Growth Accounting in Distorted Open Economies

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Abstract

We present a theory for growth accounting in the presence of distortions in open economies. In addition to domestic wedges, we include wedges derived from imported intermediate inputs used in production and exports. We bring the model to the data using administrative firm-to-firm and tax data for the universe of formal firms from Chile between 2005 and 2022. Observed TFP growth is explained by allocative efficiency rather than technological change. Around half of the allocative efficiency gains are explained by international trade.

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1 Introduction

In the presence of distortions, aggregate total factor productivity (TFP) growth reflects not only technological advancements but also allocative efficiency (AE), that is, how efficiently resources are allocated across firms and households. International trade has been argued for being an important mechanism for improving TFP but whether this happens through technological improvements or allocative efficiency is still unclear.

To this purpose, we present a theory to perform growth accounting in the presence of distortions in open economies. The theory builds on Baqaee and Farhi (2020) and extends it to open economies. While we keep AE effects driven by wedges within domestic production networks, we include wedges derived from imported intermediate inputs used in production. These wedges might propagate downward production networks affecting firms that consume intermediate inputs produced with imported goods- directly or indirectly- which in turn might affect their sales, either to other firms, final consumers, or exports.

Seminal works by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) have emphasized that departures from perfect competition introduce distortions in the allocation of production factors among firms, leading to changes in TFP that reflect not only technological advancements but also shifts in factor allocation. However, Hsieh and Klenow (2009) and much of the subsequent literature have focused on horizontal economies without firm-to-firm transactions.

Firm linkages within production networks add complexity when assessing AE. Simply comparing individual firm-level wedges is insufficient for evaluating macroeconomic inefficiencies. A more comprehensive approach, considering firm-level linkages and wedges across the entire network, becomes necessary. As Baqaee and Farhi (2020) showed, these wedges can accumulate downstream within production networks, even if individual firm-level distortions are small. However, addressing this challenge requires suitable data that accurately captures firm-to-firm connections.

We leverage an extensive transaction dataset spanning nearly two decades of the universe of formal firms operating in Chile to perform growth accounting in the presence of distortions in open economies. We assume markups are the sole distortion and estimate them using the De Loecker and Warzynski (2012) methodology. We benefit from nearly ideal data coverage for the formal Chilean economy, including data on prices and quantities for all transactions between firms. Our markup estimation is based on price variation-free measures for output and material usage, which allows us to avoid the main critique of markup estimations using price-contaminated variables (Bond et al. (2021) and Doraszelski and Jaumandreu (2021)). As markups evolution will shape AE changes and thus aggregate TFP growth, we heavily rely on the quality of our markup estimation.

Using the markup estimations, we apply the open economy growth accounting in the presence of distortions theory to Chile. In an economy where imports are used as production inputs, and their corresponding outputs are traded charging markups, the revenues generated by imports will exceed their costs. Capitalizing on our granular dataset, we dissect TFP growth components to identify its micro-drivers and separate them into domestic and international-driven forces. We are able to investigate what specific industries and firm sizes of the economy are responsible for driving TFP changes through AE and identify what fraction of drivers are domestic and which ones come from international trade.

Although our theoretical framework applies to any open economy, our application to Chile provides a potential explanation for a longstanding puzzle: the stagnation of TFP growth in Chile since the early 2010s. Our findings primarily attribute the observed TFP growth to changes in AE rather than technological change, and perhaps more importantly, 48% of cumulative TFP growth driven by AE for the period is explained by international trade forces. In cases where technology (the residual) accounts for most TFP growth, the availability of granular data becomes less relevant. Moreover, in cases where international trade forces are negligible, our proposed theoretical extension is unnecessary.

While our insights are specific to Chile, they also hold broader implications that may apply to other countries. Chile's macroeconomic experience mirrors global productivity dynamics for both developed and developing economies, characterized by a surge in productivity before the Great Recession followed by a period of stagnation until Covid.

Related Literature

The idea that markup affects a change in productivity goes back to Hall (1988) followed by Basu and Fernald (2002). In an economy that uses imported intermediate goods, if there is a markup, the imported intermediate input raises value added more than its input value. However, in GDP calculations, only nominal imports (costs) are subtracted. Thus, even if there is no change in domestic technology, an increase in the input of imported intermediate goods mechanically increases GDP and productivity, measured as the Solow residual.

While there is an extensive literature on theoretical frameworks to assess productivity implications of international trade cost reductions, Melitz and Redding (2014) and Costinot and Rodríguez-Clare (2014), we are unaware of attempts to provide a theoretical framework that accounts for international trade shocks spread through production networks and their effects on Allocative Efficiency and thus on aggregate TFP growth.

While Baqaee and Farhi (2019a) provide a theoretical framework that accounts for international trade shocks spread through production networks and their effects on Allocative Efficiency, they rely on industry rather than firm production networks.

There are at least two insightful theoretical avenues of research that address the reallocation effects of trade shocks. The first avenue, lead by Kehoe and Ruhl (2008) emphasize that the terms of trade — the price of imports relative to the price of exports — may induce production factors reallocation across goods and sectors, affecting output and measured TFP. While we rely on their inside, they do not give the structure on how terms of trade will affect aggregate TFP growth while at the same time omitting production networks terms of trade shocks spread out.

The second research avenue relies on a range of workhorse trade models used by Burstein and Cravino (2015) to analyze trade cost change effects on real GDP, real consumption, and aggregate TFP. They find that aggregate TFP increases in response to reductions in trade costs, however the models they use are not able to capture the reallocation of production towards more productive producers due to trade cost changes, which will have effects on aggregate TFP growth.

2 Theoretical Framework

To capture international trade shocks effects on aggregate TFP growth trough changes in production factor allocations (Allocative Efficiency, AE), we extend Baqaee and Farhi (2020) theoretical framework to open economies. While we keep AE effects driven by wedges within domestic production networks, we include wedges derived from imported intermediate inputs used in production. These wedges might propagate downward production networks affecting firms that consume intermediate inputs produced with imported goods- directly or indirectly- which in turn might affect their own sales, either to other firms, final consumers, or exports. We assume that the observed data originate from a particular data-generating process. We then provide equations to decompose and interpret the drivers of aggregate productivity changes. To this end, we make minimal assumptions on a general equilibrium environment.

We define N to represent the universe of firms and $X \in N$ as a subset of firms that also export. We define production functions separately for domestic and exporting goods within firms, where both exhibit Constant Returns to Scale (CRS) in production. Hence, we split the same firm in two: one that produces domestic goods and one that produces goods to be exported. The CRS production function of firm i, F_i is given by :

$$q_i = A_i F_i \left(\left\{ q_{ij} \right\}_{j \in N}, L_i, K_i, IM_i \right)$$

Where q_i is the total output of firm i, A_i is Hicks-neutral productivity, q_{ij} are the intermediate goods input from other $j \in N$ firms. Labor (L), Capital (K), and imported inputs (IM) are this economy's primary production factors. Firms minimize costs given the input prices and sell their products charging a markup (μ) over marginal cost:

$$p_i = \mu_i \cdot mc_i,$$

There is a representative household with the following utility function;

$$\mathcal{W} = \mathcal{W} \left(\{ y_i \}_{i \in N} \right),$$

The budget constraint is expressed as:

$$\sum_{i \in N} p_i y_i = \sum_{f \in \{L,K\}} w_f L_f + \sum_{i \in N+X} (1 - 1/\mu_i) p_i q_i + T$$

The firm's profits go to domestic households through an income transfer of T. We treat imports as a factor for mathematical convenience but the factor income allocated to imports does not appear in household budget constraints as it is attributed to households abroad. Finally, the foreign demand and import price are exogenous.The Resource constraints are expressed as:

$$q_i = y_i + \sum_{j \in N} q_{ji}$$

$$\sum_{i \in N+X} L_i = L, \quad \sum_{i \in N+X} K_i = K, \quad \sum_{i \in N+X} IM_i = IM,$$

General Equilibrium

Given productivity A_i, markup μ_i, and transfer T, exogenous foreign demand, and exogenous import prices, the general equilibrium is the set of prices p_i, intermediate input choices q_{ij}, factor input choices l_{if}, output q_i, and consumption choices y_i, such that: (i) the price of each good is equal to its markup multiplied by its marginal cost; (ii) households maximize utility under budget constraints, given prices; and (iii) market clearing for all goods and factors.

