International Prices, Domestic Wages, and Labor Market Power

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Abstract

This paper shows that labor market power is a key determinant of incomplete exchange rate pass-through (ERPT) to export prices and domestic wages. I develop a quantitative model featuring imperfect competition in both product and labor markets, where firms' exposure to exchange rate shocks arises from their use of imported inputs. A firm's marginal cost of labor consists of two components: a direct effect, the wage of the new hire, and a scale effect that arises when firms with labor market power must raise wages for all existing employees. Larger employers face smaller direct effects due to more variable markdowns but larger scale effects due to their size, leading to lower wage pass-through and higher price sensitivity. Using Chilean export–import transaction-level data matched with firm-level information, I find strong empirical support for these predictions. At the firm level, variable markdowns explain roughly twice as much of the incomplete ERPT to export prices as variable markups. At the aggregate level, labor markets with higher employment concentration exhibit lower wage sensitivity to exchange rate shocks. A counterfactual exercise shows that product market power mitigates the negative wage effects of labor market power.

Keywords: Exchange Rate Pass-Through, Monospony, Market Structure, Markdown, Markups, Wage.

JEL Classification: F14, F31, F33, F41.

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1 Introduction

The limited sensitivity of international prices to exchange rate fluctuations has long been a central topic in international economics, dating back to Froot and Klemperer (1988). The extensive study of incomplete exchange rate pass-through (ERPT) is motivated by its ability to provide insights into the sources of real rigidities in firms' pricing behavior, offering insights that extend well beyond open-economy macroeconomic models. The prevailing explanation attributes incomplete ERPT to product market imperfections, particularly variable markups.[1] Standard frameworks, however, assume perfectly competitive labor markets. In this paper, I show that large exporters are not only large importers (Amiti et al. (2014)) but also large employers. This paper relaxes that assumption and studies the joint contribution of labor market power and product market power in shaping incomplete ERPT to prices and wages, both at the firm and aggregate level.

To do so, I develop a model in which exporters have product market power through variable demand elasticities à la Atkeson and Burstein (2008) and labor market power through variable labor supply elasticities à la Berger et al. (2022). Exchange rate movements affect firms' labor demand through both a price channel, where higher foreign demand following a depreciation boosts labor demand and wages, and a cost channel, where more expensive imported inputs reduce output and labor demand. The net effect is positive because the demand channel dominates, raising the marginal revenue product of labor and thus wages. However, the impact on wages, and in turn on prices, depends on firms' labor market power: larger firms with more elastic markdowns on wages exhibit lower ERPT to wages but higher ERPT to export prices due to the scale effect of raising wages for all workers when expanding employment.[2]

Using Chilean transaction-level customs data matched with firm characteristics from 1997 to 2007, I find that labor market power is a key determinant of ERPT to both wages and prices, revealing that it is an equally important but previously overlooked determinant of ERPT alongside import intensity and product market power. I estimate the key structural elasticities by exploiting model-implied relationships between markups, markdowns, and market shares, finding median markups of 36% and markdowns of 30%. Quantitatively, variable markdowns account for roughly twice as much of the incomplete ERPT to export prices as variable markups, highlighting the central role of labor market power in shaping firms' pricing responses. At the aggregate level, local labor markets with higher employment concentration display significantly lower wage sensitivity, as they are dominated by large, import-intensive firms, reflecting a stronger cost channel. However, stronger strategic wage complementarities increase aggregate wage sensitivity, as competitors raise wages to attract new workers. More surprisingly, variable markups amplify the aggregate wage response to exchange rate shocks to a magnitude comparable to strategic complementarities in wages, as they increase the marginal revenue product of labor and push wages higher. This illustrates that, at the ag-

[1] See Gopinath et al. (2014) for a review of different models that generate variable markups.
[2] The intuition of the scale effect was originally popularized by Manning (2013).

gregate level, product market imperfections can offset labor market imperfections in driving up wages.[3]

In Section 2, I present the main features of the model that guides the analysis. Firms are exporters that produce differentiated goods for each destination market using two inputs: labor and intermediates, where intermediates are a composite of domestic and foreign varieties. Each firm corresponds to a distinct product. Following Atkeson and Burstein (2008), imperfect competition in product markets combined with non-constant demand elasticities generates variable markups on exported goods. More productive firms have larger market shares, face lower demand elasticities, and therefore charge higher markups in equilibrium. Importantly, they also adjust markups more in response to marginal cost shocks, implying higher markup variability. This mechanism has been the main explanation for incomplete ERPT in the previous literature. The product market is characterized by two key elasticities: the within-sector cross-product elasticity and the across-sector elasticity. Estimating these two parameters will be crucial in the main quantitative exercise to assess the relative importance of labor and product market imperfections in shaping ERPT.

The economy consists of local labor markets indexed by $j \in [0, 1]$, each populated by an exogenous and constant number of firms M_j. Following Berger et al. (2022), firms compete à la Cournot for labor within their local market and internalize the upward-sloping labor supply curve. Analogously to the product market, the labor market is characterized by two key elasticities: the within local labor market elasticity of substitution across firms, and the elasticity of substitution across local labor markets. Recovering these elasticities is crucial to quantify the relative contribution of product and labor market imperfections. In equilibrium, firms pay workers a fraction of their marginal revenue product of labor (MRPL). Wage markdowns, defined as the ratio of wages to MRPL, arise endogenously from the non-constant labor supply elasticities, which vary with each firm's payroll share within its local labor market. Larger firms face a less elastic labor supply and are therefore able to compress wages further below MRPL, resulting in lower markdowns. [4]

In the model, a firm's marginal cost of labor consists of two components. The direct effect is the standard cost of hiring an additional worker, as in a perfectly competitive labor market: it equals the worker's wage. The scale effect, in contrast, arises when firms have labor market power. In this case, hiring one more worker requires raising wages for all existing employees, so the marginal cost of labor exceeds the wage of the new hire. This distinction is crucial for understanding ERPT. Larger employers face a smaller direct effect, as their markdowns are more variable, but a larger scale effect, because they employ more workers in equilibrium. The scale effect magnifies the cost impact of exchange rate shocks across all employees, amplifying their ERPT to export prices. Consequently, large firms with substantial labor market power exhibit lower wage pass-through but higher price sensitivity.

[3] Kroft et al. (2020) shows similar theoretical and empirical results, where product market power can attenuate the effects of labor market power and vice-versa in the context of the US construction industry.

[4] The wage markdown $\mu \in [0, 1]$ is defined as the ratio between wages and MRPL. Lower values of μ indicate that firms pay a smaller share of MRPL to workers, reflecting greater labor market power.

I use the model to derive closed-form expressions that generate testable predictions for the relationship between ERPT to domestic wages and export prices as a function of a firm's payroll share, which serves as a sufficient statistic for its labor market power. Exchange rate movements affect firms' labor demand through two opposing channels. The price channel, a depreciation increases foreign demand, raises labor demand and wages, while the cost channel, higher imported input costs, reduces them. The net effect is positive because the demand channel dominates, increasing the marginal revenue product of labor and thus wages.[5] However, the strength of this effect depends on firms' labor market power. The model predicts a U-shaped relationship between ERPT to domestic wages and labor market power: very small and very large firms exhibit nearly constant labor supply elasticities and thus markdowns, leading to similar ERPT, while medium-sized firms optimally reduce their markdowns, lowering ERPT.

Similarly, I derive closed-form expressions for the ERPT to export prices. As highlighted in the existing literature, incomplete ERPT can arise from product market imperfections, which appear in the price decomposition through variable markups. However, the model introduces new terms capturing labor market power in the form of variable markdowns. ERPT to export prices in producer currency is hump-shaped in a firm's payroll share. The intuition for this result originates from the scale effect. Larger firms hire more workers and pay higher than average wages, which increases their marginal cost response to exchange rate shocks. Yet, as firms continue to expand, this effect eventually reaches a tipping point: further growth becomes increasingly hard. In the extreme case of a monopsonist that already employs the entire local workforce, the scale effect vanishes. Hence, the relationship between ERPT to export prices and firm size must feature an inflection point. This closed-form result is novel and informative. It shows that labor market power introduces a distinct, non-monotonic pattern in ERPT that interacts with product market imperfections. Qualitatively, it highlights that estimating ERPT coefficients in the data requires accounting for the firm's position in both markets. Quantitatively, it will be central to the calibration and counterfactual exercises that follow, where I assess the relative importance of variable markups and markdowns in shaping incomplete ERPT.

In Section 3, I describe the data sources used in the analysis. The empirical work relies on three main datasets. First, firm-level import and export transactions are obtained from the Chilean Customs Agency (*Aduanas*). Second, plant-level data come from the Chilean National Statistical Agency (INE, *Instituto Nacional de Estadísticas*) via the Annual National Industrial Survey (ENIA, *Encuesta Nacional Industrial Anual*). Merging these sources yields a panel of firms observed over a decade, from 1997 to 2007. Third, I use the National Survey of Employment and Unemployment (ENA, *Encuesta Nacional de Empleo*), also compiled by INE, to estimate local labor markets within Chile. A contribution of the paper is the estimation local labor markets for the Chilean economy. Rather than relying on an arbitrary or exogenous definition of labor market boundaries, I estimate them directly from the data to align

[5] See Campa and Goldberg (2001), Nucci and Pozzolo (2010), and Dai and Xu (2017) for early analyses of these mechanisms.

the empirical analysis as close as possible with the theory. Each local labor market is defined as a pair of Region $\times$ 2-digit Industry.

In Section 5, I empirically test the model's predictions. The data supports the predicted U-shaped relationship between ERPT to domestic wages and the firm's payroll share, as well as the inverted U-shaped relationship between ERPT to export prices and the firm's payroll share. Quantitatively, I find that a firm in the 75$^{\text{th}}$ percentile of the payroll share distribution has a pass-through to domestic wages approximately 13% lower than that of a smaller firm in the 25$^{\text{th}}$ percentile. Additionally, exporters in the 1$^{\text{st}}$ and 5$^{\text{th}}$ quintiles of the employment distribution exhibit a pass-through to producer prices of about 30%. By contrast, employers in the 3$^{\text{rd}}$ quintile have a pass-through that is nearly 8% higher. I conclude the section with a series of robustness checks. Section 5 provides empirical evidence that labor market power plays a qualitatively important role in shaping ERPT to both domestic wages and export prices, and should therefore be included in empirical estimates of ERPT coefficients alongside sufficient statistics of product market power.

In Section 6, I estimate the four key parameters that govern heterogeneity in pass-through to wages and prices across exporters: cross- and within-industry substitutability, and cross- and within-local labor market substitutability. Identification relies on model-implied moment conditions. [6] Following recent work by Edmond et al. (2023), I use the model's predicted cross-sectional relationships between markups and market shares, and between markdowns and payroll shares, to quantitatively identify these parameters. To implement this strategy, I estimate firm level markups and markdowns for the Chilean manufacturing sector using a production function approach closely aligned with Yeh et al. (2022). On average, markdowns are estimated at 30 percent, implying that workers receive 7 dollars for every 10 dollars of value they produce, evidence of substantial labor market power. Similarly, firms charge prices that are, on average, 36 percent above marginal cost, confirming the presence of imperfect competition in product markets as well. I estimate cross- and within-industry elasticities of substitution to be 1.8 and 12, respectively, and cross- and within-labor market substitutability to be 0.5 and 8, respectively.

In Section 7, I quantify the relative importance of labor and product market power in shaping ERPT coefficients at both the firm and local labor market level. I begin by validating the estimated model, showing that it replicates the empirical ERPT coefficients to wages and prices, both quantitatively and qualitatively, even though these moments were not targeted in the estimation. The simulated regressions closely match the empirical coefficients, validating both the model and the estimated structural parameters. Next, I use the model to quantify the contribution of variable markdowns across firms. Quantitatively, variable markdowns account for roughly twice as much of the incomplete ERPT to prices as variable markups, underscoring the central role of labor market power as a joint determinant of incomplete ERPT at the firm level. This result also shows that unlike standard models with only product

[6]In particular, the identification strategy developed in the paper can be applied to any setting in which the following assumptions hold: (i) at least one of the firm's inputs is traded in a perfectly competitive market and (ii) the demand and/or supply is modeled as nested-CES.

market power, wage responses are heterogeneous across firms depending on the size of the employers. This mechanism has different welfare implications: when labor markets are imperfect, exchange rate shocks affect not only prices and profits, but also household welfare through changes in wages.

Finally, I derive closed-form solutions describing how aggregate wages and prices in local labor markets respond to exchange rate shocks as a function of labor market concentration, export market shares, and import intensity.[7] The model predicts a monotonically negative relationship between labor market concentration and aggregate wage sensitivity, a result confirmed by both the data and the simulated panel. To interpret these patterns, I derive a decomposition that mirrors Amiti et al. (2019) for the labor market. Local labor markets dominated by large, import-intensive firms display lower wage sensitivity due to a stronger cost channel (more import intensive firms), while stronger strategic complementarities amplify wage responses. A counterfactual exercise further shows that an economy with only labor market imperfections displays lower aggregate wage sensitivity than one with both labor and product market power, highlighting that product market imperfections can partially offset the negative wage effects of monopsony power in the transmission of exchange rate shocks.

Related Literature This paper relates to several strands of literature. To start, it contributes to the literature on the sensitivity of domestic wages and employment to exchange rate changes. Seminal contributions include Goldberg and Tracy (2000), Campa and Goldberg (2001), and Goldberg and Tracy (2003). Using US state-level industry data, Campa and Goldberg (2001) finds that an exchange rate depreciation is associated with increases in both wages and employment. This finding has been confirmed using more granular firm-level data in Italy by Nucci and Pozzolo (2010), China by Dai and Xu (2017), and by Kaiser and Siegenthaler (2016), who also document heterogeneous responses across skill groups.

I contribute to this literature by showing that ERPT to wages is heterogeneous across firms because of the existence of variable markdowns and is systematically related to their degree of labor market power. Moreover, I extend this line of research by deriving and testing novel predictions on how aggregate wage sensitivity varies with labor market concentration, offering a theoretical and empirical link between local labor market structure and the macroeconomic effects of exchange rate shocks.

