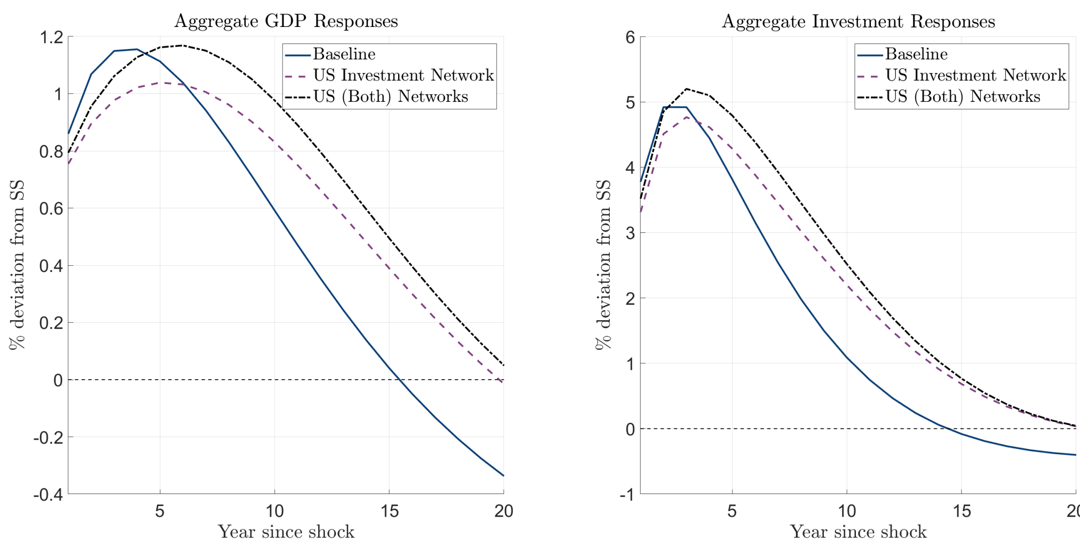
The first counterfactual, shown by the dashed magenta line, removes the investment network, effectively assuming that sectors invest using a combination of imported inputs with their own output. The second, shown by the dash-dotted black line, shuts off the intermediate input linkages, eliminating the indirect propagation of shocks through production networks. Both counterfactuals result in significantly weaker and less persistent responses in GDP and investment.

Quantitatively, the impact effect on aggregate GDP is reduced from 0.9% in the baseline economy to 0.46% without the investment network, and further to close to zero when the intermediate input links are removed. The contrast is even starker for the response of aggregate investment, which drops from 3.8% in the baseline to -0.9% in the absence of the investment network, and to 1.3% when intermediate inputs are excluded. Thus, the investment network substantially amplifies and propagates the initial shock.

5.4.2 A "US-type" denser investment network

Figure 10 explores how the structure of the investment and input-output networks affects the propagation of a mining investment shock. In this exercise, we replace Chile's empirically estimated networks with those reported for the U.S. by Vom Lehn and Winberry (2022), which are notably richer and denser (that is, they exhibit fewer zero entries and stronger cross-sectoral linkages, as shown in Figures C.4 and C.3 in Appendix C). The figure shows that this denser network structure leads to substantially greater amplification and persistence of the shock. Both aggregate GDP and investment respond more strongly and remain higher for longer than in the baseline economy. Notice, in particular, that most of the change is due to the denser investment network (the dashed magenta lines).

Figure 10: A richer/denser network generates larger amplification and persistence



Notes: Responses to a one standard deviation shock ($\sigma_y = 26\%$ with $\rho_y = 0.9$) to the global demand for Chilean mining (Y_t^*), under the baseline versus alternative versions of the model. The "US Investment Network" model replaces the Chilean investment network with the U.S. investment network, as reported in Vom Lehn and Winberry (2022). Analogously, the "US (both) Networks" replaces both the intermediate and the investment networks for the U.S. ones. The left panel illustrates aggregate GDP responses, while the right panel displays aggregate investment. All figures are in percent log-deviations from the steady state.

These results reinforce the paper's main insight: the investment network matters qualitatively and quantitatively. A more interconnected production and investment structure allows shocks to amplify more broadly and durably across the economy. The finding is also reminiscent of Casal and Caunedo (2024), which shows that more developed economies tend to have richer investment networks and that these networks account for a significant share of cross-country differences in income per worker. Our results complement theirs by showing that commodity-dependent economies could benefit more from international commodity price shocks if they had richer and denser networks—not only by enhancing short-run macroeconomic spillovers from sectoral shocks, but also, potentially, by supporting long-run development (though the latter is not the focus of this paper).