National Accounts

Nominal GDP is the sum of domestic and foreign final demand minus imports.

$$GDP = \sum_{i \in N+X} p_i y_i - p^{IM} IM,$$

GDP shares are described by the following vector:

$$b_i = \begin{cases} \frac{p_i y_i}{GDP} & \text{if } i \in N + X \\ -\frac{p^{IM} IM}{GDP} & \text{if } i \in IM \\ 0 & \text{otherwise} \end{cases}$$

A Divisia index captures the change in real variables for real output and expenditure. The GDP deflator and real GDP are defined as follows:

$$d \log P = \sum_{i \in N+X} \frac{p_i y_i}{GDP} d \log p_i - \frac{p^{IM} IM}{GDP} d \log p^{IM},$$

which can be expressed in vector form using the GDP share,

$$d \log P = b' d \log p,$$

Where $d \log p$ is a vector of $N + X + F$ prices. Then, real GDP growth is computed by chaining absolute indices:

$$d \log Y = d \log GDP - d \log P,$$

Finally, we define the aggregate factor shares and import shares as Λ_L, Λ_K, and Λ_{IM}.

$$\Lambda_L = \frac{wL}{GDP}, \quad \Lambda_K = \frac{rK}{GDP}, \quad \Lambda_{IM} = \frac{p^{IM} IM}{GDP}.$$

Input-Output Objects

The IO matrix groups together all firm-to-firm transactions in a matrix of dimensions $(N + X + F) \times (N + X + F)$. Where N, X, and F represent the sets of firms, exporters, and production factors, respectively. The revenue-based input-output matrix, denoted as Ω, is a matrix where the ij^{th} element captures the expenditure of firm i on goods produced by firm j as a share of firm i total revenue, $p_i q_i$, where q_i is the physical production.

$$\Omega_{ij} \equiv \frac{p_j q_{ij}}{p_i q_i}$$

While Ω reflects the share of intermediate expenditures relative to total revenue, the cost-based input-output matrix $\tilde{\Omega}$ describes the share of intermediate expenditures in the firm's total costs. Using Shepherd's Lemma, it is possible to express $\tilde{\Omega}$ also as the elasticity of firm i's marginal cost relative to firm j's price.

$$\tilde{\Omega}_{ij} \equiv \frac{\text{Value of input j used by firm i}}{\text{Firm i total cost}} \equiv \frac{p_j q_{ij}}{\sum_{j=1}^{N+X} p_j q_{ij}}$$

The cost-based Leontief inverse matrix $\tilde{\Psi}$ accounts for both, the direct and indirect cost exposures of every firm through an economy's production network. Each element of $\tilde{\Psi}$ measures the weighted sums of all paths (steps) of length m from producer i to producer j.

$$\tilde{\Psi} \equiv (I - \tilde{\Omega})^{-1} = I + \tilde{\Omega} + \tilde{\Omega}^2 + \dots$$

We define cost-based Domar weights, $\tilde{\lambda}$ for firms and $\tilde{\Lambda}$ for factors[1], as the interaction of firms and factors GDP exposure (b vector) with a measure firms and factors relevance throughout production networks $\tilde{\Psi}$. Cost-based Domar weights capture the impact of firm-level cost shocks (changes in productivity or markups) on GDP.

$$\tilde{\lambda}' \equiv b'\tilde{\Psi}$$

Growth Accounting

Following Baqaee and Farhi (2020) an allocation matrix $\mathcal{X}$ captures admissible allocation of resources, where each of its elements $\mathcal{X}_{ij} = q_{ij}/y_j$ is firm j output share used in production by firm i. All feasible allocations are defined by an allocation matrix $\mathcal{X}$, a vector

[1] Denote $\tilde{\Lambda}_f$ if $f \in L, K, IM$

of productivities A, and a vector of factor supplies, F, which consists of L, K, and IM. In particular, the equilibrium allocation yields an allocation matrix $\mathcal{X}(A, F, \mu)$, which in turn generates an output level of $\mathcal{Y}(A, \mathcal{X}(A, F, \mu))$.

A productivity shock ($\mathrm{d}\log A$) and a markup shock ($\mathrm{d}\log\mu$) effect in real GDP can be decomposed into a pure change in technology ($\mathrm{d}\log A$) for a given fixed allocation matrix $\mathcal{X}$ and the change in the distribution of resources allocation matrix ($\mathrm{d}\mathcal{X}$) holding technology constant. In vector notation:

$$\mathrm{d}\log Y = \underbrace{\frac{\partial \log \mathcal{Y}}{\partial \log A}\mathrm{d}\log A}_{\Delta \text{ Technology}} + \underbrace{\frac{\partial \log \mathcal{Y}}{\partial \mathcal{X}}\mathrm{d}\log \mathcal{X}}_{\Delta \text{ Allocative Efficiency}}$$

Firm-level shock relevance can be summarized by the idiosyncratic shock to firm i times its Domar weight. In addition, the shock to allocations can be broken down into a) markup changes, which will affect the relationship between marginal revenue products of factors and its wages, and b) Factor allocations changes, which will arise as factors will reallocate between firms as a consequence of markups changes; some firms will release resources while others will hire more resources to respond to shocks optimally. Hence, the above decomposition can be further decomposed, weighing firm-level technology, markups, and factors changes by its Domar Weight.

$$\mathrm{d}\log Y = \underbrace{\tilde{\lambda}'\ \mathrm{d}\log A}_{\Delta\text{Technology}} - \underbrace{\tilde{\lambda}'\ \mathrm{d}\log\mu - \tilde{\Lambda}_f'\ \mathrm{d}\log\Lambda}_{\Delta \text{ Allocative Efficiency}}$$

The traditional Solow residual weights factors by its share in aggregate income, while the distortion-adjusted Solow residual proposed by Baqaee and Farhi (2020) weights factor changes by factor cost-based Domar weights ($\tilde{\Lambda}$). The latter is the correct strategy to measure aggregate factors in distorted economies as due to a change in wedges, factors aggregate income share could remain unchanged. In contrast, its allocations between firms can change, which is captured by factor cost-based Domar weights.

Proposition 1. *Total Factor Productivity in open economies. The change in TFP in response to productivity shocks, factor supply shocks, and shocks to wedges is, to a first-order can be summa-*

rized as:[2].

$$
\underbrace{\Delta \log Y_t - \tilde{\Lambda}'_{t-1}(\Delta \log L_t + \Delta \log K_t)}_{\Delta\ Agreggate\ TFP} = \underbrace{\sum_{i \in N+X} \tilde{\lambda}_{t-1}\, d \log A_i}_{\Delta\ Tecnology}
$$

$$
\underbrace{- \sum_{i \in N+X} \tilde{\lambda}_{t-1}\, d \log \mu_i - \sum_{f \in \{L,K\}} \tilde{\Lambda}_{t-1}\, d \log \Lambda_f - \left(\tilde{\Lambda}^{IM}_{t-1} - \Lambda^{IM}_{t-1}\right) d \log \Lambda_{IM}}_{\Delta\ Allocative\ Efficiency}
$$

$$
+ \underbrace{\left(\tilde{\Lambda}^{IM}_{t-1} - \Lambda^{IM}_{t-1}\right) d \log IM}_{\Delta\ Import\ Bias}
$$

The left-hand side is the change in aggregate output discounted by factor cost-based Domar weights weighted Labor and Capital changes; Aggregate TFP changes. The technology change is represented by the firm's cost-based Domar weight weighted sum of the firm-level change in technology. The Allocative Efficiency changes term summarizes the change in firm-level markups and aggregate levels of labor and capital changes, both weighted by their cost-based Domar weights.

In addition, the Allocative Efficiency term includes aggregated imported intermediate goods changes weighted by the difference in importance between its cost and revenue exposures. In an economy where imports are used as intermediate inputs and the firm charges a markup, the revenues generated by imports exceed their costs. The last term, import bias changes, reflects the mechanical effect of GDP is computation; since TFP is the change in GDP minus factor contributions, and imports are considered as factor, the imports bias accounts for the level change in Imports weighted by its network exposure in cost minus its network exposure in revenue.

3 Data

We use data from five different sources of the Chilean IRS (Servicio de Impuestos Internos, SII). One of the advantages of SII data is that firms and workers have a unique identifier,

[2]This proposition is based on Baqaee and Farhi (2019b), but we added the different proof. The main difference is we treat imported goods as a factor and then subsequently remove them according to the GDP definition. Proof in Appendix A

which allows the merging of individuals and firms across data sets.

The first source used is the value-added tax form (F29), available from 1998, including gross monthly firm sales, materials expenditures, and investment.

Second, the SII provides information from a matched employer-employee census of Chilean firms from 2005. Specifically, firms must report their employee's form (DJ1887) that records all firms' payments to individual workers: the sum of taxable wages, overtime, bonuses, and any other labor earnings for each fiscal year. Since all legal firms must report to the SII, the data covers the total labor force with a formal wage contract, representing roughly 65% of employment in Chile[3]. For any given month, it is possible to identify the employment status of an individual worker, a measure of her average monthly labor income in that year, and a monthly measure of total employment and the distribution of average monthly earnings within the firm.

Third, data from the income tax form (F22) gathers yearly information on all sources of income and expenses of a firm. This form allows computing every individual's actual tax payments for each year. Even though details on sales and employment are available on this form, we use only data on capital stock for each firm/year to build perpetual inventories using data from the monthly F22 form. The user cost of capital is obtained by multiplying nominal capital stock by the real rental rate of capital. The real rental rate of capital is built using publicly available data. We use the 10-year government bond interest rate minus expected inflation plus the external financing premium. Also, we use the capital depreciation rate from the LA-Klems database.

Fourth, data from buying and selling books (forms 3327-3328) for 2005-2014 provides information on transactions between firms for the complete formal economy describing the production network of the economy.

Fifth, data from electronic tax documents (invoices universe) that provide information on each product, including its price and quantity, traded domestically or internationally with at least one Chilean firm participant from 2014. We use it to complement the buying and selling books to build the production network from 2014.

There is an industry identifier for each firm at the 6-digit ISIC (rev. 4) level, allowing estimations from 9 (Chilean-specific industry classification levels) productive sectors up to more than 800 (when using six-digit sectors).