Moreover, this paper contributes to the extensive empirical and theoretical literature on the incomplete pass-through of exchange rate shocks to international prices. Early work by Froot and Klemperer (1988) documented incomplete ERPT across countries and subsequent access to firm level data has advanced our understanding of its microeconomic foundations. For example, Berman et al. (2012) show that ERPT to export prices in the home currency increases with firm productivity, a finding explained through models of variable markups. Similar evidence was found for multiproduct firms in Brazil by Chatterjee et al. (2013). Building

[7] This generalizes the aggregation result in Amiti et al. (2019) to the case of imperfect labor markets.

on this, Amiti et al. (2014) are the first to separate the role of imported input costs from variable markups in explaining incomplete ERPT. The literature has since evolved to incorporate strategic complementarities in price setting Auer and Schoenle (2016); Amiti et al. (2019), information frictions Garetto (2016), and buyer market power Juarez (2025) as additional mechanisms. See Gopinath et al. (2014) for a comprehensive review and Gopinath et al. (2022) for a detailed review of the growing evidence that links currency of invoicing to ERPT.

This paper makes two contributions to this literature. First, I show that labor market power is a novel source of heterogeneity in ERPT to prices, operating through variable wage markdowns. This mechanism is observationally equivalent to product market power in firm level data and can lead to similar ERPT patterns. As a result, my findings highlight the importance of jointly accounting for heterogeneity in both product and labor market power in empirical ERPT studies.

Second, I derive and test new aggregate predictions linking labor market concentration to the sensitivity of aggregate prices, extending the framework in Amiti et al. (2019). In contrast to existing work, I treat aggregate wages as endogenous and show how labor market structure affects aggregate price responses to exchange rate shocks. As for aggregate prices, the analysis is conducted at the local labor market level, a dimension not previously explored in the ERPT literature.

Lastly, this paper contributes to the growing literature that quantifies labor market power and evaluates its implications for aggregate welfare. Recent studies have estimated wage markdowns in various settings. For example, Kroft et al. (2020) estimate a wage markdown of approximately 0.80 in the US construction industry, while Yeh et al. (2022), using plant-level US data, find a lower markdown of 0.65. In a developing country context, Felix (2021) estimate the markdown for Brazil at 0.50. I contribute to this literature by providing new estimates of wage markdowns for a developing economy, Chile, at multiple levels: firm-level, local labor market, and aggregate. I find that the median markdown in Chilean manufacturing is approximately 0.70, which falls between the estimates for a high-income country like the US and a developing economy like Brazil. In addition, I provide new estimates of labor supply elasticities, both within local labor markets and across labor markets, which help characterize the degree of labor market competition. These elasticities were first introduced by Berger et al. (2022), who estimate them at 0.42 (cross-firm within market) and 10.85 (across markets). In contrast, Felix (2021) find much lower elasticities for Brazil, 1.02 within and 0.83 across markets.

The structure of the paper is as follow. Section 2 introduces the model to guide the empirical analysis. Section 3 describes the data sources. Section 4 shows the methodology used to estimate the Chilean local labor markets and stylized facts about Chilean exporters. Section 5 reports the main empirical findings. Section 6 describes the estimation procedure to quantity the key parameters values and to recover the firm level markups and markdowns. Section 7 concludes by deriving aggregate implications for prices and wages.

2 Theoretical Framework

In this section, I present a simple theoretical framework which features I) heterogeneous exposure to exchange rate shocks through imported inputs, II) imperfect competition in the product market and III) imperfect competition in the labor market. I then show analytically the role that labor market power has in shaping heterogeneous responses of export prices and domestic wages across firms after an exchange rate depreciation. In what follows, I drop the subscript for time t for notational convenience and I introduce it only when strictly necessary.

Product Market Suppose firms export a differentiated good to destination country k at time t. Each firm i operates in one labor market $j \in [0, 1]$. Consumers located in the destination market k have a nested-CES (constant elasticity of substitution) demand over the varieties of goods supplied by the foreign firms as in Atkeson and Burstein (2008). Let ρ be the elasticity of substitution across the varieties within sector, while η the elasticity of substitution across sectoral aggregates. Assume $\rho > \eta \geq 1$. Consequently, firm i faces the following demand for its good:

$$Q_{k,ij} = \xi_{k,ij} \frac{P_k^{\rho-\eta}}{P_{k,ij}^{\rho}} D_k \tag{1}$$

where $Q_{k,ij}$ is the quantity demanded, $\xi_{k,ij}$ is a relative quality parameter of the firm, $P_{k,ij}$ is the firm's price denominated in foreign currency, P_k is the sectoral price index, and D_k is the sectoral demand shifter which the firm takes as given. The sectoral price index is given by $P_k \equiv \left[\sum_j \sum_i P_{k,ij}^{1-\rho}\right]^{1/(1-\rho)}$, where the summation is across all firms i located in different labor markets j that serve the destination market at a specific point in time.

An important characteristic of the firm's competitive position in a market is that its market share is given by

$$S_{k,ij} \equiv \frac{P_{k,ij} Q_{k,ij}}{\sum_j \sum_i P_{k,ij} Q_{k,ij}} = \xi_{k,ij} \left(\frac{P_{k,ij}}{P_k}\right)^{1-\rho} \in [0, 1], \tag{2}$$

where the market share is sector-destination-time specific. Holding the sectoral price index P_k constant, Equation (2) shows a negative relation between the firm's relative price and its market share. In case of oligopolistic competition in prices, the effective demand elasticity of the firm is

$$\sigma_{k,ij} \equiv -\frac{d \log Q_{k,ij}}{d \log P_{k,ij}} = \rho(1 - S_{k,ij}) + \eta S_{k,ij}, \tag{3}$$

because $\partial \log P_k / \partial \log P_{k,ij} = S_{k,ij}$. Hence, the firm faces an endogenous demand elasticity that is a weighted average of the within-sector and the across-sector elasticities of substitution with the weight on the latter equal to the market share of the firm. Moreover, high-market-share firms exert a stronger impact on the sectoral price index, making their demand less sensitive to their own price.

As usual, firms set a multiplicative markup $\mathcal{M}_{k,ij} \equiv \sigma_{k,ij}/(\sigma_{k,ij} - 1)$ over their costs. Firms face a demand with elasticity decreasing in the market share, and thus high-market-share firms charge higher markups. A lower price set by firm leads to an increase in the firm's market share making optimal a larger markup. In addition, I define a measure of the markup elasticity with respect to the price of the firm, without holding constant the sectoral price index:

$$\Gamma_{k,ij} \equiv -\frac{\partial \log \mathcal{M}_{k,ij}}{\partial \log P_{k,ij}} = \frac{(\rho-1)(\rho-\eta)S_{k,ij}(1-S_{k,ij})}{\sigma_{k,ij}(\sigma_{k,ij}-1)} > 0. \tag{4}$$

Markup elasticity is hump-shaped in the market share of the firm: small and large firms choose to adjust markups by less in response to shocks and therefore adjust their prices and quantities by more. By contrast, medium sized firms display the highest sensitivity of markups to change in prices and therefore adjust their prices and quantities by less. [8] This theoretical framework has two sharp predictions about the markup. First, markup variability is hump-shaped in the market share. Secondly, the variation in the market share fully characterizes the variation in the markup elasticity across firms.

Labor Market The economy is divided into a continuum of local labor markets $j \in [0,1]$. Each firm i is active in only one labor market j and each labor market j is endowed with a constant and exogenous number of firms $M_j \in [1,2,...,\infty)$. The economy consists of representative households who have nested-CES preferences over the varieties of goods produced by firms that populate the economy as in Berger et al. (2022). Therefore, firm ij faces the following inverse labor supply curve:

$$w(l_{ij}, \bar{l}_{-ij}, \mathbf{L}_t, \mathbf{W}_t) = \left(\frac{l_{ij}}{\mathbf{l}_j}\right)^{\frac{1}{\delta}} \left(\frac{\mathbf{l}_j}{\mathbf{L}_t}\right)^{\frac{1}{\theta}} \mathbf{W}_t, \tag{5}$$

where $\mathbf{W}_t = \left[\int_0^1 \mathbf{w}_j^{1+\theta}\, dj\right]^{\frac{1}{1+\theta}}$ is the economy wide aggregate wage rate, $\mathbf{l}_j \equiv \left[\sum_i^{m_j} l_{ij}^{\frac{\delta+1}{\delta}}\right]^{\frac{\delta}{\delta+1}}$ be the total labor employed in labor market j and $\mathbf{L}_t$ be the labor employed in the whole economy at time t, respectively. The inverse labor supply function in Equation (5) features two elasticities of substitution $\delta > \theta > 0$. Both elasticities affect the labor market power of firms. Let θ be the cross labor markets substitutability. Also, let δ be the cross-firms within labor market substitutability. Similarly to the product market, the firm's labor market share is given by:

$$r_{ij} \equiv \frac{w_{ij} l_{ij}}{\sum_{i \in j} w_{ij} l_{ij}} = \left(\frac{w_{ij}}{\mathbf{w}_j}\right)^{(1+\delta)}, \tag{6}$$

thus r_{ij} is the payroll share of firm i in labor market j. Firms compete à la Cournot, therefore the inverse labor supply elasticity has a closed form expression equal to:

$$\varepsilon_{ij} \equiv \left[\frac{\partial \log w(l_{ij}, \bar{l}_{-ij}, \mathbf{L}_t, \mathbf{W}_t)}{\partial \log l_{ij}}\bigg|_{\bar{l}_{-ij}}\right]^{-1} = \left[\frac{1}{\delta} + \left(\frac{1}{\theta} - \frac{1}{\delta}\right) r_{ij}\right]^{-1}. \tag{7}$$

[8] Note that if firms are atomistic and they do not influence the sectoral price index, the markup elasticity is a strictly increasing function of the the firm's market share. In case of atomistic firms, Equation (4) becomes $\Gamma_{k,ij} \equiv -\frac{\partial \log \mathcal{M}_{k,ij}}{\partial \log P_{k,ij}} = \frac{S_{k,ij}}{\left(\frac{\rho}{\rho-\eta} - S_{k,ij}\right)\left(1 - \frac{\rho-\eta}{\rho-1} S_{k,ij}\right)} > 0.$

Note that the inverse labor supply elasticity of the firm takes as given the employment decision of competitors $\bar{l}_{-ij}$. When $r_{ij} \to 0$, the elasticity of the firm is mainly influenced by δ as the firm's employment decision is not able to influence the market level employment $\mathbf{l}_j$. By contrast, when a firm is not infinitesimal, the firm affects $\mathbf{l}_j$ and therefore it also takes into account the across labor market substitutability θ. The standard Lerner condition applies in this setting, thus workers are paid a share $\mu_{ij} = \epsilon_{ij}/(\epsilon_{ij}+1) \in (0,1)$ of the marginal revenue product of labor. The markdown μ_{ij} has an upper bound equal to $\delta/(1+\delta)$ when firms are infinitesimal and a lower bound equal to $\theta/(1+\theta)$ when a firm is a monopsony. Now, I turn to my first theoretical result.

Proposition 1 *The elasticity of the markdown μ_{ij} to a firm's wage w_{ij}, without holding constant the aggregate market wage $\mathbf{w}_j$, is:*

$$\eta_{ij} \equiv \frac{\partial \log \mu_{ij}}{\partial \log w_{ij}} = (r_{ij}^2 - r_{ij})\mu_{ij,t}\left(\frac{1}{\theta} - \frac{1}{\delta}\right)(1+\delta) \leq 0. \tag{8}$$

Proof: *See Appendix A.1*

The markdown elasticity η_{ij} is derived under the assumption that a firm is not atomistic and therefore it is able to influence the market level wage $\mathbf{w}_j$. [9] Thus, given that $\delta > \theta > 0$, Equation (8) defines a negative U-shaped relationship between markdown elasticity to wages and a firm's size in the labor market. In other words, as firms grow in size, they are initially able to charge lower markdowns on wages at an increasing rate, up to an inflection point. Beyond this point, larger employers continue to charge lower markdowns, but at a decreasing rate. Thus, the function is convex and strictly negative over the relevant domain.

Intermediate Inputs I build on Halpern et al. (2015) to model the importing decision of firms. Let $A_{0,ij}$ be the set of intermediate inputs imported by firm ij. Firm uses intermediate inputs x_{ij} which is a Cobb-Douglas bundle of intermediate goods indexed by $a \in [0,1]$:

$$x_{ij} = \exp\left\{\int_0^1 \gamma_a \log x_{ij,a} da\right\}. \tag{9}$$

The types of intermediate inputs vary in their importance in the production process according to γ_a which satisfies $\int_0^1 \gamma_a da = 1$. Each type a of intermediate good comes in two varieties, domestic and foreign, which are imperfect substitutes:

$$x_{ij,a} = \left[z_{ij,a}^{\frac{\zeta}{1+\zeta}} + g_a m_{ij,a}^{\frac{\zeta}{1+\zeta}}\right]^{\frac{1+\zeta}{\zeta}}, \tag{10}$$

where $z_{ij,a}$ and $m_{ij,a}$ are the quantities of domestic and imported varieties of the intermediate good a used in production, respectively. g_a measures the productivity advantage ($g_a > 1$)

[9] In the case of atomistic firms, Equation (8) becomes $\eta_{ij} \equiv \frac{\partial \log \mu_{ij}}{\partial \log w_{ij}} = -r_{ij}\mu_{ij}\left(\frac{1}{\theta} - \frac{1}{\delta}\right)(1+\delta) \leq 0$.

or disadvantage ($g_a < 1$) of imported varieties. Since imported and domestic varieties are imperfect substitutes, firms may source fully domestically. However, firms are incentivized to use foreign goods in production because of the love of variety feature of the production function and because of the existence of productivity advantages ($g_a > 1$). The elasticity of substitution between the domestic and the foreign varieties is $\zeta > 0$. Importing a new variety requires that the firm pays a firm specific fixed cost f_{ij} in terms of unit of labor. Let $V_a^\star$ be the prices of domestic intermediates inputs and $e_k U_a$ be the prices of foreign intermediates inputs both denominated in units of producer currency (hence starred), respectively. Moreover, let U_a be the price in foreign currency of the intermediate inputs and e_k be the nominal exchange rate measured as quantity of local currency for one unit of foreign currency k. Hence, an increase in e_k implies that the variety a imported from origin country k is now more expensive in domestic currency.