6 Conclusions

We investigate the role of the investment and input-output networks in the propagation and amplification of external shocks in a commodity-dependent small open economy, at the firm, sector, and aggregate levels.

This paper offers three key contributions to the literature studying the role of production networks in the transmission of shocks in international macroeconomics. First, we advance the empirical understanding of capital investment flows by constructing a firm-level investment network for Chile from unique transaction-level data—the first detailed mapping of capital-goods linkages. Second, we provide novel empirical evidence on how copper price (terms-of-trade) shocks propagate across Chilean firms via these linkages: we document that upstream firms supplying capital goods to the mining sector experience significant gains when copper prices rise, whereas non-mining export-oriented firms suffer declines due to the accompanying real exchange rate appreciation. Third, we develop and calibrate a multi-sector general equilibrium model that incorporates input-output and investment network linkages, and use it to quantify the role of the investment network in amplifying external shocks.

Our counterfactual and comparative exercises underscore the importance of the production network in shaping macroeconomic outcomes. We find that a one-standard-deviation global demand surge for mining (which raises the world price of copper by around 15%) leads to a substantial and persistent expansion of economic activity. In our model, GDP increases by about 0.9% and aggregate investment by 3.8%, on impact. Crucially, absent investment linkages, the impact of the shock on GDP and investment would be roughly halved, while replacing Chile's relatively sparse investment network with a denser U.S.-style network produces substantially stronger and more persistent macroeconomic responses. These findings highlight the powerful amplification role of the investment network.

Our model also shows that the impact of the shock is highly heterogeneous between sectors: key upstream mining suppliers, such as construction, utilities and professional services, enjoy the greatest gains, while other tradable sectors (for example, agriculture and food manufacturing) contract, consistent with the dynamics of Dutch disease caused by appreciation of the real exchange rate. In general, these findings show that investment links act as a critical propagation channel for external commodity price shocks, significantly shaping aggregate fluctuations and the cross-sectoral distribution of gains and losses in a small open economy.

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A Huffman Wynne (HW) friction

Sector j's intratemporal investment allocations are given by the solution to:

$$\max_{I_{ijt}} \quad p_{jt}^{I^H} I_{jt}^H - \sum_{i=1}^N p_{it} Z_{it} \quad \text{s.t.} \quad I_{jt}^H = \prod_{i=1}^N I_{ijt}^{\lambda_{ij}} \quad \text{and} \quad Z_{jt} = \left(\sum_{i=1}^N I_{jit}^{-\nu} \right)^{-\frac{1}{\nu}}$$

with $\nu \leq -1$. Higher values of $|\nu|$ introduce higher degrees of investment production friction. Plugging restrictions

$$\max_{I_{ijt}} \quad p_{jt}^{I^H} \prod_{i=1}^N I_{ijt}^{\lambda_{ij}} - \sum_{i=1}^N p_{it} \left(\sum_{j=1}^N I_{ijt}^{-\nu} \right)^{-\frac{1}{\nu}}$$

with FOC

$$\lambda_{ij} p_{jt}^{I^H} I_{jt}^H = p_{it} I_{ijt} \left(\frac{Z_{it}}{I_{ijt}} \right)^{1+\nu} = p_{it} I_{ijt}^{-\nu} Z_{it}^{1+\nu}$$

Note that under the "no friction" value $\nu = -1$, the FOC collapses back to the baseline model. Manipulating the FOC, we derive the sectoral price of investment:

$$p_{jt}^I = \prod_{i=1}^N \left(\frac{p_{it}}{\lambda_{ij}} \right)^{\lambda_{ij}} \prod_{i=1}^N \left(\frac{Z_{it}}{I_{jt}^H} \right)^{\lambda_{ij}(1+\nu)}$$

Finally, under the HW friction, the market-clearing conditions become:

$$Q_{jt} = C_{jt} + \sum_{i=1}^N M_{jit} + \left(\sum_{i=1}^N I_{jit}^{-\nu} \right)^{-\frac{1}{\nu}} + X_{jt} \equiv C_{jt} + \sum_{i=1}^N M_{jit} + Z_{jt} + X_{jt}$$

Noting that

$$Z_{jt} = \sum_{i=1}^N \lambda_{ji} \frac{p_{it}^{I^H}}{p_{jt}} I_{it}^H$$

The market-clearing conditions become

$$p_{jt} Q_{jt} = p_{jt} C_{jt} + \sum_{i=1}^N \gamma_{ji} p_{it}^{M^H} M_{it}^H + \sum_{i=1}^N \lambda_{ji} p_{it}^{I^H} I_{it}^H + p_{jt} X_{jt}$$

making explicit the role of both networks.