The data is anonymized to ensure confidentiality regarding the firm's and workers' identities. A set of filters is applied over the raw data to obtain the final data set for the

[3]Central Bank of Chile (2018)

empirical analysis. First, for the complete data set, a firm is defined as a taxpayer with a tax ID, positive sales, positive materials, positive wage bill, and capital for any given year. Second, firms that hire less than two employees or capital valued below US$20 a year are dropped. Third, all variables are winzorized at 1% and 99% levels to avoid as much measurement error as possible. These criteria generate an economy-wide yearly firm panel for 2005-2021.

4 Aggregating TFP in the presence of markups

Following Baqaee and Farhi (2020), product market markups are the sole source of deviation from competitive markets, which is assumed to be a wedge. When firms charge markups, they maximize profits at a lower output level than they would in a competitive environment. In a vertical economy without firm linkages, as in Hsieh and Klenow (2009), markups generate that firms under-produce, distorting the resource allocations.

However, in vertical economies with firm linkages, a second distortion arises. When a firm charges a markup downstream of the production network, its buyer's demand for intermediate inputs is also distorted. These distortions can accumulate downstream, distorting firms' input demands that buy directly or indirectly to an upstream firm that charges markups. We will rely on Chilean data to assess how production network distortions shape aggregate TFP.

Markups

A precise estimation of the unique wedge becomes critical for accurately characterizing the path of (distorted) aggregate TFP. Since De Loecker and Warzynski (2012), the literature on market power has been actively engaged in estimating markups using the production approach. However, the production approach to markup estimation presents challenges, particularly in estimating the production function using revenue ($P \cdot Q$) instead of output (Q) to recover the output elasticity of a variable input. While Bond et al. (2021) raises concerns about using revenue, De Loecker (2021) explains that the seminal strategy proposed in De Loecker and Warzynski (2012) addresses this issue by treating prices as a relevant omitted variable in the production estimation process.

Given our available data, we do not intend to delve into the markup estimation debate but to employ the best available estimation method following the production approach.

Since price data is accessible in our dataset, we adopt a markup estimation approach following De Loecker and Warzynski (2012)'s method without using proxy variables. A detailed explanation of this approach is presented in Appendix B[4].

We have transaction-level price data between two firms from 2014 onward, while detailed firm variables are available from 2005. For this reason, we opt for a Cobb-Douglas production function with time-invariant coefficients as our benchmark[5]. The main advantage of adopting this approach is that it allows us to recover the production function coefficients by estimating the production function over the entire period for which price data is available. Subsequently, we can use these coefficients to estimate markups right from the start of the period.

We estimate the production function separately for each 6-digit industry (626 industries) with at least 100 observations during our sample to recover material-output elasticities. Following Foster et al. (2022), we aim to permit output elasticities to vary as much as possible within the same aggregate industry. We can estimate production functions for 97% firm-year observations at a 6-digit industry with at least 100 observations. For the remaining 3% of firms-year observations that do not have enough data, we complement the production function estimation at 160 sectors and 9 sectors. Appendix B provides an overview of various moments in the evolution of markups over time.

While markup moments offer insights to assess the presence of product market power, they can potentially lead to misleading conclusions regarding Allocative Efficiency (AE) in two dimensions. First, markup moments do not account for the effects of firms within production networks. A firm imposing a high markup on other firms might seem to generate substantial inefficiencies. However, if this firm has only one downstream connection, and that connection sells products to final consumers, the distortionary potential is limited. This stands in contrast to a firm charging a similar markup level but positioned as a more central player in the network, selling its products with markups to many other central firms.

[4]Note that markup estimation is sensitive to several factors, including the parametric assumptions of the production function, the choice of the output variable in the production function, the variable input used to estimate markups, the methodology employed for production function estimation, control for output and materials prices, the consideration of time-variant versus time-invariant output variable input elasticity, and the level of disaggregation in the production function estimation

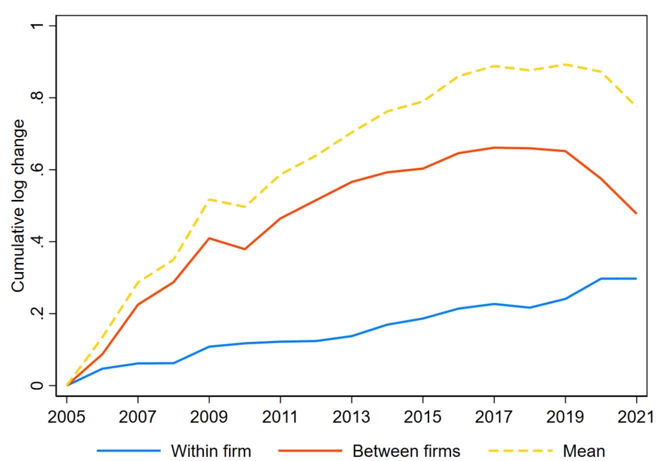
[5]By making this choice, we assume that firms' technology, i.e., how they combine inputs to generate output, remains constant over the period. We conduct robustness checks by considering a second-order translog production function, time-variant coefficients, and omitting price correction coefficients. While the levels of markups differ under these alternative assumptions, the time variations remain equivalent. Detailed results are presented in Appendix B

And second, it's worth noting that market power can, in certain situations, reintroduce efficiency. When a firm has buyer power, it can counteract the market power of its suppliers by paying prices close to marginal costs, which may lead to less inefficient outcomes. As discussed earlier, the appropriate approach to assess markup AE effects involves examining how markups accumulate throughout production networks while considering the full spectrum of firm-to-firm linkages.

A first step towards explaining the aggregate efficiency effects of markups, though limited, involves investigating the composition effects behind the average markup growth[6].

This analysis entails breaking down the average markup growth into within and between components. The within-component represents how the average increase in markups is influenced by the growth of markups themselves, all while keeping firm size constant. Conversely, the between-component sheds light on how changes in the relative sizes of firms impact average markup growth while maintaining markup levels at a constant level. We remain agnostic about the correct way to decompose markup growth. Still, As shown in Figure 1, the predominant factor driving average markup growth is the between component (similar findings have been reported for US large firms by Baqaee and Farhi (2020) and De Loecker et al. (2020)).

Figure 1: Within-Between firm markup decomposition



This observation implies that a composition effect predominantly explains markup

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[6] $$\underbrace{\Delta \log \frac{1}{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}}}}_{\text{Harmonic Sales-Weighted Average}} = \underbrace{\frac{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}} \Delta \log \mu_{it}}{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}}}}_{\text{Within}} + \underbrace{\text{Residual}}_{\text{Between}}$$

changes, suggesting that the average markup is increasing because of changes in the relative size of firms rather than markup increases. As we will elucidate in the subsequent discussion, this effect has implications for the evolution of Allocative Efficiency.

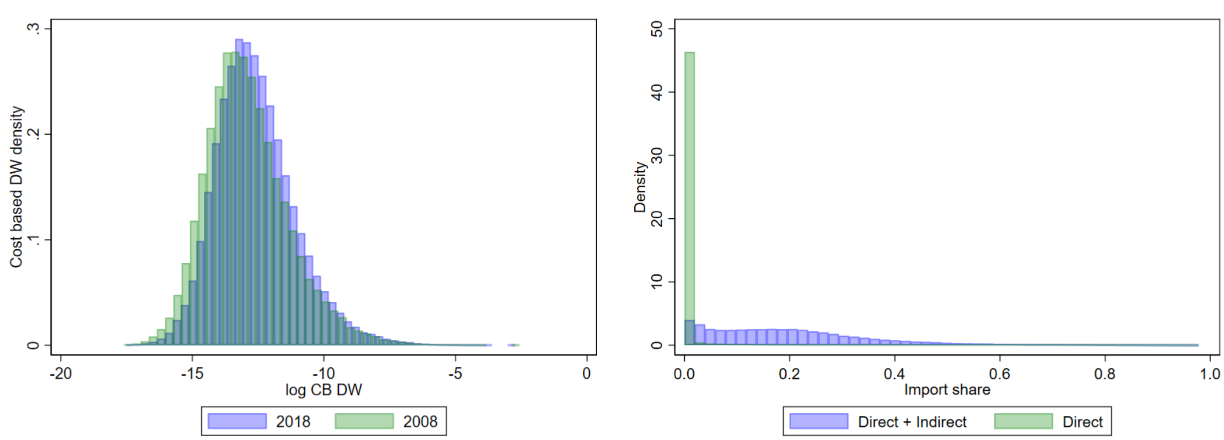
Production Networks exposure to imported inputs

To accurately capture the effects of markups on TFP growth, we estimate the Proposition 1 equation. Before delving into the estimation procedure, it's worth highlighting two factors. First, the analysis of production networks adds information because shocks to one or a few high-cost-based Domar weights firms can trigger widespread repercussions through the network. As demonstrated in Figure 2 Panel A, the distribution of cost-based Domar weights exhibits a small right tail that remains relatively stable over the study period. While Baqaee and Farhi (2020) acknowledges this importance, its theoretical framework is primarily designed for closed economies.

Second, our analysis incorporates international trade. It recognizes that firms are exposed to shocks associated with imported intermediate inputs, both directly and indirectly. This exposure occurs when firms procure materials from other firms upstream that have directly or indirectly obtained production inputs from international markets. As shown in Figure 2 Panel B, while around half of firms do not import inputs directly, only 4% of firms are not exposed to international trade when accounting for direct and indirect exposure.