Firm Marginal Cost Given total output y_{ij} and the set of imported varieties $A_{0,ij}$, the firm minimizes total cost $\text{TC}_{ij}^\star$ in producer currency: [10]

$$\min_{\substack{x_{ij},\{x_{ij,a},z_{ij,a}\},\\ \{m_{ij,a}\},l_{ij}}} \quad \text{TC}_{ij}^\star(y_{ij} \mid A_{0,ij}) = \underbrace{w(l_{ij},\bar{l}_{-ij},\mathbf{L}_t,\mathbf{W}_t)l_{ij}}_{\text{Labor Cost}} + \underbrace{\int_0^1 V_a^\star z_{ij,a}da}_{\text{Local Intermediate Cost}} + \underbrace{\int_{A_{0,ij}} e_k U_a m_{ij,a}da}_{\text{Foreign Intermediate Cost}}$$

subject to:

$$\begin{aligned}
y_{ij} &= \Omega_{ij} x_{ij}^{\phi} l_{ij}^{1-\phi}, && \phi \in [0,1] \\
x_{ij} &= \exp\left\{\int_0^1 \gamma_a \log x_{ij,a} da\right\}, && \int_0^1 \gamma_a da = 1 \\
x_{ij,a} &= \left[z_{ij,a}^{\frac{\zeta}{1+\zeta}} + g_a^{\frac{1}{1+\zeta}} m_{ij,a}^{\frac{\zeta}{1+\zeta}}\right]^{\frac{1+\zeta}{\zeta}}, && \zeta > 0 \\
w(l_{ij},\bar{l}_{-ij},\mathbf{L}_t,\mathbf{W}_t) &= \left(\frac{l_{ij}}{\mathbf{l}(l_{ij},\bar{l}_{-ij})}\right)^{\frac{1}{\delta}} \left(\frac{\mathbf{l}(l_{ij},\bar{l}_{-ij})}{\mathbf{L}_t}\right)^{\frac{1}{\theta}} \mathbf{W}_t.
\end{aligned}$$

Firms use a Cobb-Douglas production function with constant return to scale. Therefore, labor output elasticity and intermediate output elasticity is $1-\phi$ and ϕ, respectively. This cost structure results in the following marginal cost:

$$\text{MC}_{ij}^\star = \frac{1}{\Omega_{ij}} \left[\frac{\exp\left\{\int_0^1 \gamma_a \log \frac{V_a^\star}{\gamma_a} da\right\}}{\phi \exp\left\{\int_{A_{0,ij}} \gamma_a \log b_{ij,a} da\right\}}\right]^{\phi} \left[\frac{w_{ij}}{\mu_{ij}(1-\phi)}\right]^{1-\phi} = \frac{\text{C}_{ij}^\star}{\text{B}_{ij}^\phi \Omega_{ij}}$$

[10]Here, I briefly describe the intuition that pins down the optimal set of intermediate inputs $A_{0,ij}$ in the absence of uncertainty. The optimal set of intermediate input $A_{0,ij} = [0, a_{0,ij}]$ is pinned down by the cutoff intermediate variety $a_{0,ij} \in [0,1]$. Indeed, the cutoff varieties $a_{0,ij}$ is such that $b_{ij,a_{0,ij}} = \exp^{f_{ij} - \gamma_{a_{0,ij}} \text{TMC}}$. I refer to Amiti et al. (2014) for a detailed exposition of the case with uncertainty.

where

$$\mathrm{C}^{\star}_{ij} = \underbrace{\left[\frac{\exp\left\{\int_0^1 \gamma_a \log \frac{V^{\star}_a}{\gamma_a} da\right\}}{\phi}\right]^{\phi}\left[\frac{w_{ij}}{\mu_{ij}(1-\phi)}\right]^{1-\phi}}_{\text{Local Cost Index}}, \quad \mathrm{B}_{ij} = \underbrace{\exp\left\{\int_{A_{0,ij}} \gamma_a \log b_{ij,a} da\right\}}_{\text{Cost Reduction Factor of Importing}}.$$

Note that the marginal cost of the firm depends on the degree of labor market power that the firm has which is summarized by the markdown μ_{ij}. In particular, the marginal cost of the firm is a strictly decreasing function of the markdown μ_{ij} on wages. In other words, it holds that $\frac{\partial \mathrm{MC}^{\star}_{ij,t}}{\partial \mu_{ij}} < 0$. This implies that firms whose payroll share r_{ij} is higher will also have in equilibrium lower markdowns, $\mu_{ij} \to 0$, and thus higher marginal costs. Therefore, large employers have higher marginal costs compared to small employers. This result follows the textbook intuition that when a monopsonistic firm hires a new worker it needs to increase the wage paid not only to its additional employee but to all its existing workforce. See Appendix A.2 for a detailed derivation of the marginal cost of the firm.

Lastly, following the result originally developed by Amiti et al. (2014), the elasticity of the marginal cost to an exchange rate depreciation is equal to:

$$\frac{\partial \log \mathrm{MC}^{\star}_{ij}}{\partial \log e_k} = \phi \int_0^{a_{ij,0}} \gamma_a (1 - b^{-\zeta}_{ij,a}) da \equiv \varphi_{ij}$$

where φ_{ij} is the share of total variable cost spent on intermediate inputs imported from foreign countries. In other words, φ_{ij} measures the import intensity of the firm. Intuitively, firms which use more foreign varieties will see their marginal cost increase by more when the domestic currency depreciates with respect to the currency of the source country k. Formally, the import intensity of the firm φ_{ij} is equal to the product between the share of material input in total variable cost (ϕ) and the summation of the individual share of material cost that the firm spends to import variety a, $(1 - b^{-\zeta}_{ij,a})$, each weighted by its relative importance in production (γ_a).

Firm Maximization Problem Firm maximization problem

$$\max_{y_{ij}, \{P_{k,ij}, Q_{k,ij}\}_k} \left\{ \sum_{k \in K_{ij}} e_k P_{k,ij} \times Q_{k,ij} - \mathrm{MC}^{\star}_{ij} \times y_{ij} \right\}$$

subject to

$$y_{ij} = \sum_{k \in K_{ij}} Q_{k,ij},$$

$$Q_{k,ij} = \xi_{k,ij} P^{-\rho}_{k,ij} P^{\rho-\eta}_{k} D_k, \qquad \forall\, k \in K_{ij}$$

Note that e_k measures the amount of local currency per unit of foreign currency and an increase of e_k is interpreted as a depreciation of the local currency with respect to the currency of the destination country k. The F.O.C for the optimal producer currency price $P^{\star}_{k,ij}, \forall k \in K_{ij}$, is:

$$P^{\star}_{k.ij} = \mathcal{M}_{k,ij} \times \text{MC}^{\star}_{ij}, \tag{11}$$

The F.O.C for labor input is:

$$w_{ij} = \mu_{ij} \times \text{MPL}_{ij} \times \text{MC}^{\star}_{ij}, \tag{12}$$

where Equation (12) makes it explicit that the optimal labor input chosen by the firm depends also on the market power of the firm in the product market through the market share $S_{k,ij}$ which pins down markups and thus prices. The same expressions can be found in Kroft et al. (2020) who study the interplay of labor market power and product market in the context of the US construction industry.

Wage Change Decomposition In what follows, I derive closed form solutions for the expected change in export price and domestic wages after an exchange rate depreciation. This step is crucial in the analysis as it pins down the relationship between ERPT to price and to wage and the firm payroll share. Essentially, the closed form solutions are informative of the model predictions that I will further test in the data.

First, I derive the expression for the wage change decomposition. Perform a total log differentiation of Equation (12) to obtain the predicted relationship between the exchange rate pass-through to domestic wages with the firm I) exposure to the cost shock, φ_{ij}, II) the competitive position in the product market, $S_{k,ij}$, and III) the competitive position in the labor market, r_{ij}.

Proposition 2 *If $d\log P_{k,j} = 0$, $d\log W_j = 0$, then the pass-through of a bilateral exchange rate shock to the domestic wage w_{ij} is equal to:*

$$\frac{d\log w_{ij}}{d\log e_k} = \underbrace{f_{k,ij}}_{MR(+)} - \underbrace{f_{k,ij} \times \varphi_{ij}}_{MC(-)} = f_{k,ij}(1 - \varphi_{ij}),$$

where $f_{k,ij}(S_{k,ij}, r_{ij}) \in (0,1)$. Also, $\frac{\partial}{\partial r_{ij}}\left[\frac{d\log w_{ij}}{d\log e_k}\right] < 0$ down till an inflection point and then $\frac{\partial}{\partial r_{ij}}\left[\frac{d\log w_{ij}}{d\log e_k}\right] > 0$ after. [11]

Proof: *See Appendix A.3*

[11] The assumption that $d\log P_{k,j} = 0$ and $d\log W_k = 0$ is consistent with a partial equilibrium perspective and is reflected in the choice of fixed effects included in the empirical specification, as originally noted by Amiti et al. (2014). In addition, it is motivated by the goal of this section which is to relate the ERPT to wages to firm level characteristics. Lastly, those assumptions do not alter the main predictions reported here. I will relax these assumptions when analyzing the aggregate sensitivity of prices and wages, where market-level equilibrium effects on the price and wage indices become essential for the interpretation of the results. Same applies to Proposition 3.

Proposition 2 highlights the two main channels through which exchange rate shocks affect firm-level wages: the export price channel (first term) and the import cost channel (second term). These channels were initially discussed conceptually by Campa and Goldberg (2001) and later formalized by Nucci and Pozzolo (2010) and Dai and Xu (2017). The novelty in this setting lies in how these two channels interact with a proxy for the firm's labor market power, its payroll share, to determine the expected ERPT to domestic wages.

The export price channel captures the standard mechanism whereby, given the home-currency prices constant, a depreciation of the home currency reduces the price of exports in the foreign market, thereby boosting export demand and consequently labor demand.

The import cost channel operates through two effects. First, a substitution effect: as the home-currency price of imported intermediate inputs rises due to depreciation, firms may substitute away from inputs toward labor, increasing labor demand. Second, a scale effect: the increase in marginal cost may reduce output, thereby lowering labor demand. Under a Cobb-Douglas production function and standard values for product market elasticities, the net effect of the import cost channel is negative. This is evident from the fact that, all else equal, firms with higher import intensity experience lower expected ERPT to wages.

Lastly, the framework predicts that firms with higher market shares, and hence more variable markups, exhibit lower sensitivity of domestic wages to exchange rate shocks, ceteris paribus. That is, a higher export share shifts downward the level of expected ERPT, acting as a scaling factor that reduces the wage response to exchange rate changes. Formally, $\frac{\partial}{\partial S_{k,ij}}\left[\frac{d\log w_{ij}}{d\log e_k}\right] < 0$.

To sum up, Proposition 2 states that the ERPT to domestic wages is i) U-shaped in the payroll share of the firm r_{ij} ii) decreasing in the firm import intensity φ_{ij}, and iii) decreasing in the firm export market share $S_{k,ij}$.

Price Change Decomposition Similarly, perform a total log differentiation of Equation (11) to obtain an expression for the exchange rate pass-through to producer prices as a function of exogenous parameters, product market shares, import intensity, and labor market payroll shares.

Proposition 3 *If $d\log P_{k,j} = 0$, $d\log W_k = 0$, then the pass-through of a bilateral exchange rate shock to the domestic export price $P^{\star}_{k,ij}$ is equal to:*

$$\frac{d\log P^{\star}_{k,ij}}{d\log e_k} = \frac{\rho z_{ij} + \Gamma_{k,ij}}{1+\rho z_{ij} + \Gamma_{k,ij}} + \frac{1}{1+\rho z_{ij} + \Gamma_{k,ij}}\varphi_{ij},$$

where $z_{ij}(r_{ij})$. Also, $\frac{\partial}{\partial r_{ij}}\left[\frac{d\log P^{\star}_{k,ij}}{d\log e_k}\right] > 0$ up till an inflection point and then $\frac{\partial}{\partial r_{ij}}\left[\frac{d\log P^{\star}_{k,ij}}{d\log e_k}\right] < 0$ after.

Proof: *See Appendix A.4*

Proposition 3 highlights two channels that shape the ERPT to producer currency export prices: the average effect channel (first term) and the import intensity channel (second term). It delivers the second key prediction of the model: ERPT is U-shaped in the firm's payroll share.

Moreover, the coefficients in Proposition 3 reduce to those found in many earlier works under the assumption of perfectly competitive labor markets. In particular, prior literature has typically invoked variable markups to explain incomplete ERPT, expressed as $\frac{\Gamma_{k,ij}}{1+\Gamma_{k,ij}}$, even in the absence of imported inputs ($\varphi_{ij} = 0$). [12]

A novel insight from this proposition is that variable markdowns, in the absence of both variable markups and imported inputs, can yield observationally equivalent ERPT, namely $\frac{\rho z_{ij}}{1+\rho z_{ij}} \in [0, 1)$. Thus, incomplete pass-through need not imply the presence of variable markups as it may instead arise from imperfect labor markets and variable markdowns.

Similarly, prior literature has used variable markups to explain why changes in marginal cost, such as through import intensity, are not fully passed through to prices. Here, I show that even under monopolistic competition with constant markups, variable markdowns can generate similar patterns. To my knowledge, this is a new insight: while variable markups affect consumer prices, variable markdowns affect wages, and the two have very different policy implications.

To sum up, Proposition 2 states that the ERPT to producer currency export prices is i) inverted U-shaped in the payroll share of the firm r_{ij} ii) increasing in the firm import intensity φ_{ij}, and iii) increasing in the firm export market share $S_{k,ij}$. The last two predictions have been already widely explored and confirmed by previous literature.

Model Predictions Here, I show how heterogeneity in labor market power shapes different responses in export prices and domestic wages across firms after an exchange rate depreciation.

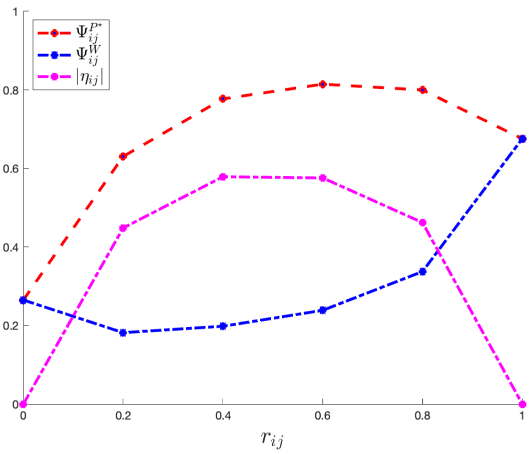

Figure 1: Exchange Rate Pass-Through and Labor Market Power

Note: Figure (1) shows graphically the exchange rate pass-through to producer currency export prices and the exchange rate pass-through to domestic wages. The graph plots the equations in Proposition 1 and Proposition 2. Parameters are set to the their estimated values: $\rho = 12$, $\eta = 1.8$, $\delta = 8$, $\theta = 0.5$. See Section 6 for a detailed discussion of the estimation strategy and results. Lastly, $\varphi_{ij} = 0.2$ is calibrated to its median value in the sample and $\phi = 0.45$.

[12] See Gopinath et al. (2014) for a review of models that generate variable markups.