B Balance of payments

Plugging aggregate profits Π_t into the household's budget constraint,

$$B_t = R_{t-1}B_{t-1} - p_t C_t + \sum_{j=1}^{N} p_{jt}Q_{jt} - \sum_{j=1}^{N} p^I_{jt} I_{jt} - \sum_{j=1}^{N} p^M_{jt} M_{jt}$$

Using $p^I_{jt}I_{jt} = p^{I^H}_{jt} I^H_{jt} + p^{I^F}_{jt} I^F_{jt}$ and $p^M_{jt}M_{jt} = p^{M^H}_{jt} M^H_{jt} + p^{M^F}_{jt} M^F_{jt}$,

$$B_t = R_{t-1}B_{t-1} - p_t C_t + \sum_{j=1}^{N} p_{jt}Q_{jt} - \sum_{j=1}^{N} p^{I^H}_{jt} I^H_{jt} - \sum_{j=1}^{N} p^{I^F}_{jt} I^F_{jt} - \sum_{j=1}^{N} p^{M^H}_{jt} M^H_{jt} - \sum_{j=1}^{N} p^{M^F}_{jt} M^F_{jt}$$

Using $Q_{jt} = C_{jt} + \sum_{i=1}^{N} I_{jit} + \sum_{i=1}^{N} M_{jit} + X_{jt}$, $p_t C_t = \sum_{j=1}^{N} p_{jt}C_{jt} + p^F_t C^F_t$ and $p^{I^F}_t = p^{M^F}_t = p^F_t$,

$$B_t = R_{t-1}B_{t-1} - p^F_t C^F_t - \sum_{j=1}^{N} p^{I^H}_{jt} I^H_{jt} - \sum_{j=1}^{N} p^F_t I^F_{jt} - \sum_{j=1}^{N} p^{M^H}_{jt} M^H_{jt} - \sum_{j=1}^{N} p^F_t M^F_{jt}$$
$$+ \sum_{j=1}^{N}\sum_{i=1}^{N} p_{jt}I_{jit} + \sum_{j=1}^{N}\sum_{i=1}^{N} p_{jt}M_{jit} + \sum_{j=1}^{N} p_{jt}X_{jt}$$

Recall $p_{it}I_{ijt} = \lambda_{ij} p^{I^H}_{jt} I^H_{jt}$, $p_{jt}I_{jit} = \lambda_{ji} p^{I^H}_{it} I^H_{it}$ and,

$$\sum_j p_{jt}I_{jit} = \sum_j \lambda_{ji} p^{I^H}_{it} I^H_{it} = p^{I^H}_{it} I^H_{it} \sum_j \lambda_{ji} = p^{I^H}_{it} I^H_{it}$$
$$\sum_j \sum_i p_{jt}I_{jit} = \sum_j p^{I^H}_{jt} I^H_{jt}$$

Using an analogous derivation for the intermediate bundle, we get:

$$B_t = R_{t-1}B_{t-1} + \sum_{j=1}^{N} p_{jt}X_{jt} - p^F_t \left(C^F_t + \sum_{j=1}^{N} I^F_{jt} + \sum_{j=1}^{N} M^F_{jt} \right)$$

Defining the **trade balance**:

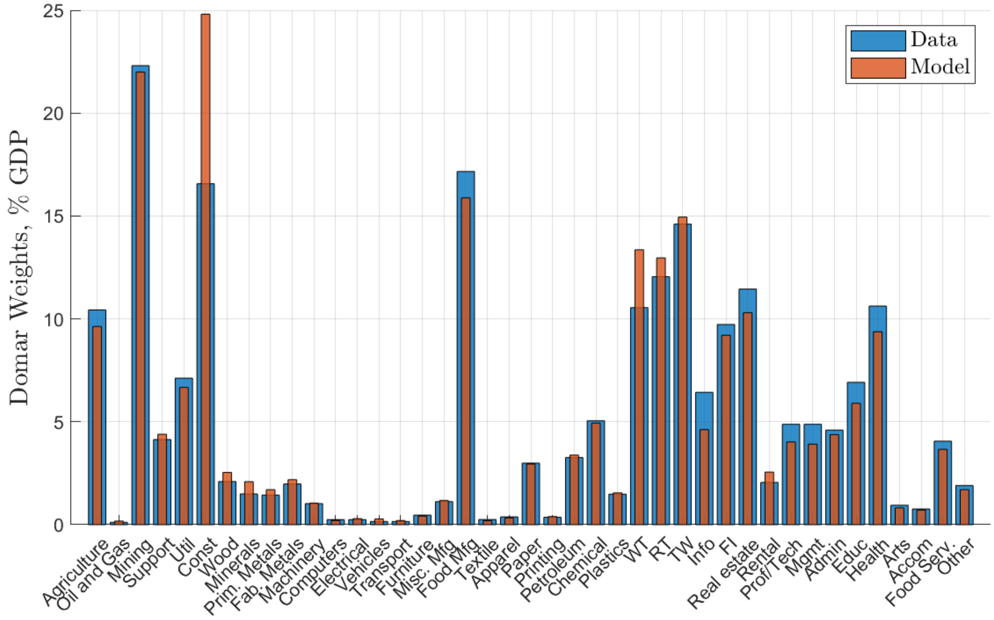
$$TB_t = \sum_{j=1}^{N} p_{jt}X_{jt} - p^F_t \left(C^F_t + \sum_{j=1}^{N} I^F_{jt} + \sum_{j=1}^{N} M^F_{jt} \right),$$