Figure 2: Production network with international trade facts

Panel A. Cost-based DW distribution Panel B. Imports cost exposure



Estimation Procedure

The estimation procedure for the Proposition 1 equation can be summarized in two steps. In the first step, we use data on all firm-to-firm transactions and factor expenditures to build, annually, each element of the cost-based input-output matrix denoted by $\tilde{\Omega}$. Specifically, we compute the denominator of each element (indexed by ij) by summing a firm's purchases from all its suppliers, its wage bill, and its capital level multiplied by its relevant user cost rental rate of capital. For the first N elements corresponding to domestic firm-to-firm transactions, the numerator is calculated as the value flow of transactions between firm i and firm j. The numerator is set to zero for the subsequent X elements of exporting firms. The last three elements of the matrix have wage bill, capital expenditures, and imported materials as their numerators.

In the second step, we proceed to compute cost-based Domar weights. This involves two sub-components. The first sub-component is the cost-based Leontief inverse ($\tilde{\Psi}$). The second sub-component comprises the b vector. Each element of this vector represents the final consumption of firms and is computed by subtracting intermediate sales (sales to other firms recorded in the revenue-based IO matrix) from a firm's total sales. The first N elements of the b vector contain domestic sales, while the subsequent X has each firm's exported value. Combining both sub-components, we compute the cost-based Domar weight ($\tilde{\Lambda}$) by multiplying the transpose of the b vector with the revenue-based Leontief inverse ($\tilde{\Psi}$). The technology term is then built as a residual by substracting AE and Import Bias from $d \log TFP$.

Results

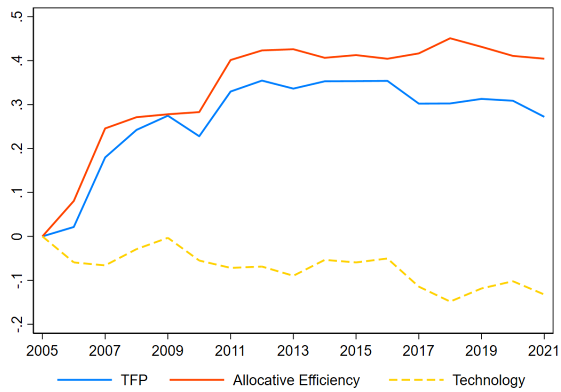
Figure 3 displays each component of the distortion-adjusted Solow residual for the Chilean economy from 2005 to 2021. In line with results from the Chilean Central Bank[7], the evolution of TFP, measured using the distorted Solow residual (solid blue line), exhibited growth from the early 2000s to 2010. Subsequently, TFP growth stagnated until 2015 and has experienced a gradual decline since.

The growth in TFP is primarily driven by resource allocation, measured through Allocative Efficiency (solid red line), where the cumulative growth surpasses TFP growth. However, TFP itself has been adversely affected by a continuous and smooth decline in Technology (dashed gold line). Although the technology term is a residual, its time evolution aligns with data on Research and Development (R&D) expenditure as reported by OECD (2023), indicating relatively low and decreasing levels of R&D spending as a per-

[7]Central Bank of Chile (2021)

centage of GDP in the country. In Appendix C, we present a robustness of Figure 3 using a different estimation strategy for markups. We also showcase its closed economy version and compare it to results replicating Baqaee and Farhi (2020) strategies with Chilean data.

Figure 3: Distorted Solow residual decomposition
Percentage growth relative to 2005 levels



We conducted two unpackings to describe TFP growth drivers further based on Allocative Efficiency (AE). First, we break down AE into domestic and international trade drivers, distinguishing between exports and imports. We extend the notation to encompass the import bias within the AE term, treating it as if it were part of the AE component. Second, we further unpack AE into markup-related drivers versus factor-related drivers.

Figure 4 Panel A reveals that domestic factors explain 52% of the cumulative AE growth up to 2021, while exports and imports contribute equally to the remaining 48% (24% each). Simultaneously, Figure 4, Panel B illustrates that markups and factor allocations equally account for the cumulated AE growth. Up to 2010, factor allocations predominantly explained AE movements, with markups taking over for the subsequent years from 2010 to 2013. Both components have remained relatively stable since 2013.

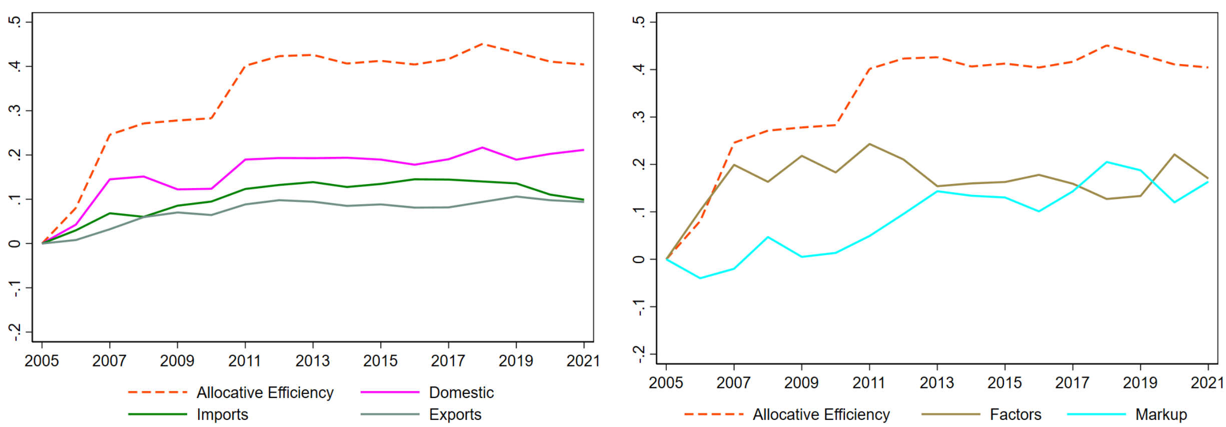
$$\Delta \text{ Allocative Efficiency} = \underbrace{-\sum_{i \in N} \tilde{\lambda}_{t-1}\, d\log \mu_i - \sum_{f \in \{L_D, K_D\}} \tilde{\Lambda}^D_{t-1} d\log \Lambda_f}_{\text{Domestic}} \underbrace{-\sum_{i \in X} \tilde{\lambda}^X_{t-1}\, d\log \mu_i - \sum_{f \in \{L_x, K_x\}} \tilde{\Lambda}^X_{t-1} d\log \Lambda_f}_{\text{Exports}} \tag{1}$$

$$\underbrace{-\left(\tilde{\Lambda}_{t-1}^{IM} - \Lambda_{t-1}^{IM}\right) d\log \Lambda_{IM} + \left(\tilde{\Lambda}_{t-1}^{IM} - \Lambda_{t-1}^{IM}\right) d\log IM}_{\text{Imports}}$$

Figure 4: Allocative Efficiency

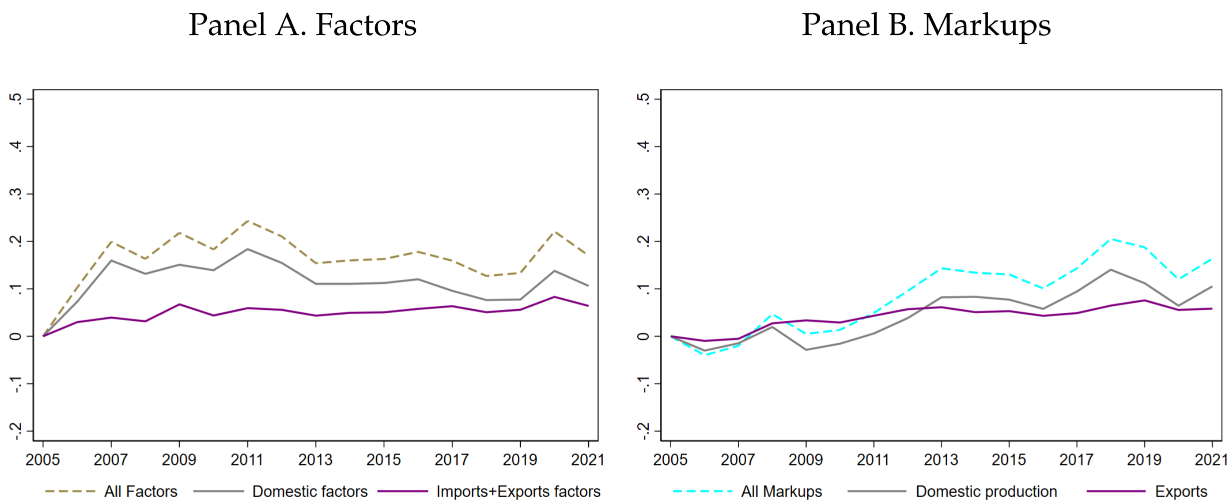
Panel A. Domestic vs. International Trade

Panel B. Factors vs. Markups



Next, we compare the domestic and international trade components of AE. Figure 5 Panel A illustrates the evolution of factors explaining changes in AE. The cumulative growth of AE factors is primarily dominated by factors used to produce domestically traded products (65%), with the remainder explained by imported factors and factors used in producing exported goods. Similarly, the cumulative contribution of markups to AE is mainly driven by markups charged in domestically traded goods, representing 64%, while the remaining share is attributed to markups on exported goods.