Figure (1) shows the model based predictions of the shape of the expected exchange rate pass-through to export prices in producer currency and that to domestic wages as a function of the firm payroll share r_{ij}. The model predicts an inverted U-shape relationship (blue dashed line) between the sensitivity of export prices and the labor market power of the firm measured by r_{ij}. Also, the model predicts a non linear U-shape relationship (red dashed line) between the response of domestic wages to exchange rate shocks and, again, the payroll share of the firm. Lastly, the purple dashed line plots the value of the markdown elasticity to wages in absolute values $|\eta_{ij}|$.

Compare the extreme cases of a monopsonistic firm whose $r_{ij} \to 1$ and that of an infinitesimally small firm, $r_{ij} \to 0$. Both firms charge constant markdowns on wages. Thus, any change in wages is fully passed through to prices. After an exchange rate depreciation, the marginal revenue product of labor increases for all firms. Small and large employers fully pass this increase into wages because their markdowns are constant. Consequently, any change in wages is also passed through to prices. By contrast, a medium-sized firm features variable markdowns and therefore passes through only part of the increase in marginal revenue product into wages.

However, medium-sized employers adjust their export prices more than both small and large employers. This occurs because small and large employers experience minimal changes in their marginal cost of labor, but for different reasons: small firms have low wage bills and limited ability to attract new workers while large firms already employ almost the entire local labor force. For medium-sized employers, the increase in marginal cost is the largest and it is driven by a larger change in the marginal cost of labor. Formally, the marginal cost of labor is the product of the wage and the inverse of the markdown, w_{ij}/μ_{ij}. For small and large employers, μ_{ij} is constant, so any increase in the marginal cost of labor is equal to the wage change. For medium-sized firms, μ_{ij} decreases, amplifying the increase in marginal cost, and thus their prices rise more.

Mechanism Figure (2) shows the effect of an exchange rate depreciation on prices. The x-axis measures the labor input l_{ij}. The y-axis measures the export price $P^{\star}_{k,ij}$ expressed in domestic currency or the (productivity-adjusted) marginal cost of labor MCL_{ij}.

Start from analyzing the labor market. The light red line is the productivity adjusted MCL_{ij} in the absence of labor market power that is simply equal to w_{ij}/MPL_{ij}. Differently, when firms charge a markdown on the marginal revenue product of labor, the marginal cost of labor shifts upward by an amount equal to the inverse of the markdown. Thus, now the (productivity adjusted) $\text{MCL}_{ij} = \mu_{ij}^{-1} \times w_{ij}/\text{MPL}_{ij}$ is represented by the solid red line.

Next, turn to the product market. The light blue line represents the marginal cost of the firm in the absence of any product market imperfections. The marginal cost of the firm is then shifted upward by an amount equal to the markup in the case of imperfect competition in product market (solid blue line). The left panel of Figure (2) shows the equilibirum export price expressed in producer currency before an exchange rate depreciation. Indeed, the optimal labor input l_{ij} is pinned down by equating MCL_{ij} to the $\text{MC}^\star_{ij}$ which simply implies equating marginal revenue product of labor to its corresponding marginal cost. Then, equilibirum prices $P^\star_{k,ij}$ are a markup on the marginal cost.

The right panel of Figure (2) shows the new equilibrium price $\widehat{P}^\star_{k.ij}$ and the new labor input $\hat{l}_{ij}$ after an exchange rate depreciation of the domestic currency. As it is clear from Equation (12), the exchange rate depreciation causes the marginal cost of the firm to shift to the right. Now, even under the assumption that firms have homogenous exposure to the cost shocks, that is $\varphi_{ij} = \varphi \ \forall i$, the resulting change in prices across firms can still be heterogeneous. Indeed, the variation in price caused by the exchange rate depreciation will differ across firms because of differences in both the product market power and the labor market of the firm. Formally, combining Equation (12) and Equation (11) makes it clear that any any price change can be decomposed as follow:

$$\Delta P^\star_{k,ij} = \Delta \mathcal{M}_{k,ij} + \Delta \mu^{-1}_{ij} + \Delta W_{ij} - \Delta \text{MPL}_{ij}$$

where all the terms on the right-hand side of the equation are endogenous objects that depend on either the firm market share $S_{k,ij}$ or on the firm payroll share r_{ij}. In Section 7, I will use the following price change identity to quantify the role of variable markdowns across exporters.

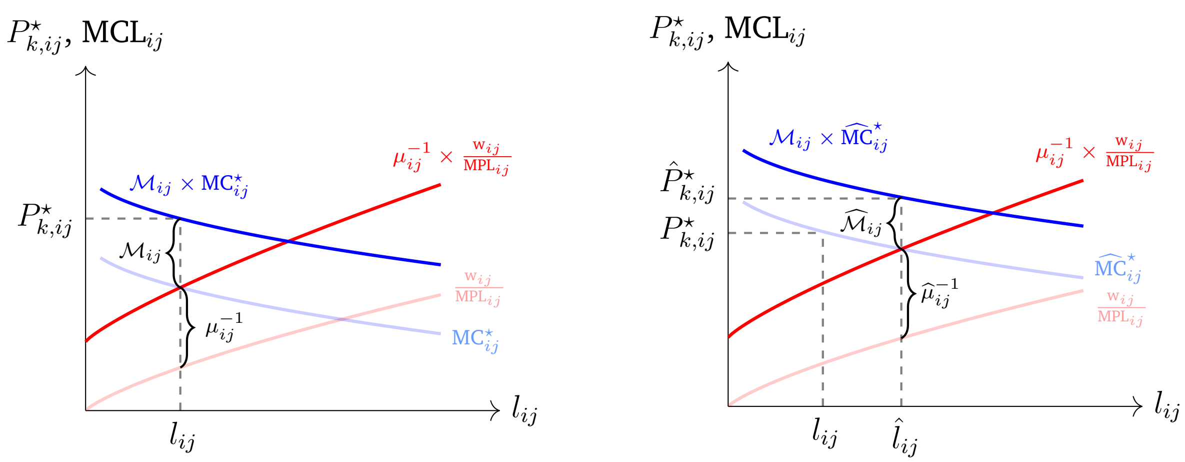

Figure 2: Visualizing the Effect of an Exchange Rate Depreciation on Prices

Note: Figure (2) shows the effect of an exchange rate depreciation on prices. The x-axis measures the optimal labor input l_{ij}. The y-axis measures the optimal export price $P^\star_{k,ij}$ or the (productivity-adjusted) marginal cost of labor MCL_{ij}. The left panel of Figure (2) shows the equilibrium export price expressed in producer currency and in the labor market before an exchange rate depreciation. The right panel shows the new equilibrium after an exchnage rate depreciation of the domestic currency. The The light red line is the productivity adjusted MCL_{ij} in the absence of labor market power simply equal to w_{ij}/MPL_{ij}. When firms charge a markdown on the marginal revenue product of labor, the marginal cost of labor shifts up by an amount equal to the inverse of the markdown, thus now $\text{MCL}_{ij} = \mu^{-1}_{ij} \times w_{ij}/\text{MPL}_{ij}$ (solid red line). The light blue line represents the marginal cost of the firm which is shifted up by an amount equal to the markup in the case of imperfect competition in product market. The optimal labor input is pinned down by equating MCL_{ij} to the $\text{MC}^\star_{ij}$ which simply implies equating marginal revenue product of labor to its corresponding marginal cost. Then, prices are a markup on the marginal cost.

To summarize, the model predicts: I) hump-shaped relationship between exchange rate pass-through to export prices in producer currency and payroll shares, II) U-shaped relationship between exchange rate pass-through to domestic wages and payroll shares, III) a monotone increasing relationship between exchange rate pass-through to export prices and to domestic wages and the import intensity of the firm, and IV) hump-shaped relationship between exchange rate pass-through to export prices in producer currency and the export market shares.

3 Data

The empirical analysis is based on the use of four different data sources. The first two datasets are the transaction level import and export data for Chile collected by the Chilean Customs Agency (*Aduanas*). Export transactions are available from 1997 to 2017 and import transactions are available from 1997 to 2015. The Chilean Customs Agency publishes information for each firm exporting and/or importing from Chile at the year, product, destination/origin country level. A very detailed set of information is provided for each exchange in which the Chilean firm is involved. The dataset reports the quantity of the good exchanged, expressed both in the unit of the good and in weight of the transaction measured in kilograms (KG), the value of each transaction is measured and reported in US Dollars. For export transactions, the value is reported in FOB, while for import transactions, the value is reported in both FOB and CIF. In addition, the good exchanged is classified at the 8-digit Harmonized System (HS8) level. Crucially, the Chilean Customs Agency assigns a unique, time-invariant, identifier to each Chilean firm which therefore makes possible to generate a panel of import and export transactions at the firm level.

Since the main objective of the empirical section of the paper is to relate the firm's characteristics to its variation in export prices and wages, I complement the custom level data with firm level information for the Chilean manufacturing sector covering the years between 1997 to 2007. Plant level data are collected by the Chilean National Statistical Agency (INE, *Instituto National de Estadisticas*) from the survey of manufacturing (ENIA, *Encuesta Nacional Industrial Anual*) and it covers all plants with ten or more workers. Since the unit of observation is at the plant level, the standard concern arises for firms which are multi-plants. Indeed, the survey reports a unique identifier for each plant even though they belong to the same firm. However, the dataset has already been extensively used in the literature (e.g. Levinsohn and Petrin (2003), Alvarez and López (2005), Petrin and Sivadasan (2013), and Banerjee et al. (2022)) and, as noted by Pavcnik (2002) and Fernandes and Paunov (2012) more than 90% of the firms in the survey are single-plant firms. Thus, this gives confidence in the reliability of the survey.

Each plant is uniquely classified in a 4-digit economic activity classification based on the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3 from the United Nations (UN) classification system. The survey contains extremely detailed plant level characteristics. The dataset reports both the total employment bill and the total employment for each firm. Thus, I am able to construct a measure of average wage at the establishment level. In addition, the survey reports information on the geographic region in which the plant is located, the value of material input expenditure, the value of the capital stock, the value of total investments, the electricity consumed in megawatt (MW), the value of the expenditure on electricity consumed, and the expenditure on total fuel (e.g. petroleum) used in production. These detailed balance sheet information are crucial for the estimation of the markups and markdowns of the Chilean manufacturing sector and for the subsequent estimation of the four structural elasticities which govern the model dynamics. All values are reported in Chilean Peso.

I match the custom level transactions from the Chilean Customs Agency to the balance sheet information provided by Chilean National Statistical Agency using confidential information on Chilean tax identification number (RUT, *Rol Único Tributario*). I obtain an unbalanced panel of Chilean exporters and importers spanning a 10 years time periods.

The fourth dataset that I use is the National Survey of Employment and Unemployment (ENA, *Encuesta Nacional de Empleo*) compiled by the Chilean National Institute of Statistics (INE, *Insituto Nacional de Estadisticas*). I use this dataset to construct the Chilean local labor markets. The National Survey of Employment and Unemployment is a household survey which is representative at the national and regional levels. The ENA interviews individuals of working age (15 years and older). The questionnaire is divided into four sections: (I) whether the individual is employed or unemployed, (II) for those employed, a series of detailed questions about their job, such as occupation category and job duties, (III) the number of hours worked, and (IV) whether the individual is seeking a new job and, if so, the reasons for switching. [13] The ENA provides essential data to construct the employment transition probability matrix for the Chilean labor market. Households report the region where their employer is located and the industry classification of the employer. Additionally, individuals indicate whether they have changed jobs during the survey period, allowing me to compute transition probabilities at the region $\times$ 2-digit industry level. Section 4 provides a detailed discussion of the methodology used to define Chilean local labor markets. I use two rounds of the ENA survey covering 2010 and 2011, the earliest available years, making them the closest in time to the periods covered by ENIA and customs transaction data.

Lastly, I rely on standard sources to obtain a series of macroeconomic variables. The daily bilateral exchange rates between the Chilean Peso and the currency of Chilean trade partners for the time period under analysis is obtained from Bloomberg and Datastream. The domestic inflation rate for Chile and its trade partners from the Central Bank of Chile and the IMF, respectively. A time series of price level deflators used in the production function estimation is also obtained from the Central Bank of Chile.

[13] For a complete list of questions in the National Survey of Employment and Unemployment, visit INE Chile.

Construction of Variables In what follows, I describe how I construct the variables used in the empirical specifications. Since firm can only be located in one labor market, I drop the subscript j where it does not generate confusion.

The main dependent variable is the log change in a firm i's export price of good g to destination country k at time t active in the local labor market j. The dependent variable is defined as the change in a firm's export unit value

$$\Delta P^{\star}_{k,g,i,t} \equiv \Delta \log \left[\frac{\text{Export Value}_{k,g,i,t}}{\text{Export Quantity}_{k,g,i,t}} \right]$$

where export quantities are measured both as total units and total KG. The export prices are expressed in the producer currency and the growth rate are measured at the annual frequency. The resulting distribution of the export price change is trimmed symmetrically at the 1% and the 99% level. The observed annual price changes are bounded between -100% and $+100\%$.

The second key dependent variable of the empirical analysis is the annual change in the average firm wage. I construct the log change in a firm i's average wage at time t in labor market j as

$$\Delta w_{ij,t} \equiv \Delta \log \left[\frac{\text{Wage Bill}_{ij,t}}{\text{Employment}_{ij,t}} \right].$$

I follow the same procedure and trim the outliers in the resulting distribution of the growth rate of domestic wages which are either below the 1st or above the 99th percentile. The wage is expressed in domestic currency.

The availability of both the region in which the plant is located and the industry classification paired with the balance sheet information of the employment bill allow me to construct a straightforward empirical counterpart of the payroll share r_{ij} described in the model. Indeed, consistently with the model, a sufficient statistic for the firm labor market power in its local labor market is computed by using the firm payroll share in its local labor market as follows:

$$r_{ij,t} \equiv \frac{w_{ij,t} l_{ij,t}}{\sum_{k \in I_j} w_{kj,t} l_{kj,t}},$$

where I_j contains the list of all firms k which are active in the same labor market j as firm i.

Equivalently to the labor market, the model predicts that the firm export market share $S_{k,ij}$ is a sufficient statistic that characterizes the product market power of the firm in the destination market and across the Chilean exporters. I construct the exporter market share as follows

$$S_{k,s,i,t} \equiv \frac{\text{Export Value}_{k,s,i,t}}{\sum_{i' \in I_{k,s,t}} \text{Export Value}_{k,s,i',t}} \tag{13}$$

where s is the 4-digit HS sector in which firm i sells good g and $I_{k,s,t}$ is the set of Chilean firms that export to destination k, in sector s at time t. Thus, $S_{k,s,i,t}$ proxies firm i's market share in sector s and destination country k relative to all the other Chilean exporters. In the robustness checks, I change the definition of sector to the 6-digit HS code and the 2-digit HS code.