we can write the **balance of payments** as:

$$B_t = (1 + r_{t-1})B_{t-1} + TB_t.$$

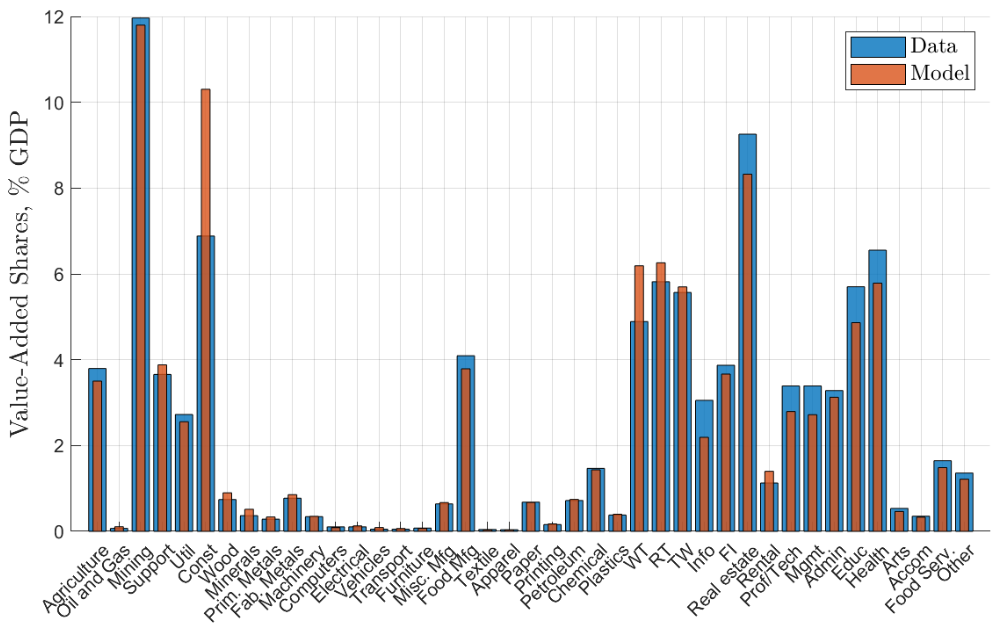
C Sectoral moments and calibration

Figure C.1: Steady State Fit: Domar Weights



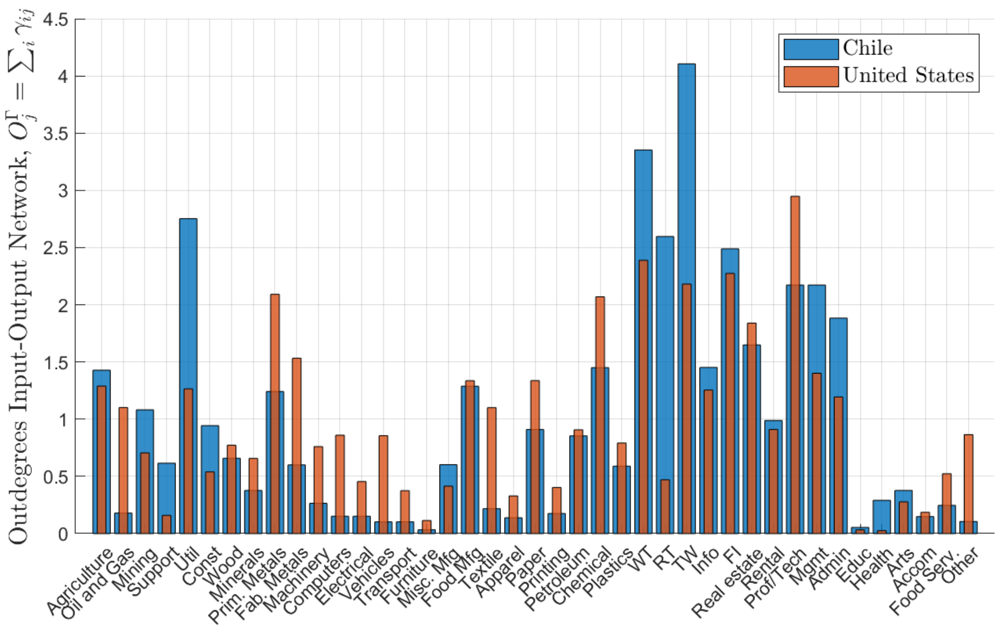
Notes: The Domar weights are sectoral gross output over aggregate value-added $\left(\frac{p_j Q_j}{p^Y Y}\right)$.