Figure 5: Allocative Efficiency components: Domestic vs. International Trade



The granularity of our dataset allows us to delve even deeper into the breakdown of AE, specifically dissecting its industry-level drivers. We leverage industry classifications using 9 categories to analyze each industry's contribution to the dynamics of AE. The markup component of AE is computed at the firm level. We aggregate these firm-level markup changes to derive industry-level insights by interacting them with their respective Domar Weights. To unpack factors, we follow Equation 2:

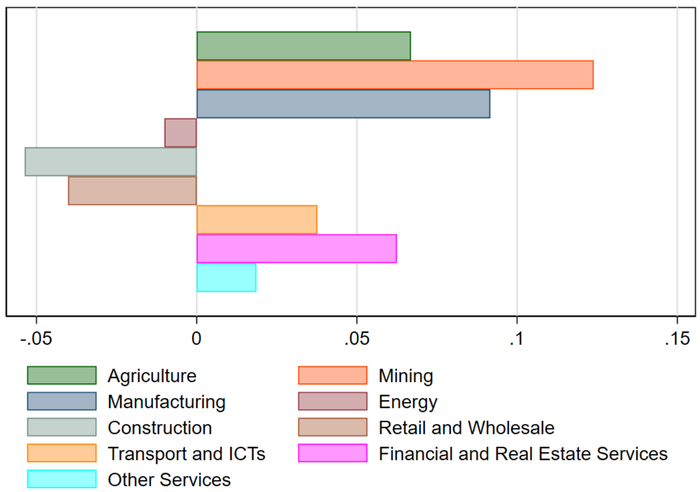
$$\frac{w_f F_t}{gdp_t} - \frac{w_f F_{t-1}}{gdp_{t-1}} = \sum_{i=1}^{9} \frac{w_f F_t^i}{gdp_t} - \frac{w_f F_{t-1}^i}{gdp_{t-1}} \tag{2}$$

$$d\Lambda_F = \sum_{i=1}^{9} d\lambda_F^i$$

$$\frac{d\Lambda_F}{\Lambda_{F,t-1}} = \sum_{i=1}^{9} \frac{d\lambda_F^i}{\Lambda_{F,t-1}}$$

The cumulative growth of AE is predominantly attributed to Tradable sectors, as illustrated in Figure 6, with Agriculture, Manufacturing, and Mining having the most prominent contributions, especially the former with the highest contribution. Industries related to services, including Transport services, contribute positively to changes in AE. However, Energy, Construction, Retail, and Wholesale sectors exhibit negative contributions. The negative impact in these sectors is primarily driven by domestic forces, as highlighted in Figure 7. Domestic forces are the primary drivers for sectors that are making positive contributions to AE. In addition to domestic factors, international trade forces also play a role, explaining 25% of Agriculture, 38% of Mining, and 17% of Manufacturing.

Figure 6: Cumulative Allocative Efficiency by industry



The contributions vary across industries when opening AE components into domestic and international trade, as well as factors and markups. International trade markups, for instance, are predominantly influenced by the Mining sector, accounting for 82%. Conversely, domestic markups are positively influenced by Services and Mining in equal proportions. However, they are negatively influenced by the Construction and Retail and Wholesale sectors, with the former making the highest negative contribution to AE at 6 percentage points.

Figure 7: Cumulative Allocative Efficiency by industry: Domestic vs. International Trade

Panel A. Domestic

Panel B. International Trade

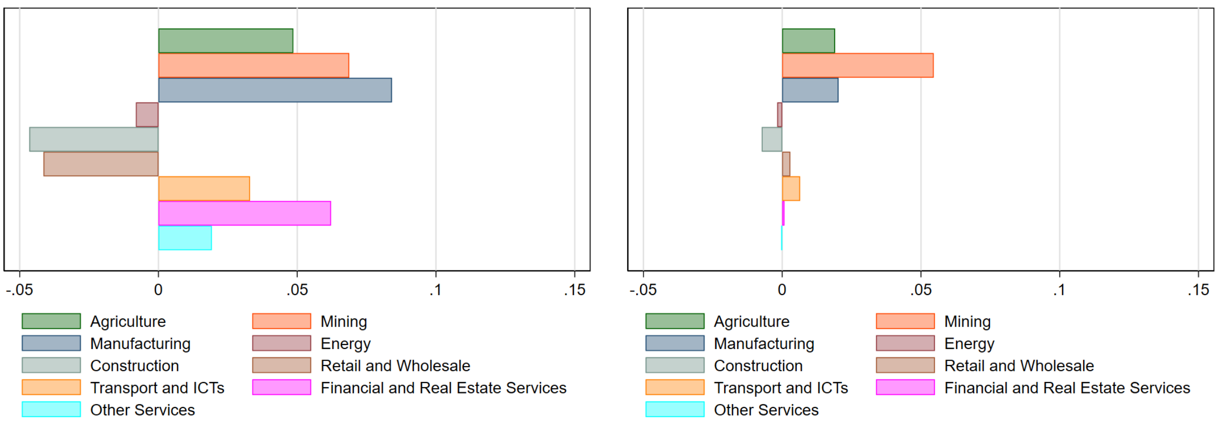
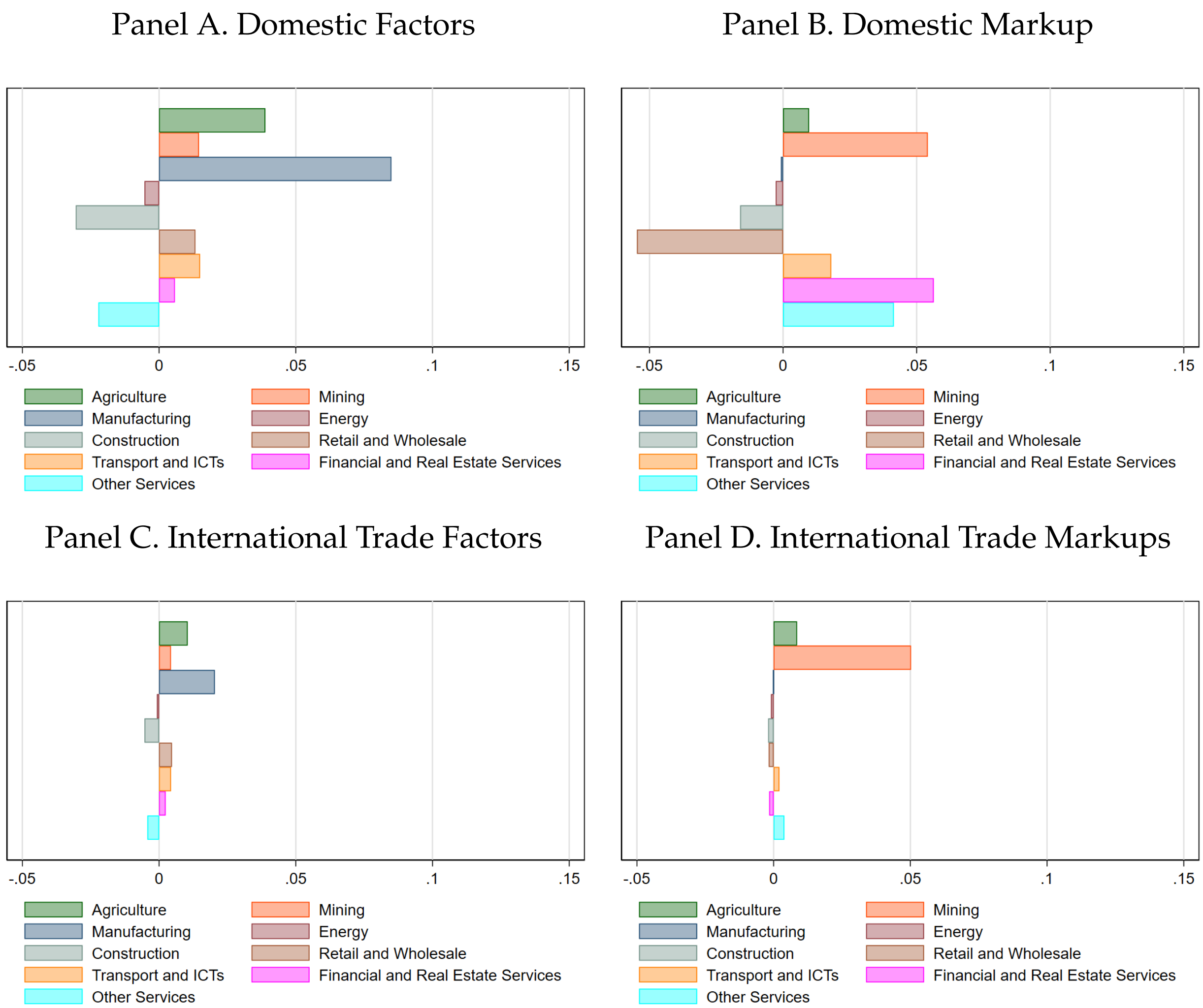


Figure 8: Cumulative Allocative Efficiency components by industry: Domestic vs. International Trade



We finally analyze AE based on firm size, using workers' headcount percentiles as the criterion. As depicted in Figure 9, most of the contribution to AE comes from firms above the 95th percentile. Figure 10 reveals that 67% of the contribution stems from the domestic production of large firms, while 27% is attributed to the international trade-driven forces of these same large firms. The remaining 6% is explained by both domestic and international forces pertaining to firms below the 95th percentile of headcounts of workers.