Lastly, I compute the empirical counterpart of the firm import intensity as follows:

$$\varphi_{k,ij,t} \equiv \frac{\text{ToT Import Value}_{k,ij,t}}{\text{Wage Bill}_{ij,t} + \text{TMC}_{ij,t}} \tag{14}$$

where the denominator sums the wage bill of the firm to its total material cost (TMC) which consists of total raw materials and materials expenditure. The denominator is a proxy for the total variable costs of the firm. Importantly, to be coherent with the production function of the firm, I omit any imports from the construction of $\varphi_{k,ij,t}$ that is defined as a final product accordingly to the Broad Economic Codes (BEC). The definition in Equation (14) slightly departs from its model counterpart as it takes advantage of the granular information available in the custom level data and measures the import intensity of the firm from the origin country k. Results are robust to the definition of the import intensity at the firm level.

4 Stylized Facts

In the following sections, I show the methodology used to estimate the Chilean local labor markets and present some simple new stylized facts on Chilean exporters.

Estimation of the Chilean Local Labor Markets The first key step of the empirical analysis consists in the definition of the Chilean local labor markets by restoring to the estimation of the employment transition probability matrix of the Chilean economy. I use the monthly National Survey of Employment and Unemployment (ENA, *Encuesta Nacional de Empleo*) compiled by the Chilean National Institute of Statistics (INE, *Insituto Nacional de Estadisticas*) between the years 2010 and 2011 to estimate the Chilean local labor markets.

Even though the ENA is not a matched employer-employee dataset, it asks very detailed questions to household about their employment condition. The worker, if employed at the time of the survey, answers in which region the employer plant is located. In addition, the workers also specify the industry classification of the company where they are currently employed. Based on the intuition that a local labor market should delimitates both a geographical area where workers and employers meet and a demand and supply for job content skills, I define a local labor markets as the region×industry level. [14] To estimate the employment transition probabilities for the Chilean economy, I use two measures: job-to-job transitions

[14] The definition of local labor markets as a one-dimensional object, for instance only as region or only as industry classification, would not be appropriate as it would miss the fundamental idea that, the match of demand and supply in the labor market, is not only skill specific but also geographically delimited and vice-versa. Moreover, the survey asks also to the households in which municipalities the employer plant is located, however the ENA is not representative at a granular level below the regional one.

(J2J) and the job-unemployment-job transitions (JUJ). [15]

Figure (3) shows the transition matrix of workers across local labor markets for J2J and JUJ transitions. Figure (3) reports the transition matrix for Chilean labor markets in the top 50$^{\text{th}}$ percentile of the employment distribution. In the sample, there are 14 different 1-digit industry classification and 15 region. Thus, there are 210 labor markets. However, half of the employment share is concentrated in only 39 labor markets reported in Figure (3). On the y-axis it is reported the labor markets in which the worker was previously employed and on the x-axis the labor markets in which the new work is located. Figure (3) lands support to the definition of local labor markets at the region$\times$industry level as most of the transitions happen within the same local labor markets. Indeed the 45°line shows that, conditional on a J2J or a JUJ, on average almost 8 workers out of 10 decide to remain in the same region and industry. In conclusion, I adopt the definition of local labor markets as region$\times$industry throughout the paper.

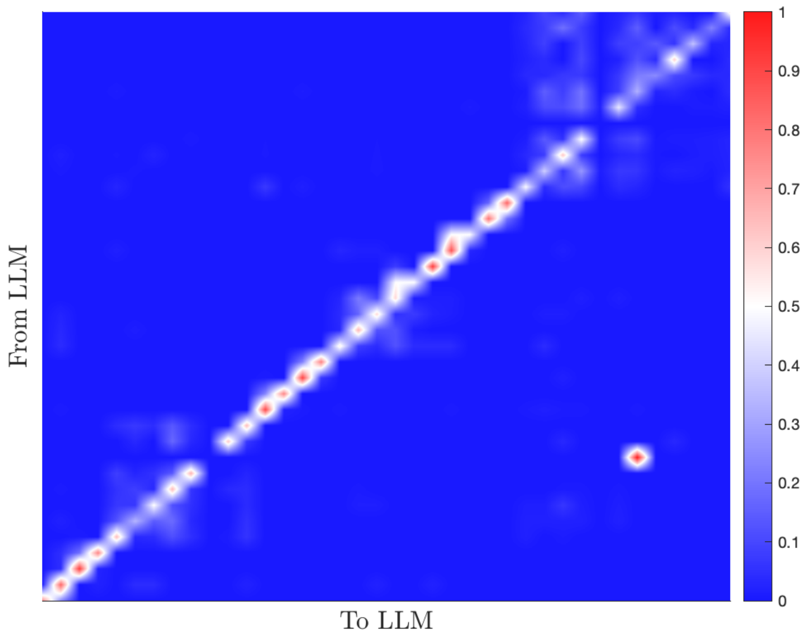

Figure 3: Local Labor Market Transitions of J2J and JUJ (Top 50).

Note: Figure (3) shows the estimated employment transition probability matrix for the Chilean economy. A local labor market is defined as region$\times$industry. The plot reports 39 labor markets (out of 210) which employ half of the total employment in Chile. The transition matrix is estimated using the monthly National Survey of Employment and Unemployment (ENA, *Encuesta Nacional de Empleo*) compiled by the Chilean National Institute of Statistics (INE, *Insituto Nacional de Estadisticas*) between the years 2010 and 2011.

[15]The ENA asks workers to report the year and month they started working for their current employer. This information allows the identification of job-to-job (J2J) transitions. A J2J transition occurs when a worker was employed in the previous survey round and reports having started a new job with a different employer in the current round. A job-unemployment-job (JUJ) transition is defined as a sequence in which the worker experiences one to three periods of unemployment before becoming re-employed. Unfortunately, due to data limitations, it is not possible to distinguish job switches from recalls.

Chilean Exporters and Labor Market Power I first present summary statistics linking firm characteristics to their degree of labor market power, proxied by the payroll share r_{ij}. I split the distribution of r_{ij} at the median, classifying firms above the 50th percentile as high labor market power (LMP) and those below as low LMP. Table 1 reports mean values for key firm-level variables.

The results align closely with the model's predictions. Firms with higher labor market power employ, on average, 166 more workers and pay wages that are approximately 41% higher than their low-LMP counterparts. They also exhibit 20% greater import intensity and a 60% higher export market share. Furthermore, high-LMP firms source more than three times as many foreign varieties from more than twice as many origin countries. A similar pattern emerges in export activity: high-LMP firms export over twice as many products to more than double the number of destinations.

Table 1: Summary Statistics for Chilean Exporters by Labor Market Power

	Low LMP	**High LMP**
Employment	46	212
Monthly Wage (USD)	603	854
Import Intensity $\varphi_{ij,t}$	0.15	0.18
Material Cost (Thous. USD)	1.585	14.117
Import Origins	8	16
Imported Products	35	114
Export Destinations	4	9
Exported Products	6	19
Export Share $S_{k,ij,t}$	0.15	0.24
Observations	23023	

Note: Table 1 reports summary statics for Chilean exporters. Firms are classified as high labor market power (LMP) if their payroll share r_{ij} lies above the median of the distribution, and as low LMP otherwise. Table 1 reports mean values for selected firm-level variables across these two groups.

In addition, as reported in Table B.1, the average firm has a payroll share of approximately 2.29%, while the median is just 0.28%, indicating the prevalence of small employers in the sample. However, this aggregate pattern masks considerable heterogeneity across local labor markets. For instance, some local labor markets host over 200 firms, while others are effectively monopolized by a single employer. This variation in market structure is evident in Table B.2, which reports the average firm-level payroll share in local labor markets closest to selected percentiles of the distribution. For example, the local labor market defined by the "Food, Beverages, and Tobacco" industry in Santiago (Región Metropolitana) has an average payroll share of just 0.0081%, while the same industry in Maule reports a significantly higher value of 0.0742%. These examples underscore the importance of jointly considering industry and geography when analyzing labor market concentration. Lastly, one of the most concentrated LLMs in the data is the "Wood and Furniture" industry in Valparaíso, where the average firm controls 44.57% of the local payroll highlighting extreme cases of employer concentration in the sample.

To conclude, a central prediction of the model introduced in Section 2 is that, within a local labor market, the most productive firms tend to pay higher-than-average wages and employ a larger share of the local workforce. This prediction is supported by the data. Figure 4 displays the estimated density of (log) wages by total factor productivity (TFP), while Figure 5 shows the density of (log) employment by TFP.[16] Firm productivity is normalized relative to the average productivity in the local labor market in which the firm operates. Firms are then categorized as either "High TFP" or "Low TFP" depending on whether their productivity lies above or below the within-market average (results are robust to using the median as the cutoff). The figures lend empirical support to the model: within local labor markets, more productive firms tend to offer higher wages (Figure 4) and employ more workers (Figure 5).

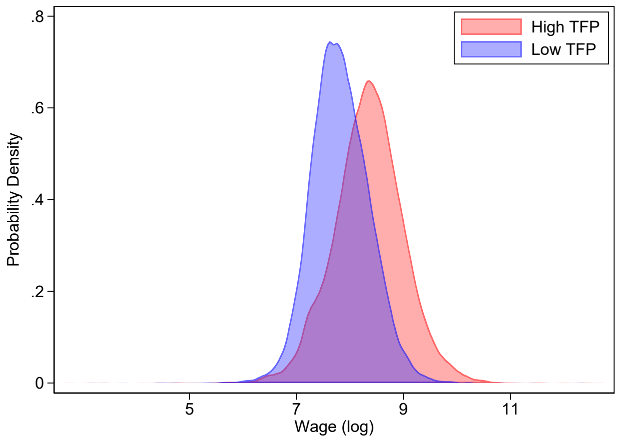

Figure 4: Wage Distribution by TFP

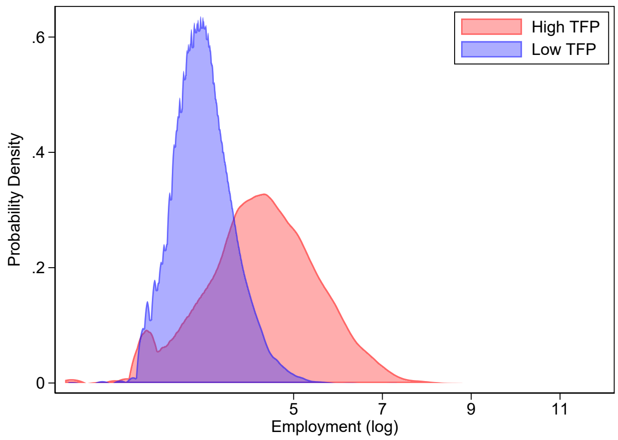

Figure 5: Employment Distribution by TFP

Note: Figure 4 and Figure 5 plot the estimated density distribution of the (log) of the firm level average wage and of the (log) of the firm level total employment by productivity, respectively. Firm productivity is normalized relative to the average productivity in the local labor market in which the firm operates. Firms are then categorized as either "High TFP" or "Low TFP" depending on whether their productivity lies above or below the within-market average. See Section 6 for a detailed description of the procedure used to estimate firm-level productivity.

5 Empirical Analysis

In this section, I proceed in two steps: I) I derive closed form expressions for the structural coefficients that determine the exchange rate pass-through to export prices and to domestic wages as a function of the firm labor market power, product market power, and import intensity. Then, II) I derive the main specifications to empirically estimate the pass-through coefficients using Chilean administrative custom level data paired with firm level characteristics.

The estimated coefficients are coherent with the model predictions. The estimates confirm an inverted U-shaped relationship between the exchange rate pass-through to producer currency prices and the firm payroll share. The shape of the pass-through to domestic wages is U-shaped in the firm wage bill share.

[16]See Section 6 for a detailed description of the procedure used to estimate firm-level productivity.

Exchange Rate Pass-Through to Wages To estimate the effect of an exchange rate variation on domestic wages for firms with different degree of labor market power, I compute a second-order approximation of the equation reported in Proposition 2 around r_{ij}, S_{ij}, φ_{ij}. [17] This yields to:

Proposition 4 *In any general equilibrium, the second-order approximation to the exchange rate pass-through elasticity into domestic-currency wage of the firm is given by*

$$\Psi_{ij}^{W} \equiv \mathbb{E}\left\{\frac{d\log w_{ij}}{d\log e_k}\right\} \approx \kappa_{ij} + \xi_{ij}\varphi_{ij} + \pi_{ij}S_{ij} + p_{ij}S_{ij}^2 + \sigma_{ij}r_{ij} + o_{ij}r_{ij}^2$$

where the coefficients are firm-local labor market (ij) specific parameters and depend only on average moments of equilibrium comovement between aggregate variables common to all firms.
Proof: *See Appendix A.5.*

The pass-through elasticity Ψ_{ij}^{W} measures the equilibrium log change of the producer currency wage of firm ij relative to the log change in the bilateral exchange rate, averaged across all possible states of the world and shocks that hit the economy. Proposition 4 states that, independently of the general equilibrium specifics, the market share, the import intensity and the payroll share of the firm form a sufficient statistics for the cross-sectional variation in the pass-through within local labor market. The values of the coefficients are firm-local labor market specific parameters.

Clearly, Proposition 4 suffers of the usual problem that the theoretical pass-through Ψ_{ij}^{W} is not observed in the data. However, I can identify the theoretical coefficients in the relationship between pass-through to wage and labor market power. To do so, I linearize the decomposition of the log wage change in Equation (12) and replace differentials with Δ. Then, I obtain the first main empirical specification:

$$\begin{aligned}\Delta w_{ij,t} = {} & \left(\alpha_j + \beta\varphi_{ij,t-1} + \gamma S_{ij,t-1} + \delta r_{ij,t-1}\right)\Delta e_{ij,t} + \\ & + \left(\theta S_{ij,t-1}^2 + \lambda r_{ij,t-1}^2\right)\Delta e_{ij,t} + \\ & + \mu_j + \nu\varphi_{ij,t-1} + \xi S_{ij,t-1} + \omega r_{ij,t-1} + \tilde{u}_{ij,t},\end{aligned} \tag{15}$$

where $\Delta w_{ij,t}$ is the log annual change in the wage of firm i active in labor market j expressed in domestic currency and $\Delta e_{ij,t}$ is a firm specific trade-weighted annual change in the bilateral exchange rate. An increase in $\Delta e_{ij,t}$ indicates a (trade-weighted) depreciation of the domestic currency relative to its trading partners.[18] Ceteris paribus, after a 1% depreciation of the Chilean Peso with respect to the currency of country k, a representative Chilean firm with a payroll share of $r_{ij,t}$ experiences a wage pass-through equal to $\alpha_j + \delta r_{ij,t-1} + \lambda r_{ij,t-1}^2$. The theory predicts the exact sign of δ and λ. Indeed, the model predicts a U-shaped relationship

[17] The motivation for computing a second-order approximation, rather than a first-order approximation, lies in the presence of non-non-linearities in the model. In particular, both markdown variability and markup variability.