Figure C.2: Steady State Fit: Value-Added Shares



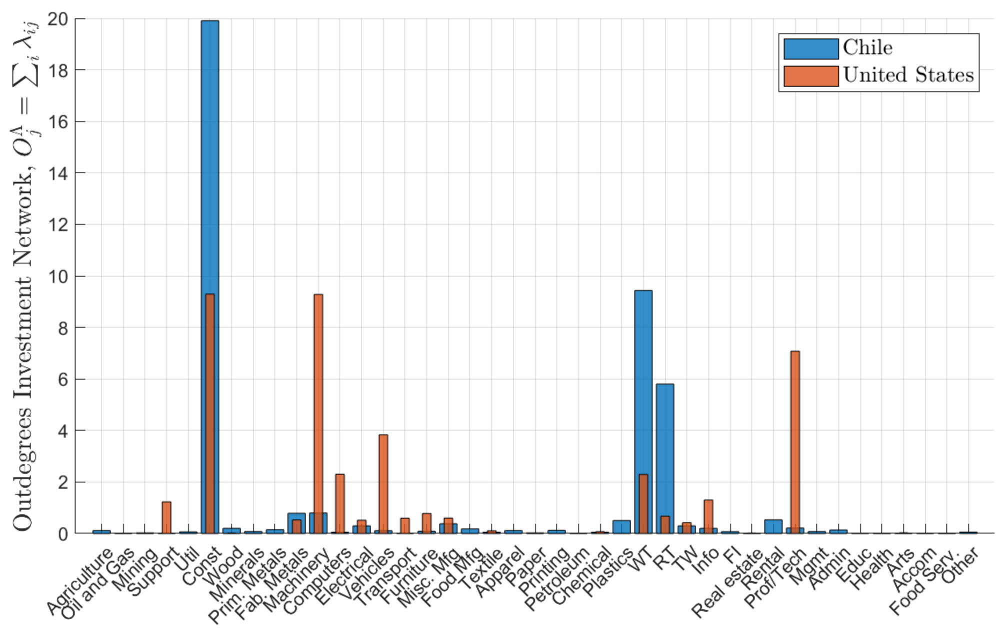
Notes: The value-added shares are sectoral value-added over aggregate value-added $\left(\frac{p_j^Y Y_j}{p^Y Y}\right)$.

Figure C.3: Comparison with Vom Lehn and Winberry (2022): Outdegrees Input-Output Network Γ



Notes: Outdegrees for sector j is computed as $O_j^{\Gamma} = \sum_j \gamma_{ij}$.

Figure C.4: Comparison with Vom Lehn and Winberry (2022): Outdegrees Investment Network Λ



Notes: Outdegrees for sector j is computed as $O_j^{\Lambda} = \sum_j \lambda_{ij}$.

Table 6: Comparison with Casal and Caunedo (2024): Investment Network Λ

	Outdegree		Homophily	
Sector	Casal-Caunedo	This Paper	Casal-Caunedo	This Paper
Agriculture	0.32	0.07	0.13	0.04
Construction	4.22	5.13	0.68	0.86
Durables	0.44	0.46	0.07	0.07
Electronics	0.06	0.11	0.01	0.05
ICT	2.73	0.15	0.33	0.03
Machinery	0.49	0.28	0.07	0.11
Nondurables	0.34	0.15	0.09	0.04
Services	1.08	4.47	0.06	0.36
Transportation	0.13	0.04	0.01	0.01
Transport. Services	0.20	0.11	0.06	0.04

Notes: Comparison between our Chilean investment network constructed from transaction-level data and the estimates for the Chilean *domestic* investment network as reported in Casal and Caunedo (2024). This table reports the row sum of the networks (outdegrees) as well as the weight of the diagonal in the network (homophily).

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