Figure 9: Cumulative Allocative Efficiency by Size

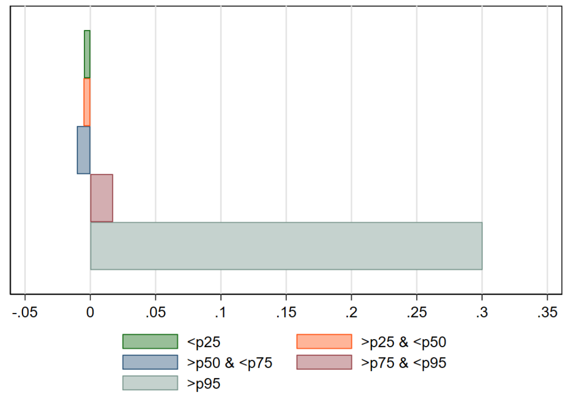
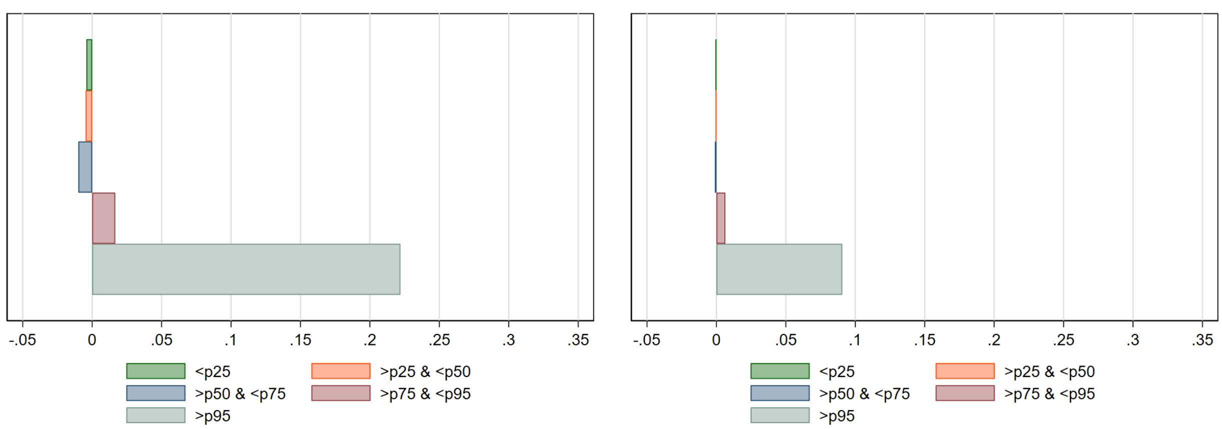


Figure 10: Cumulative Allocative Efficiency by Size: Domestic vs. International Trade

Panel A. Domestic Panel B. Trade



[SECTION FINAL REMARKS MISSING]

5 Conclusion

We extend Baqaee and Farhi (2020) theoretical framework to perform growth accounting in the presence of distortions within production networks in open economies. In addition to domestically driven wedges, we include wedges derived from imported intermediate inputs used in production. We bring this model to the data leveraging on a extensive transaction dataset spanning nearly two decades of the universe of formal firms operating in Chile.

Although our theoretical framework applies to any open economy, our application to Chile provides a potential explanation for a longstanding puzzle: the stagnation of TFP growth in Chile since the early 2010s. Our findings primarily attribute the observed TFP growth to changes in Allocative Efficiency (AE) rather than technological change, and perhaps more importantly, 48% of cumulative TFP growth driven by AE for the period is explained by international trade forces.

While our insights are specific to Chile, they also hold broader implications that may apply to other countries. Chile's macroeconomic experience mirrors global productivity dynamics for both developed and developing economies, characterized by a surge in productivity before the Great Recession followed by a period of stagnation until Covid.

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Appendix

A Proof of proposition 1

Proof. We start from the price equation; for all $i \in N+X$

$$d\log p_i = -d\log A_i + d\log \mu_i + \sum_{j\in N} \tilde{\Omega}_{ij} d\log p_{ij} + \sum_{f\in L,K,IM} \tilde{\Omega}_{if} d\log w_f,$$

In matrix notation, we have

$$\begin{aligned} d\log p &= (I-\tilde{\Omega}^{(N+X)\times(N+X)})^{-1}\left[-d\log A + d\log\mu + \tilde{\Omega}^{(N+X)\times F} d\log w_f\right] \\ &= -(I-\tilde{\Omega}^{(N+X)\times(N+X)})^{-1}[d\log A - d\log\mu] + (I-\tilde{\Omega}^{(N+X)\times(N+X)})^{-1}\tilde{\Omega}^{(N+X)\times F} d\log w_f \end{aligned}$$

where $\tilde{\Omega}^{(N+X)\times(N+X)}$ is the square matrix extracted for the first $(N+X)\times(N+X)$ of the cost-based IO matrix, $\tilde{\Omega}$. From the property of inverse matrix , $(I-\tilde{\Omega}^{(N+X)\times(N+X)})^{-1}$ is equal to the first $(N+X)$ matrix extracted from cost-based Leontief inverse matrix, $\tilde{\Psi}$. Therefore, we could express

$$\begin{aligned} d\log p_i &= -\sum_j \tilde{\Psi}_{ij}[d\log A_j - d\log\mu_j] + \sum_{f\in L,K,IM} \tilde{\Psi}_{if} d\log w_f, \\ &= -\sum_j \tilde{\Psi}_{ij}[d\log A_j - d\log\mu_j] + \sum_{f\in L,K,IM} \tilde{\Psi}_{if}\left(d\log\Lambda_f - d\log L_f\right) \end{aligned}$$

using the definition of GDP deflator, we know

$$d\log P = \sum_{i\in N+X} \frac{p_i y_i}{GDP} d\log p_i - \frac{p^{IM} IM}{GDP} d\log p^{IM}$$

Therefore,

$$\begin{aligned} d\log P &= b' d\log p \\ &= \sum_{i\in N+X} \tilde{\lambda}_i\left(d\log A - d\log\mu\right) + \sum_{f\in L,K,IM} \tilde{\Lambda}_f w_f - \Lambda^{IM} d\log p^{IM}, \\ &= \sum_{i\in N+X} \tilde{\lambda}_i\left(d\log A - d\log\mu\right) + \sum_{f\in L,K,IM} \tilde{\Lambda}_f\left(d\log\Lambda_f - d\log L_f\right) - \Lambda^{IM}\left(d\log\Lambda_{IM} - d\log IM\right) \end{aligned}$$

Since we know $d\log Y = d\log GDP - d\log P$ and nominal GDP is numeraire,

$$\begin{aligned}
d\log Y &= d\log GDP - d\log P,\\
&= -\left(-\sum_{i\in N+X}\tilde{\lambda}_i\left(d\log A - d\log\mu\right) + \sum_{f\in L,K,IM}\tilde{\Lambda}_f\left(d\log\Lambda_f - d\log L_f\right) - \Lambda^{IM}\left(d\log\Lambda_{IM} - d\log IM\right)\right),\\
&= -\sum_{i\in N+X}\tilde{\lambda}_i d\log A + \sum_{i\in N+X}\tilde{\lambda}_i d\log\mu + \sum_{f\in L,K,IM}\tilde{\Lambda}_f\left(d\log\Lambda_f - d\log L_f\right) - \Lambda^{IM}\left(d\log\Lambda_{IM} - d\log IM\right)
\end{aligned}$$

Following to Baqaee and Farhi (2020), define distortion-adjusted TFP as

$$d\log TFP = d\log Y - \sum_{f\in L,K}\tilde{\Lambda}_f d\log L_f$$

Therefore, we have

$$\begin{aligned}
d\log TFP &= d\log Y - \sum_{f\in L,K}\tilde{\Lambda}_f d\log L_f,\\
&= -\sum_{i\in N+X}\tilde{\lambda}_i d\log A + \sum_{i\in N+X}\tilde{\lambda}_i d\log\mu - \sum_{f\in L,K}\tilde{\Lambda}_f d\log\Lambda_f - \left(\tilde{\Lambda}_{IM} - \Lambda_{IM}\right)\left(d\log\Lambda_{IM}\right)\\
&+ \left(\tilde{\Lambda}_{IM} - \Lambda_{IM}\right)d\log IM
\end{aligned}$$

, which is the desired result. □

B Markup estimation strategy and results

Estimation strategy

Our chosen benchmark estimation strategy for production functions is output-based, providing several advantages. The primary benefit of utilizing output-based production functions lies in recovering the markup associated with materials. This flexibility in assessing intermediate inputs, in contrast to labor (the other input used for markup estimation), enables better identification of markups, as it reduces potential frictions that may result in a wedge between the marginal product and the input price. An illustrative example is the absence or lower magnitude of hiring or firing costs associated with materials compared to labor.

Consequently, we adopt a Cobb-Douglas production function with three factors:

$$q_{it} = A_{it} + \beta_l \, l_{it} + \beta_k \, k_{it} + \beta_m + \epsilon_{it} \tag{3}$$

From the cost minimization problem faced by firm i, we can define markup (μ) as the price over the marginal cost:

$$\mu_{it} = \frac{\theta_{it}^V}{s_{it}^V} \tag{4}$$

The markup measure relies on two key elements: the variable input share (s_{it}^V), typically available in the data, and the output elasticity of a variable input (θ_{it}^V). Estimating the output elasticity of a variable input represents the principal challenge in this approach. Importantly, this methodology does not necessitate any assumptions regarding the demand structure or competitive dynamics. We assume that intermediate inputs are the most variable input in production, allowing us to estimate the markup using the output elasticity and the share of materials. Consequently, θ_{it}^M can be calculated as the derivative of the production function with respect to m:

$$\theta_{it}^M = \frac{\partial q_{it}}{\partial m_{it}} = \beta_m \tag{5}$$

To ensure parameter identification, we will draw upon Ackerberg et al. (2015). The sequence of decisions required for identification proceeds as follows: Capital is a state variable determined at period $t-1$. Labor can be selected between $t-1$ and t, but always after the capital decision and before the materials decision. While it is acknowledged that demand-side shocks can potentially impact markup measures (Doraszelski and Jaumandreu (2021)), addressing these concerns goes beyond the scope of this work.