[18] Formally, $\Delta e_{ij,t} = 0.5\sum_k \frac{\text{ToT Imp}_{k,ij,t}}{\text{ToT Imp}_{ij,t}}\Delta e_{k,t} + 0.5\sum_k \frac{\text{ToT Exp}_{k,ij,t}}{\text{ToT Exp}_{ij,t}}\Delta e_{k,t}$.

between the firms proxy for labor market power and its wage pass-through. Thus, I expect λ to be positive. If $\Delta e_{k,t}$ is uncorrelated with ($r_{ij,t-1}$, $S_{ij,t-1}$, $\varphi_{ij,t-1}$) then the OLS estimates of the coefficients identify the structural theoretical coefficients in Proposition (4).

Results for Wages In Table 2, I report the results for my benchmark empirical specification for the exchange rate pass-through to domestic wages. The dependent variable is the annual growth rate of the firm level average wage expressed in Chilean Peso. To bring the empirical specification in line with the model's prediction, I regress the log change in domestic wages on each firm's trade-weighted annual change in the bilateral exchange rate, which captures its exposure to currency movements through trade linkages. Also, I regress the lag of the independent variables to avoid any possible simultaneity problem.

The results reported in Table 2 confirms the model presented in Section 2. First, Column (1) reports the average exchange rate pass-through in the sample. On average, a 1% depreciation in the Chilean Peso is correlated with an increase in the domestic wage of approximately 0.09%. Column (2) reports the estimated coefficients for Equation (15) without controlling for the import intensity of the firm and its product market share. I find a statistically significant positive coefficient for the interaction term between the bilateral exchange rate and the square of the firm payroll share equal to 0.95. This confirms the model predictions. This coefficient defines the concavity of the relationship between the sensitivity of domestic wages to exchange rate and firm payroll share to be a convex function. Column (2) implies that a firm in the 75$^{\text{th}}$ percentile in the distribution of the payroll share has a pass-through to domestic wages that is approximately 13% lower compared to a smaller firm in the 25$^{\text{th}}$ percentile. Column (3) uses a different set of fixed effects and leads to a similar estimates and thus conclusion.

Table 2: **ERPT to Wage and Labor Market Power**

	(1)	(2)	(3)	(4)
	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$
$\Delta e_{ij,t}$	0.088***	0.115***	0.112***	0.113***
	(0.001)	(0.002)	(0.002)	(0.002)
$r_{ij,t-1}\Delta e_{ij,t}$		-0.600***	-0.582***	-0.624***
		(0.165)	(0.150)	(0.165)
$r^2_{ij,t-1}\Delta e_{ij,t}$		0.953***	0.909***	0.973***
		(0.235)	(0.214)	(0.233)
$S_{ij,t-1}\Delta e_{ij,t}$				-0.335**
				(0.143)
$S^2_{ij,t-1}\Delta e_{ij,t}$				-0.998
				(0.786)
$\varphi_{ij,t-1}\Delta e_{ij,t}$				-0.742***
				(0.036)
Year X LLM	YES	YES	NO	YES
Year + LLM	NO	NO	YES	NO
Observations	89143	89173	89826	89170

Note: Table 2 reports the estimated exchange rate pass-through coefficients to domestic wages. The dependent variable is the log annual change in the average firm wage. The explanatory variables are I) the firm level trade-weighted bilateral exchange rate $\Delta e_{ij,t}$, II) $r_{ij,t-1}$ measures the firm level payroll share in local labor market j at year $t-1$, II) the market share of the firm $S_{ij,t-1}$ and its import intensity $\varphi_{ij,t-1}$. All specification include the level of the variables not interacted with the bilateral exchange rate. The local labor markets (LLM) are defined as region $\times$ 2-digit industry. Standard errors are clustered at the Year $\times$ LLM . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, I move to Column (4) which shows the estimated coefficients for my preferred specification displayed in Equation (15). Again, the estimated coefficients are very similar to those reported in Column (2) and Column (3) and they confirm the theoretical prediction that the relationship between pass-through to wages and the proxy for firm labor market is U-shaped. Column (4) lands support to the model predictions. A 1% increase in the import intensity of the firm is correlated with a decrease in the domestic wage of approximately -0.74%. Column (4) also confirms a negative correlation between product market shares and the sensitivity of domestic wages. The coefficient on the linear interaction is statistically significant and equal to -0.334. This finding is consistent with the closed-form expression derived in Proposition 2, which shows that firms with more elastic markups exhibit lower wage responsiveness to exchange rate changes. However, the statistically insignificant quadratic interaction term suggests the absence of a nonlinear relationship.

Exchange Rate Pass-Through to Prices To estimate the effect of an exchange rate variation on export prices for firms with different labor market power, I compute a second-order Taylor approximation of the equation reported in Proposition 3 around φ_{ij}, $S_{k,ij}$, and r_{ij}. This yields to:

Proposition 5 *In any general equilibrium, the second-order approximation to the exchange rate pass-through elasticity into producer-currency export prices of the firm is equal to*

$$\Psi^{P^*}_{k,ij} \equiv \mathbb{E}\left\{\frac{d\log P^\star_{k,ij}}{d\log e_k}\right\} \approx \alpha_{k,s,ij} + \beta_{k,s,ij}\varphi_{ij} + \gamma_{k,s,ij}S_{k,s,ij} + j_{k,s,ij}S^2_{k,s,ij} + \delta_{k,s,ij}r_{ij} + z_{k,s,ij}r^2_{ij}$$

where the coefficients are destination-sector-firm (k, s, ij) *specific parameters and depend only on average moments of equilibrium comovement between aggregate variables common to all firms.*

Proof: *See Appendix A.6*

The pass-through elasticity $\Psi^{P^\star}_{k,ij}$ measures the equilibrium log change of the destination-k producer currency price of firm ij relative to the log change in the bilateral exchange rate, averaged across all possible states of the world and shocks that hit the economy. Proposition 5 states that, independently of the general equilibrium specifics, the market share, the import intensity and the payroll share of the firm form a sufficient statistic for the cross-sectional variation in the pass-through within sector, destination, and local labor market. The values of the coefficients are destination-sector-firm.

Proposition 5 defines the theoretical pass-through coefficients that link the variations in the export prices of the firms to its characteristics. However, the equation defined in Proposition 5 can not be directly estimated. Thus, I proceed as follow to empirically estimate the relationship between labor market power, import intensity, market share and pass-through. I step back from Proposition 5 and linearize the log price change equation in Proposition (3) in payroll share, import intensity, and market share and replace differentials with changes over time Δ. Then, I obtain the second main empirical specification:

$$\begin{aligned}\Delta P^\star_{k,g,i,t} = {} & \left(\eta_{k,s,j} + \zeta\varphi_{k,ij,t-1} + \kappa S_{k,s,ij,t-1} + \rho r_{ij,t-1}\right)\Delta e_{k,t} + \\ & + \left(\chi S^2_{k,s,ij,t-1} + \tau r^2_{ij,t-1}\right)\Delta e_{k,t} + \\ & + \sigma_{k,s,j} + \upsilon\varphi_{k,ij,t-1} + \phi S_{k,s,ij,t-1} + \varsigma r_{ij,t-1} + \tilde{\epsilon}_{k,g,ij,t},\end{aligned} \tag{16}$$

where $P^\star_{k,g,i,t}$ is the log annual change in price of good g expressed in producer-currency to destination k from exporter i located in labor market j and $e_{k,t}$ is the nominal bilateral exchange rate between the Chilean Pesos and the destination-k currency. Thus, an increase in $e_{k,t}$ measures a depreciation of the Chilean Pesos with respect to the destination-k currency.

I estimate the coefficients of Equation (16) with values averaged across firm, product, destination, labor market, and time. The second main empirical contribution of the paper is to consistently estimate the coefficients ρ and τ which govern how the labor market power of a firm affects its exchange rate pass-through. Ceteris paribus, the model predicts an inverted U-shape relationship between the change in the destination-currency price after an exchange rate depreciation and the firm payroll share. Thus, I expect τ to be a negative number. This implies that a low productivity firm that employs a small share of total employment in its local labor market has the same pass-through to destination prices as a bigger, high productivity firm, that employs a larger share of the workers in the same labor market.

Lastly, Equation (16) is a structural equation that is derived from the model outlined above. If $\Delta e_{k,t}$ is uncorrelated with $(\varphi_{k,ij,t-1}, S_{k,s,ij,t-1}, r_{ij,t-1})$, then the OLS estimates of the coefficients identify the structural theoretical coefficients in Proposition 5.

Results for Prices Table (3) report the estimated coefficients from Equation (16). Column (1) reports an average annual exchange rate pass-through to producer currency equal to approximately 13%. Next, Column (2) shows the estimated coefficients that shape the relationship between the exchange rate pass-through to prices and the labor market power of the firm. Column (2) confirms the predicted hump-shape relationship between the payroll share of the firm in its local labor market and the predicted exchange rate pass-through to prices. Indeed, the quadratic term of the payroll share interacted with the growth rate of the exchange rate is negative and equal to -0.98. The coefficient is statistically different from zero at less than 1% level. Column (1) implies that an average firm in the first quintile of the payroll share distribution has an expected ERPT to producer prices equal to $0.15 + (0.85 - 0.98) * 0.002 \approx 0.14$. Similarly, an average firm in the fifth quintile of has a pass-through approximately equal to 0.11.

Column (3) and Column (4) control for the export share of the firm and for its import intensity. Consistently with the model predictions, an higher import intensity implies higher pass-through to export prices. Ceteris paribus, a firm with a very low productivity which has virtually no imported inputs in production has an expected pass-through equal to 10%. By contrast, a firm that belongs to the top 1% of the importer distribution with an import intensity of 27$\%$ has pass-through to producer prices which is $0.10 + 0.88 * 0.27 \approx 0.33$. Also, the model predicts an hump-shape relationship between market share and sensitivity of prices to exchange rates. Indeed, Column (3) reports the coefficients for the linear term and the quadratic term of the export market share to be equal to approximately 0.87 and 0.85, respectively. Column (4) leads to similar conclusion.

In conclusion, Table (2) and Table (3) confirm the model predictions. Table (2) shows a new empirical facts that the sensitivity of domestic wages to exchange rate shocks is a function of the labor market power of the firm. Through the lens of the model, infinitesimal employers and very large employers have similar pass-through to domestic wages because both charges constant markdowns. Differently, employers in the middle of the distribution have a higher sensitivity of markdowns to change in wages and are able to adjust their wages by less. Moreover, Table (3) estimates new ERPT coefficients to producer currency prices and shows that small and large employers fully pass-through change in wages to changes in the destination prices. Differently, medium sized employers are able to keep their destination prices more stable because they adjust the markdown on domestic wages by a greater amount. In other words, they are able to better absorb the cost shock.

Table 3: **ERPT to Prices and Labor Market Power**

	(1)	(2)	(3)	(4)
	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$
$\Delta e_{k,t}$	0.134***	0.155***	0.074**	0.106***
	(0.026)	(0.031)	(0.037)	(0.036)
$r_{ij,t-1}\Delta e_{k,t}$		0.857**	0.900**	1.113***
		(0.422)	(0.436)	(0.422)
$r^2_{ij,t-1}\Delta e_{k,t}$		-0.988***	-1.142***	-1.297***
		(0.381)	(0.392)	(0.379)
$S_{k,s,i,t-1}\Delta e_{k,t}$			0.873***	0.921***
			(0.266)	(0.260)
$S^2_{k,s,i,t-1}\Delta e_{k,t}$			-0.895***	-0.971***
			(0.276)	(0.272)
$\varphi_{k,i,t-1}\Delta e_{k,t}$			0.936***	0.884***
			(0.105)	(0.104)
Year + Destination X HS4	YES	NO	NO	NO
Year + LLM X Destination X HS4	NO	YES	NO	YES
Year + LLM + Destination X HS4	NO	NO	YES	NO
Observations	112432	109430	112422	109430

Note: Table 3 reports the estimated exchange rate pass-through coefficients to producer currency export prices. The dependent variable is the log annual change in the export price expressed in Chilean Peso. The explanatory variables are I) the bilateral exchange rate $\Delta e_{k,t}$, II) $r_{ij,t-1}$ measures the firm level payroll share in local labor market j at year $t-1$, II) the market share of the firm $S_{k,ij,t-1}$ and its import intensity $\varphi_{k,ij,t-1}$. All specification include the level of the variables not interacted with the bilateral exchange rate. The local labor markets are defined as region $\times$ 2-digit industry. Standard errors are clustered at the Year $\times$ Destination $\times$ LLM. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.1 Robustness

Here, I report a series of robustness checks. I estimate the exchange rate pass-through to prices and wages by quintile of the payroll share distribution. Next, I re-estimate the exchange rate pass-through to both prices, wages, and labor input using alternative definitions of exchange rate. Then, I re-estimate the exchange rate pass-through to prices and wages using alternative samples and alternative definitions of local labor markets. Lastly, I conclude with a discussion on the role of currency of invoicing and nominal rigidities as a determinant of the expected exchange rate pass-through to international prices.

Non Parametric Estimation To allow for more flexibility and not impose a particular function form, I re-estimate both Equation (16) and Equation (15) non-parametrically by splitting the distribution of the payroll share r_{ij} into equal sized quintiles. The means of r_{ij} in the five bin are $0.2, 0.7, 1.6, 3.4$, and 36 percent, respectively. Then, I estimate a separate average pass-through coefficient for each quintile of the employment share distribution and plot the results in Figure 6. The left panel shows the five coefficients for the pass-through to export prices, while the right panel displays the corresponding coefficients from the wage regression.

I estimate three different specifications. First, the red dotted connected line reports the five estimated coefficients for the unconditional specification, that is not controlling for neither the import intensity nor the export market share of the firm. Clearly, the elasticity of export prices in producer currency with respect to the exchange rate is concave across the payroll share distribution, whereas the sensitivity of domestic wages is convex. Second, the blue dotted connected line controls for export market share of the firm. For each labor market share quintile, the estimated pass-through coefficients to both prices and wages are very similar to those estimated in the unconditional specifications. Third, the black dotted connected line mirrors exactly the benchmark specification reported in Equation (16) and Equation (15) as it controls also for the firm level import share.

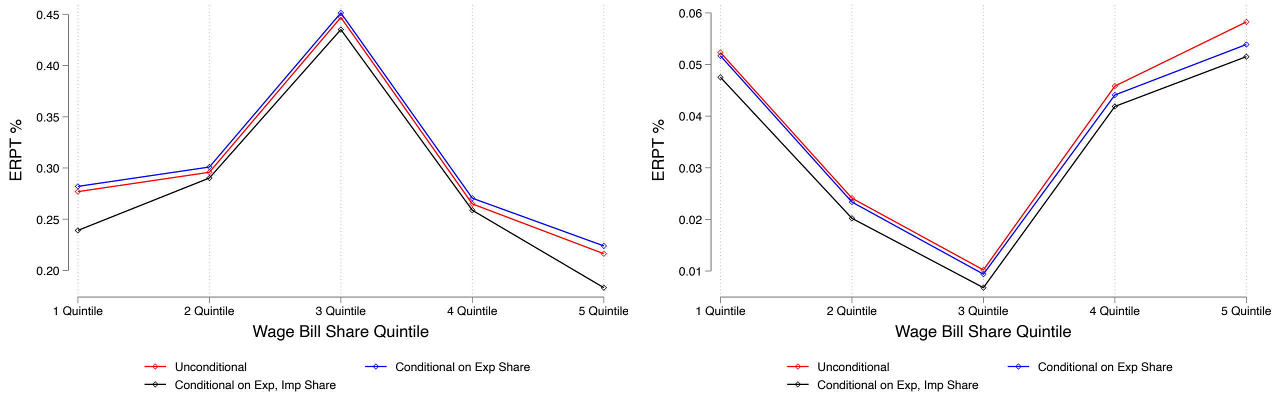

Figure 6: ERPT To Price and Wage and Labor Market Power: Non-Parametric Specification

Note: Figure 6 reports the estimated pass-through coefficients of $\Delta p^{\star}_{k,g,ij,t}$ (left panel) and $\Delta w_{ij,t}$ (right panel) on $\Delta e_{k,t}$ (left panel) and $\Delta e_{ij,t}$ (right panel) for each quintile of the wage bill share r_{ij}. Each dot represents the estimated average coefficient for a quintile of the payroll share distribution r_{ij}. The red line is the unconditional specification, the blue line controls for the export market share of the firm, the black line controls also for the firm import share. Across all the specifications, the coefficients in the first and fifth bins are not statistically different. In contrast, they are statistically different at the 5% level to those in the third bin. Table B.3 and Table B.4 in Appendix B reports the coefficients, standard errors, and the p-values of the F-test of the non-parametric regressions for price and wage, respectively.

The estimated coefficients are similar in magnitude across all the three specification. Across the three specifications, small employers belonging to the first quintile of the payroll share distribution have an expected pass-through to export price below 30% and a growth rate of domestic wages equal to 5%. Quantitatively similar coefficients are estimated for big employers belonging to the fifth quintile. Importantly, performing a Wald test of simple linear hypothesis supports the model. Indeed, the estimated coefficients of the first and fifth quintile are not statistically different across the three specifications landing support to the theoretical prediction that big and small employers have similarly pass-through coefficients to prices and wages. By contrast, firms in both the first and fifth quintile have statistically different pass-trough coefficients compared to those in the third quintile with p-values of less than 5%. A similar conclusion holds when comparing the third and the fourth quintile. Table B.3 and Table B.4 in Appendix B report the coefficients, standard errors, and the p-values of the F-test of the non-parametric regressions for price and wage, respectively.

Alternative Exchange Rate Definitions The Chilean custom data are extremely detailed as they report each import and export transactions carried out by the universe of the Chilean firms at a very granular level. Thus, this makes possible to use different firm specific exchange rate definitions. In Table B.6 and Table B.5, I estimate the exchange rate pass-through relationship between prices and wages and labor market power using a firm-specific import weighted exchange rate, respectively. Table B.6 and Table B.5 confirm the main findings. Results are qualitatively invariant.

Alternative Samples I re-estimate Equation (16) using alternative sample definitions by excluding certain destinations and products, and by focusing on specific subsets of firm-level exports. Table B.7 in Appendix B presents four robustness checks. First, I exclude exports to the United States to ensure that results are not driven by this single destination, which accounts for approximately 10% of the sample. Second, I restrict the sample to products whose export share is above the firm-specific median at the HS8 level. Third, I apply the same restriction at the HS4 level. These two specifications address the presence of multiproduct firms by focusing on goods that likely share similar production technologies. Finally, I exclude HS2 category "74" ("Copper and articles thereof"), since Chile is one of the world's largest exporter of copper and may exert price-setting power that goes beyond what my model can capture. The hump-shaped relationship between export prices and the payroll share remains robust across all four specifications reported in Table B.7.

Alternative Definition of Local Labor Market Table B.8 in Appendix B re-estimates Equations (16) and (15) using two alternative definitions of local labor markets, each producing a different payroll-share distribution across firms. The first specification replaces regions with the municipalities where firms are located, yielding a finer spatial unit. The second retains the regional definition but makes the skill environment more granular by defining a local labor market as region $\times$ 4-digit industry. Columns (1)–(2) of Table B.8 report the price regressions, while Columns (3)–(4) present the wage regressions. Across both alternative definitions, the hump-shaped relationship between export prices and payroll share, and the corresponding U-shaped relationship for wage sensitivity, remain robust.

Exchange Rate Pass-Through to Labor Input Table B.9 in Appendix B reports estimates of exchange rate pass-through to labor input at the firm level using alternative exchange rate definitions: the import-weighted exchange rate, and the trade-weighted exchange rate. Across specifications, the results are quantitatively similar. Ceteris paribus, a depreciation is associated with an increase in labor input. As expected, this effect is smaller for firms whose costs are more exposed to exchange rate fluctuations. The same holds for firms with a higher payroll share. This is intuitive: firms with higher payroll shares face steeper labor supply curves and thus experience smaller changes in labor input for a given change in the marginal revenue product of labor.[19]

Currency of Invoicing and Sticky Prices Recent advancement in international economics have shown that, in the presence of sticky prices, firms actively choose to invoice in a particular currency since it guarantees firms an expected mechanical pass-through to export prices (e.g. Amiti et al. (2022)). However, in the medium and long-run prices are supposed to be flexible and therefore the choice of the currency of invoicing is irrelevant to exchange rate pass-through. For instance, Gopinath and Rigobon (2008) shows that the median US import price flexibility is of around 12 months. In this paper, I am not able to control for the role played by the currency of choice in shaping exchange rate pass-through in the short-term as the Chilean custom agency started to properly record this variable from 2004 onwards. Thus, I assume fully flexible pricing and no role for the currency of invoicing. Nonetheless, the coefficients are estimated over a 1-year horizon which is in line with the median price flexibility length reported in Gopinath and Rigobon (2008). Moreover, recent findings by De Gregorio et al. (2024) use Chilean custom data from 2010 to 2019 and find evidence that the bilateral exchange rate between Chile and the destination country, and not the one with the so called dominant currency, shapes the pass-thorough over a 1-year horizon and thus this suggests that also Chilean prices have a medium price stickiness of a year.

6 Estimation & Calibration

This section estimates the four structural parameters of the model:

$$\Theta = \{\rho, \eta, \delta, \theta\},$$

where ρ and η are product market elasticities and δ and θ are labor market elasticities.

I begin by outlining the identification strategy for each parameter. Since the estimation hinges on recovering the full distribution of markups and markdowns across firms, I then detail the methodology used to estimate production functions for the Chilean manufacturing sectors. The section concludes with a discussion of both externally and internally calibrated parameters.

Identification of Product Market Elasticities To recover the product market elasticities, I implement a procedure similar to the one developed and implemented by Edmond et al. (2015), Edmond et al. (2023), and Autor et al. (2020). The identification strategy relies on a key implication of the model: a negative relationship between a firm's market share $S_{s,ij,t}$ and the inverse of its markup $1/\mathcal{M}_{s,ij,t}$, where s denotes the sector in which the firm operates.

[19] Importantly, this reasoning does not extend to expected changes in wages across firms with different payroll shares, since observed wage adjustments under labor market power also reflect changes in markdowns.

The starting point is the model-implied expression for the inverse markup at the firm level, written as a function of the firm market share:

$$\frac{1}{\mathcal{M}_{s,ij,t}} = \left(1 - \frac{1}{\rho}\right) - \left(\frac{1}{\eta} - \frac{1}{\rho}\right) S_{s,ij,t}. \tag{17}$$

This equation highlights how the slope of the relationship between markup and market share identifies the difference between the two inverse elasticities $1/\eta - 1/\rho$. Crucially, this relationship has a direct empirical counterpart, which takes the form:

$$\frac{1}{\mathcal{M}_{s,ij,t}} = \alpha + \alpha_i + \alpha_{s,t} + \beta S_{s,ij,t}, \tag{18}$$

where α_i and $\alpha_{s,t}$ are firm and sector-by-year fixed effects, respectively. The coefficient β corresponds to the slope in Equation (17) and is expected to be negative. An estimate of β thus recovers the gap between $1/\eta$ and $1/\rho$.

To move from firm-level to sector-level analysis, I aggregate Equation (17) across firms in each sector. This is done by multiplying both sides of the equation by $S_{s,ij,t}$ and summing over all firms active in sector s, which yields:

$$\frac{1}{\mathcal{M}_{s,t}} = \left(1 - \frac{1}{\rho}\right) - \left(\frac{1}{\eta} - \frac{1}{\rho}\right) \sum S^2_{ij,s,t},$$

where I use the fact that the sectoral markup $\mathcal{M}_{s,t}$ is the inverse of the sales-weighted harmonic average of firm-level markups: $\mathcal{M}_{s,t} = \left[\sum S_{s,ij,t} \times \mathcal{M}^{-1}_{s,ij,t}\right]^{-1}$. This aggregation results also holds in Edmond et al. (2023) and is also used by Yeh et al. (2022).

Aggregating once more to the level of the entire economy leads to the final model-implied moment condition:

$$\frac{1}{\mathcal{M}_t} = \left(1 - \frac{1}{\rho}\right) - \left(\frac{1}{\eta} - \frac{1}{\rho}\right) \sum_s \mathrm{HHI}_{s,t} \times S_{s,t}. \tag{19}$$

where $\mathrm{HHI}_{s,t} = \sum_i S^2_{s,ij,t}$ is the Herfindahl-Hirschman Index (HHI) index in sector s, and $S_{s,t}$ is sector s's share in aggregate sales.

Conditional on two objects, (i) an estimate of the inverse elasticity gap from Equation (18), and (ii) observed sectoral concentration terms $\mathrm{HHI}_{s,t} \times S_{s,t}$, the aggregate markup $\mathcal{M}_t$ allows identification of ρ. Given the estimate of $\beta = 1/\eta - 1/\rho$, the value of η then follows mechanically.

In summary, the cross-sectional relationship between markups and market shares pins down the difference between the inverse elasticities. Combined with the aggregate moment relating the markup to sales concentration, this strategy allows recovery of the product market elasticities ρ and η.

Identification of Labor Market Elasticities To recover the labor market elasticities, I follow an equivalent procedure. In this case, the identification strategy relies on the model implied positive relationship between a firm's payroll share $r_{ij,t}$ and the inverse of its markdown $1/\mu_{ij,t}$.

Indeed, start from the expression that links the inverse markdown at the firm level to its payroll share in local labor market j:

$$\frac{1}{\mu_{ij,t}} = \left(1 + \frac{1}{\delta}\right) + \left(\frac{1}{\theta} - \frac{1}{\delta}\right) r_{ij,t}. \tag{20}$$

Analogously to the product market case, this equation highlights how the slope of the relationship between markdowns and payroll share identifies the difference between the two inverse elasticities $1/\theta - 1/\delta$. This relationship has also a direct empirical counterpart, which takes the form:

$$\frac{1}{\mu_{ij,t}} = \alpha + \zeta_i + \zeta_{j,t} + \gamma r_{ij,t}, \tag{21}$$

where ζ_i and $\zeta_{j,t}$ are firm and local labor market-by-year fixed effects, respectively. The coefficient γ corresponds to the slope in Equation (20) and is expected to be positive. An estimate of γ thus recovers the gap between $1/\theta$ and $1/\delta$.

To move from firm-level to local labor market-level analysis, I aggregate Equation (20) across firms within each local labor market. This is done by multiplying both sides of the equation by $r_{ij,t}$ and summing over all firms active in labor market j, which yields:

$$\frac{1}{\mu_{j,t}} = \left(1 + \frac{1}{\delta}\right) + \left(\frac{1}{\theta} - \frac{1}{\delta}\right) \sum_i r_{ij,t}^2$$

where I use the fact that the local labor market markdown $\mu_{j,t}$ is the inverse of the payroll share-weighted harmonic average of firm-level markdowns: $\mu_{j,t} = \left[\sum_i r_{ij,t} \times \mu_{ij,t}^{-1}\right]^{-1}$. This aggregation result mirrors the product market result presented above.

Aggregating once more to the level of the entire economy leads to the final model-implied moment condition:

$$\frac{1}{\mu_t} = \left(1 + \frac{1}{\delta}\right) + \left(\frac{1}{\theta} - \frac{1}{\delta}\right) \sum_j \mathrm{HHI}_{j,t} r_{j,t} \tag{22}$$

where $\mathrm{HHI}_{j,t} = \sum_i r_{ij,t}^2$, and $r_{j,t}$ is labor market j's share in the economy wide wage bill.

Conditional on two objects, (i) an estimate of the inverse elasticity gap from Equation (21), and (ii) observed sectoral concentration terms $\mathrm{HHI}_{j,t} \times r_{j,t}$, the aggregate markdown μ_t allows identification of δ. Given the estimate of $\gamma = 1/\theta - 1/\delta$, the value of θ then follows mechanically.

In summary, the cross-sectional relationship between markdowns and wage bill shares pins down the difference between the inverse elasticities. Combined with the aggregate moment relating the markdown to employment bill concentration, this strategy allows recovery of the labor market elasticities θ and δ.

6.1 Markups & Markdowns: Estimation

In this section, I use detailed administrative data on establishments' inputs and outputs to estimate markups and markdowns in the Chilean manufacturing sector following the framework of Yeh et al. (2022). First, adopting a production approach in the spirit of Hall (1988), De Loecker (2011), and De Loecker and Warzynski (2012), I derive closed-form expressions for markups and markdowns as functions of output elasticities and revenue shares. This step rests on a standard set of assumptions common in the IO literature; see Appendix A.8 for a detailed exposition. Second, I estimate the Chilean production function, and hence the required output elasticities, using the proxy variable methodology originally developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), De Loecker and Warzynski (2012), and Ackerberg et al. (2015). Details appear below and in Appendix A.7. I conclude with the main results.