Data ussage

We start our data analysis by obtaining firm accounting variables from IRS registers. The level of capital is derived using the perpetual inventory method, while worker headcounts are directly observed from the data. Similarly, quantities produced and the amount of intermediate inputs are directly collected by the IRS. However, due to our assumption of a uniform markup across firms and the consolidation of all materials used, it is necessary to create aggregated firm-level quantity produced and material usage indices.

To achieve this, we construct firm-level output and intermediate goods input price indexes, leveraging the richness of invoice-level price information available. For every formal firm in Chile, we have records of all the goods a firm sells and all the goods it purchases as intermediate inputs. This comprehensive data allows us to generate quantity indices for both aggregate production and aggregate intermediate goods inputs. Price indices for output and intermediate inputs are established using standard Tornqvist indices. We selected the year 2014 as the base year for constructing our price indices due to it being the first year in which we observed prices for firm-to-firm transactions. This method is widely recognized for estimating aggregate production functions at the firm or plant level when price data is accessible (Dhyne et al. (2022) and De Roux et al. (2021)).

To maintain consistency in our approach, we compute firm-specific annual weighted average prices (P_{igt}) for each product (g) sold by firm i during year t. Subsequently, we construct firm-specific price indices (ΔP_{it}) for products observed in consecutive years using the product-level weighted average price and the share of the product present in both year $t-1$ and year t:

$$\Delta \log P_{it} = \sum_{g} \frac{s_{igt} + s_{igt-1}}{2} \Delta \log(P_{igt}) \tag{6}$$

s_{igt} represents the revenue share of product g for firm i at time t.

Consequently, we utilize the following output value for estimating the production function:

$$q_{it} = \frac{\text{Revenue}_{it}}{P_{it}} \tag{7}$$

A similar procedure is applied to materials, ensuring that the measure for materials used in the production function estimation is also free from price variation [8]:

$$m_{it} \approx \frac{\text{Material expenditure}_{it}}{P^{M}_{it}} \tag{8}$$

Results

We conduct separate production function estimations for every 626 industries at the 6-digit level present on the IRS records. Our sample selection is contingent upon having a

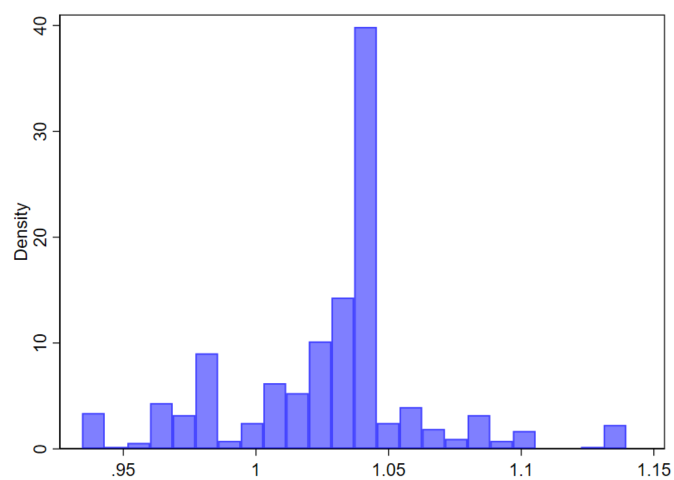
[8] We have set the base year as 2014, when price data will be available for both input and output prices.

minimum of 100 observations in each sector. Building on the approach outlined in Foster et al. (2022), our objective is to allow output elasticities to exhibit as much variation as possible within the same aggregate industry.

We successfully estimate production functions for 97% of firm-year observations within the 6-digit industries that meet the minimum data requirement. However, for the remaining 3% of firm-year observations, where data is insufficient, we extend our production function estimation to 160 sectors and 9 sectors.

Our analysis commences with examining the returns to scale obtained from our benchmark estimation, as illustrated in Figure 11.There is a predominant presence of constant returns to scale, with a slight inclination towards increasing returns to scale.

Figure 11: Returns to Scale



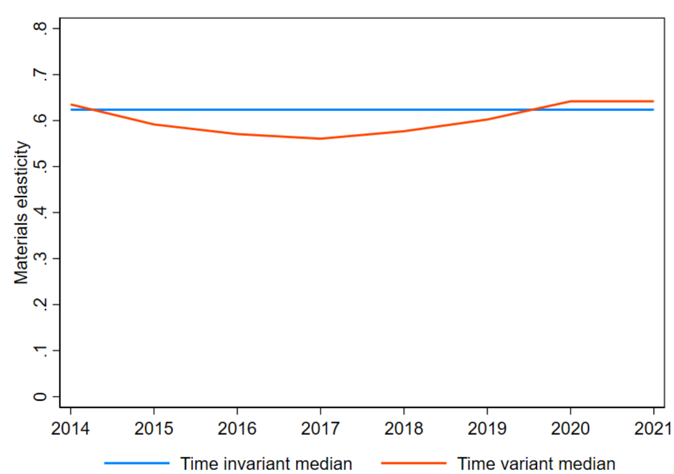
In Table 1, we present the mean material-output elasticities derived from production functions estimated across a range of industry levels, from 6-digit to 1-digit industries. On average, the elasticity increases as we estimate the production function at more finely disaggregated industry levels.

Table 1: Material-Output elasticities by granular of estimation

	6 digits	3 digits	2 digits	1 digit
Agriculture	0.683	0.666	0.664	0.639
Mining	0.610	0.593	0.593	0.624
Manufacturing	0.622	0.620	0.624	0.593
Energy	0.575	0.599	0.612	0.603
Construction	0.615	0.576	0.576	0.583
Retail and Wholesale	0.662	0.620	0.624	0.651
Transportation and ICTs	0.610	0.619	0.619	0.540
Financial and Real Estate Services	0.525	0.527	0.527	0.561
Other Services	0.588	0.566	0.552	0.494

In addition, we calculate time-varying elasticities for the period in which we can obtain price-free measures, and we present the median of these elasticities in Figure 12. Despite some fluctuations observed in the data, it is noteworthy that the time-varying elasticities tend to revolve around the values of the time-invariant elasticities for the overlapping period where both sets of measurements are available.

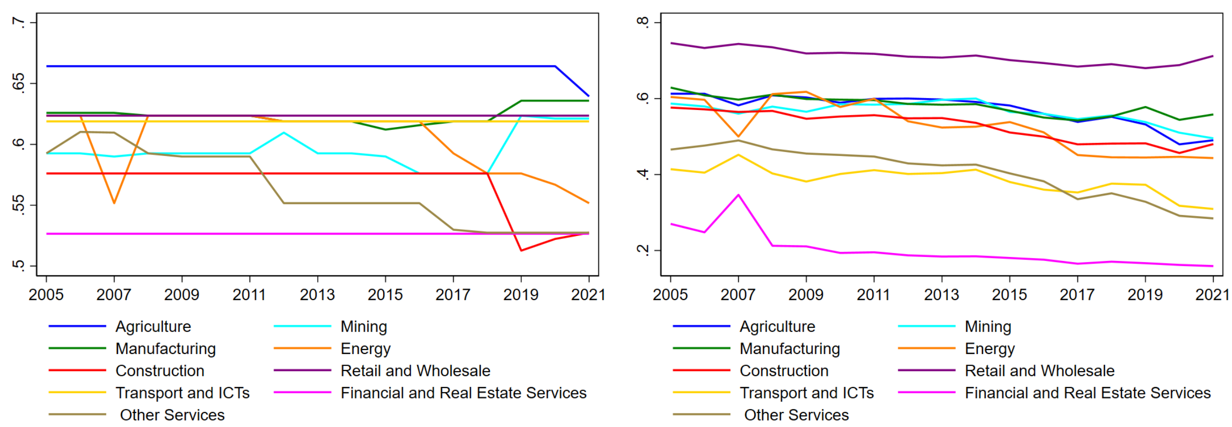
Figure 12: Time-varying elasticities



Material shares and median elasticities over time are displayed in Figure 13. While the production functions parameters remain time-invariant, note that the composition of the sample of firms changes over time, leading to variations in the median of material-output elasticities.

Figure 13: Markup components Median

Panel A: Material-Output Elasticities Panel B: Material share



We document the evolution of markup moments over time in Figure 14. Additionally, we illustrate sector and labor heterogeneity in Figure 15.

Figure 14: Markup evolution in time

Panel A: Markups moments Panel B: Markup different weights

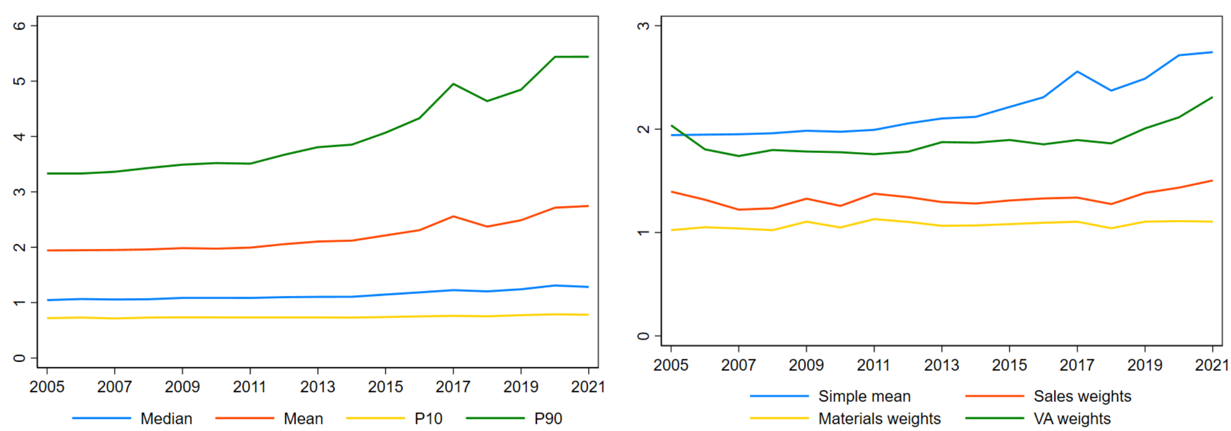
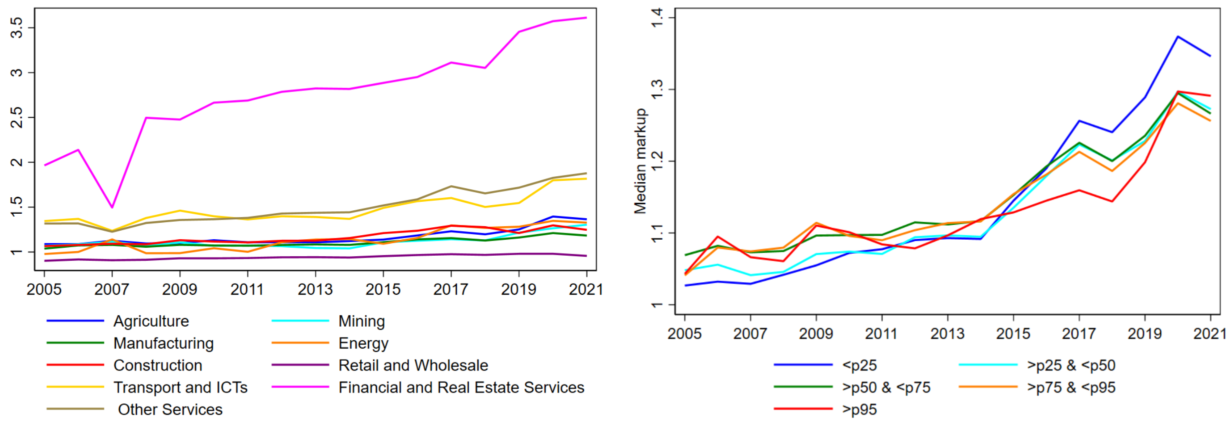


Figure 15: Markup heterogeneity by sector and firm size

Panel A: Markups by sector

Panel B: Markup by firm size



Note: Labor headcounts percentiles describe firm size.

Figure 16 displays distributions of various markup estimation strategies. These strategies are categorized based on the choice of functional form, differentiating between Cobb-Douglas (C-D) and Translog (TL) models. Furthermore, we classify them according to whether they are output-based or value-added-based production functions, and we distinguish between labor markups and materials markups. The sensitivity of markups to the chosen estimation approach is evident. However, our benchmark strategy is selected to optimize identification following the conditions outlined in De Loecker and Warzynski (2012). This choice is made while considering the available price-variation-free measures to achieve the best possible identification.

Figure 16: Different Markup Strategies distribution for 2018

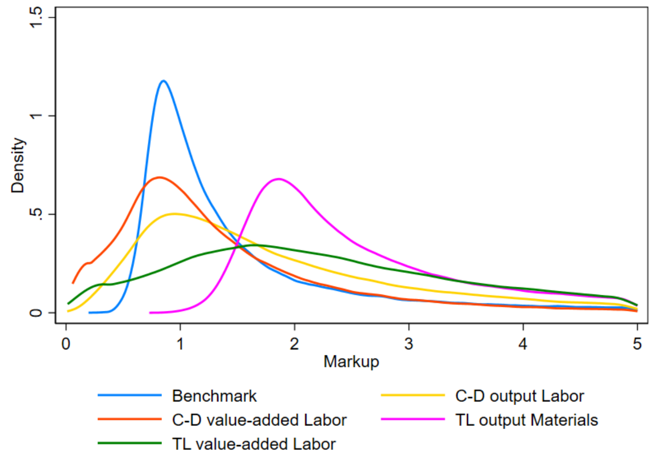


Table 2: Markups different strategies covariance matrix

	Benchmark	Output PF TL Materials	Output PF CD Labor	VA PF TL Labor	VA PF CD Labor
Benchmark	1.000				
Output PF TL Materials	0.835	1.000			
Output PF C-D Labor	-0.085	-0.071	1.000		
VA PF TL Labor	0.006	0.117	0.624	1.000	
VA PF C-D Labor	0.099	0.149	0.606	0.927	1.000

C TFP robustness

In Figure 17, we compare our Benchmark estimation with an alternative one using labor markups instead of material markups, both derived from the same production function. Despite the consistent direction of Allocative Efficiency (AE) growth in both cases, the use of labor markups results in an AE component level more than twice as high as that obtained using material markups. This leads to a nearly 50% decrease in the technology level over the same time period, which is challenging to rationalize. One plausible explanation is that, as labor is less variable than materials, markups from labor may not be well-identified, potentially invalidating their estimation.

Figure 17: TFP with different markup strategy

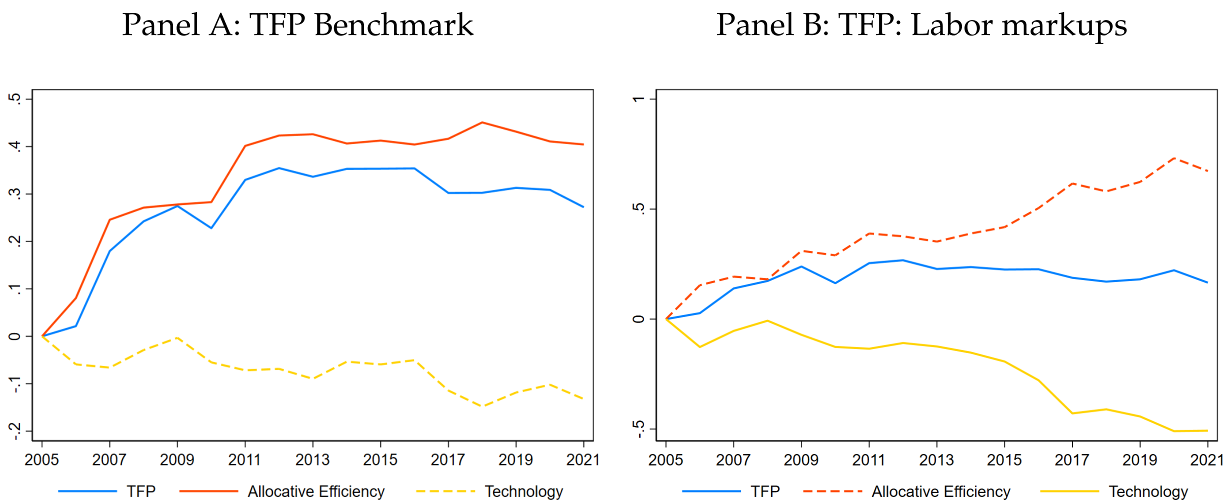
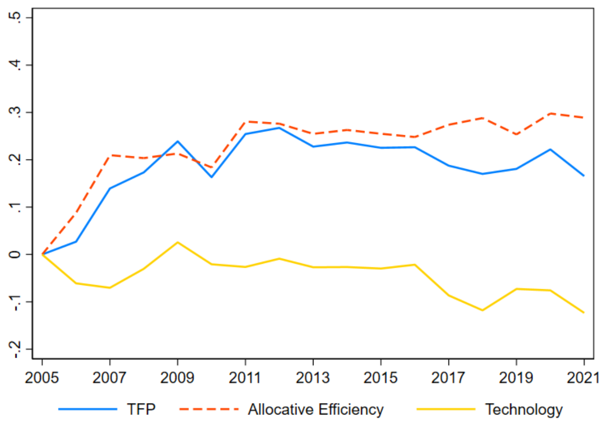


Figure 18, Panel A presents the results of Total Factor Productivity (TFP) in a closed economy, while Panel B illustrates the TFP evolution within a production Input-Output structure across nine industries. In line with the findings of Baqaee and Farhi (2020), a significant portion of factor reallocation occurs between firms within sectors, resulting in limited reallocation between sectors. This suggests that TFP is primarily driven by the residual term, representing technological changes. This underscores the importance of having appropriate data to describe TFP changes at the firm level rather than using industry level data.

Figure 18: Markup heterogeneity by sector and firm size

Panel A: Closed Economy



Panel B: TFP: Closed economy 9 sectors IO structure