Markups Let the material input M serve as the *flexible input*. An input is flexible if it satisfies two conditions: (i) it is a static input not subject to adjustment costs and (ii) firms are price-takers in its market.[20] Under these conditions, the plant-level product-market markup is

$$\mathcal{M}_{s,ij,t} = \frac{\epsilon^M_{ij,t}}{\alpha^M_{ij,t}}, \tag{23}$$

where $\epsilon^M_{ij,t}$ is the output elasticity of materials and $\alpha^M_{ij,t}$ is the share of material costs in total revenue. The latter is directly observable in the Chilean manufacturing survey (ENIA), whereas the elasticities must be recovered by estimating firms' production functions.

Markdowns Assuming labor is also chosen statically and without adjustment costs, the plant-level labor markdown is [21]

$$\mu_{ij,t} = \frac{\epsilon^L_{ij,t}}{\alpha^L_{ij,t}} \times \frac{1}{\mathcal{M}_{s,ij,t}}, \tag{24}$$

where $\epsilon^L_{ij,t}$ is the labor output elasticity, $\alpha^L_{ij,t}$ is labor's share of revenue, and $\mathcal{M}_{s,ij,t}$ is given by Equation (23). After estimating the production function, these components yield the plant-level distribution of markdowns for Chile.

[20] In fact, materials must satisfy six assumptions. The two most demanding are the absence of adjustment costs and monopsony power; the remaining four are typically less stringent. See Appendix A.8 for the full list.

[21] Labor must meet four assumptions, of which the two most stringent are costless adjustment and static choice. See Appendix A.8.

Production Function Estimation The proxy variable methodology, widely used in the IO literature, provides a flexible and consistent framework to estimate output elasticities. In what follows, I outline the main steps used to apply this approach to the Chilean manufacturing sector. The assumptions required to implement the method are standard and closely follow those in Ackerberg et al. (2015) and Yeh et al. (2022). Appendix A.7 provides a detailed discussion of these assumptions as well as a step-by-step description of the procedure used to recover output elasticities.

To estimate output elasticities, I rely on plant-level data from the Chilean Survey of Manufacturing (ENIA) spanning 1995–2015, and estimate production functions separately for each 2-digit ISIC industry code. The starting point is a flexible production function specification given by

$$y_{ij,t} = f(\mathbf{I}_{ij,t}; \boldsymbol{\beta}) + \omega_{ij,t} + \varepsilon_{ij,t}, \tag{25}$$

where $y_{ii,t}$ denotes log output, and $\mathbf{I}_{ij,t} = (k_{ij,t}, l_{ij,t}, m_{ij,t}, e_{ij,t})$ is a vector of logged inputs, capital, labor, materials, and energy, expanded to include first-order, second-order, and interaction terms. The term $\omega_{ij,t}$ captures firm-specific Hicks-neutral productivity shocks observed by the firm but not by the econometrician, while $\varepsilon_{ij,t}$ is an i.i.d. measurement error. The goal is to estimate the vector of output elasticities, $\boldsymbol{\beta}$, using a proxy variable method that addresses the endogeneity of inputs due to the presence of unobserved productivity shocks.

Following Levinsohn and Petrin (2003), I write the so-called *control function*, which takes the following form:

$$m_{ij,t} = m_t(\omega_{ij,t}; k_{ij,t}, \mathbf{C}_{ij,t}), \tag{26}$$

This equation states that a firm chooses its flexible input material based on observed productivity $\omega_{ij,t}$, the state variable capital $k_{ij,t}$, and potentially other control variables grouped in $\mathbf{C}_{ij,t}$. Crucially, similar to prior works, I assume that Equation (26) is monotonic in firm productivity, ensuring a unique mapping from productivity to observed inputs. This assumption is essential, as it allows me to rewrite Equation (25) as a function of observables only:

$$\begin{aligned} y_{ij,t} &= f(\mathbf{I}_{ij,t}; \boldsymbol{\beta}) + g_t(m_{ij,t}; k_{ij,t}, \mathbf{C}_{ij,t}) + \varepsilon_{ij,t} \\ &= \psi_{ij,t} + \varepsilon_{ij,t}, \end{aligned}$$

where $\omega_{ij,t} = g_t(m_{ij,t}; k_{ij,t}, \mathbf{C}_{ij,t})$ is the inverse function of $m_t(.; k_{ij,t}, \mathbf{C}_{ij,t})$. The estimation procedure follows three steps.

Step 1: Fit a third-order polynomial regression of log output $y_{ij,t}$ on $\mathbf{I}_{ij,t}$, a vector of input variables defined above. From this regression, I obtain an estimate of log output net of measurement error, $\widehat{\psi}_{ij,t}$, as well as residuals $\widehat{\varepsilon}_{ij,t}$.

Step 2: Next, I assume that the unobserved productivity term $\omega_{ij,t}$ follows a first-order Markov process. Given this, I construct a measure of firm productivity $\omega_{ij,t}(\widehat{\boldsymbol{\beta}})$ as the difference between the predicted output $\widehat{\psi}_{ij,t}$ and the deterministic part of the production function:

$$\omega_{ij,t}(\widehat{\boldsymbol{\beta}}) = \widehat{\psi}_{ij,t} - f(\mathbf{I}_{ij,t}; \widehat{\boldsymbol{\beta}}).$$

Then, I construct a proxy for the innovation in productivity, $\vartheta_{ij,t}(\widehat{\boldsymbol{\beta}})$, by estimating the following autoregressive process of order three:

$$\omega_{ij,t}(\widehat{\boldsymbol{\beta}}) = \sum_{p=0}^{3} \rho_p \omega^p_{ij,t-1}(\widehat{\boldsymbol{\beta}}) + \vartheta_{ij,t},$$

and obtain $\vartheta_{ij,t}(\hat{\boldsymbol{\beta}})$ as the residual from this regression.

Step 3: Because capital $k_{ij,t}$ is chosen at time $t-1$, while the flexible inputs $l_{ij,t}, m_{ij,t}, e_{ij,t}$ are chosen at time t, the input choices are assumed to be orthogonal to future productivity innovations. This leads to the following moment conditions that identify the vector of production function coefficients $\boldsymbol{\beta} \in \mathbb{R}^Z$:

$$\mathbb{E}(\vartheta_{ij,t}(\boldsymbol{\beta})\mathbf{z}_{ij,t}) = 0_{\mathbf{Z}\times 1}$$

where the vector $\mathbf{z}_{ij,t}$ includes one-period lagged values of all polynomial terms involving $l_{ij,t}, m_{ij,t}, e_{ij,t}$ in the production function, while keeping capital $k_{ij,t}$ fixed at its current value. Based on these moment conditions, I obtain estimates of the output elasticities by solving the following minimization problem:

$$\hat{\hat{\beta}} = \arg\min_{\beta\in\mathbb{R}^Z} \sum_{m=1}^{Z} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \vartheta_{i,t}(\boldsymbol{\beta}) z^m_{i,t} \right]^2 \quad \text{where} \quad z_{it} = (z_{1,it}, \ldots, z_{Z,it})'.$$

Once $\boldsymbol{\beta}$ is recovered, the output elasticities are either directly equal to the parameters in the case of a Cobb-Douglas specification, or they can vary across firms under a translog specification that allows for heterogeneity. In the latter case, elasticities depend linearly on the product of the parameter vector $\boldsymbol{\beta}$ and the firm specific input intensity vector $\mathbf{I}_{ij,t}$.

6.2 Markups & Markdowns: Results

Here, I report the main empirical results on markups and markdowns. The analysis is based on a non-balanced panel of Chilean manufacturing plants (ENIA), covering two decades from 1995 to 2015. The dependent variable is gross output, proxied by nominal revenues. The vector of input variables includes total nominal expenditures on capital, materials, and energy. Capital is measured as the total value of land, buildings, machinery, and vehicles. Materials include the total value of raw and intermediate inputs. Energy input is captured either by total electricity usage (in T/KWh) or by the total value of fuels used in production (e.g., coal and petroleum). Labor input is measured as total headcount. Deflated variables are constructed using deflators provided by the Central Bank of Chile. Specifically, output deflators are industry-specific, while input deflators are economy-wide.

Table 4 reports the estimated plant-level markups for the Chilean manufacturing sector. The results lend strong support to the existence of substantial market power over the sample period: the median plant charges a price that is 36% above marginal cost. Markups also vary widely across industries. The average interquartile range is 0.60, indicating that some industries enjoy markedly greater market power than others. For example, "Textiles, Clothing, and Leather" has a median gross markup of 1.10 which is only slightly above the perfectly competitive benchmark of one whereas "Paper and Printing" has median markups of 1.77 that are 52% higher than those in "Textiles, Clothing, and Leather." Table 4 further shows sizable dispersion within industries, suggesting that firm-specific characteristics drive market-power differences even among direct competitors.

Table 4: **Estimated Firm-Level Markups in Chilean Manufacturing**

	Median	**Mean**	**IQR**	**SD**
Basic Metals	1.20	1.33	0.59	0.47
Chemicals, Petroleum, Rubber, and Plastic	1.30	1.42	0.68	0.49
Food, Beverages, and Tobacco	1.38	1.46	0.56	0.43
Manufacture of Non-Metallic Mineral Products	1.17	1.34	0.63	0.48
Metal Products, Machinery, and Equipment	1.28	1.41	0.67	0.50
Others	1.38	1.47	0.62	0.45
Paper and Printing	1.73	1.77	0.88	0.55
Textiles, Clothing, and Leather	1.10	1.25	0.56	0.44
Wood and Furniture	1.36	1.46	0.58	0.46
Whole Sample	1.36	1.46	0.65	0.48
Observations	47663			

Note: Table 4 reports the estimated firm-level markups for the Chilean manufacturing sectors. Markups are estimated under the assumption of a Cobb-Douglas production function for gross output. The flexible input is material which is the total value of raw materials and intermediate materials. Production functions are estimated by 2-digit ISIC classifications. Nominal values are deflated using industry level output deflators and economy-wide deflators for capital, material, and energy provided by the Central Bank of Chile (*Banco Central de Chile*).

Next, I turn to Table 5, which reports the corresponding results for markdowns. Table 5 paints a similar picture regarding labor market power among Chilean firms. The median markdown in the sample is 0.70, implying that firms pay workers only 70% of their marginal revenue product in the form of wages. Put differently, for every dollar of output a worker helps produce, they take home just 70 cents. As with markups, markdowns vary across industries: the interquartile range is 0.75, even higher than in the markup distribution, suggesting greater dispersion in labor market power. Again, firm-specific characteristics also drive variation within industries, leading to substantial heterogeneity even among firms operating in the same sector. For instance, in the "Basic Metals" industry, the standard deviation of markdowns is 0.50. This indicates that markdowns in that sector are widely dispersed around the mean, some firms may have near competitive wage-setting (markdowns close to 1), while others may exercise significant labor market power, paying a much smaller share of the marginal revenue product to workers.

Table 5: **Estimated Firm-Level Markdowns in Chilean Manufacturing**

	Median	**Mean**	**IQR**	**SD**
Basic Metals	0.65	0.78	0.65	0.45
Chemicals, Petroleum, Rubber, and Plastic	0.45	0.57	0.37	0.33
Food, Beverages, and Tobacco	1.06	1.11	0.88	0.49
Manufacture of Non-Metallic Mineral Products	0.76	0.86	0.78	0.48
Metal Products, Machinery, and Equipment	0.61	0.73	0.52	0.40
Others	0.91	0.96	0.71	0.45
Paper and Printing	1.06	1.06	0.86	0.49
Textiles, Clothing, and Leather	0.44	0.52	0.25	0.28
Wood and Furniture	0.80	0.90	0.70	0.46
Whole Sample	0.70	0.85	0.75	0.48
Observations	42196			

Note: Table 5 reports the estimated firm-level markdowns for the Chilean manufacturing sectors. Markdowns are estimated under the assumption of a Cobb-Douglas production function for gross output. The flexible input is material which is the total value of raw materials and intermediate materials. Production functions are estimated by 2-digit ISIC classifications. Nominal values are deflated using industry level output deflators and economy-wide deflators for capital, material, and energy provided by the Central Bank of Chile (*Banco Central de Chile*).

In summary, Table 4 and Table 5 provide strong evidence of substantial market power in both output and labor markets. I use the estimated distributions of markups and markdowns to pin down the differences in inverse elasticities in Equation (17) and Equation (20), which serve as two of the targeted moments in the estimation of the four elasticities. These distributions also inform the construction of the aggregate markup and markdown, which constitute the two remaining targeted moments in the estimation strategy. Further details are provided below.

6.3 Calibration

I begin by describing the set of externally calibrated parameters of the model. These parameters are calibrated using data moments from both ENIA and customs-level data. I then outline the methodology used to internally estimate the four key elasticities of the model. Together, the externally calibrated parameters and the internally estimated elasticities form the full set of parameters used in the quantitative analysis and in deriving the aggregate implications discussed in Section 7.

Externally Calibrated Parameters Table 6 lists the externally calibrated parameters. The number of local labor markets, J, is set to 210, matching the estimate for Chile in Section 4. The upper bound on firms per market, M_j, equals the maximum observed in ENIA, after which the actual count in each market is drawn once from a uniform distribution and held fixed. Each firm serves three destinations, so N_k equals three. Firm productivity, Ω_{ij}, follows a log-normal distribution with mean μ_Ω equal to -1.35 and variance σ^2_Ω of 0.84, parameters obtained via maximum-likelihood estimation on productivity estimates obtained from the production-function estimation reported above. Figure B.6 in Appendix B compares the empirical productivity distribution with this fitted log-normal. Exchange rate shocks are drawn from a standard normal distribution. I assume that firms use only foreign intermediate inputs in production. This implies that the share of intermediate inputs in production, denoted by ϕ, directly determines the sensitivity of marginal cost to exchange rate fluctuations. I calibrate ϕ using the empirical distribution of import intensity, φ_{ij}. [22] Specifically, I model φ_{ij} as log-normally distributed, with mean μ_φ equal to -2.62 and variance σ^2_φ equal to 1.72, estimated via maximum likelihood using firm-level data (see Figure B.7 in Appendix B). Finally, the quality term $\xi_{k,ij,t}$ in Equation (1) is drawn from an exponential distribution with scale parameter $\lambda_\xi = 1$.

Table 6: **Calibrated Parameters**

Parameter	**Description**	**Value**
J	Number of Labor Markets	210
M_j	Max Firms per Labor Market	310
N_k	Number of Destinations	3
μ_Ω	Mean of $\log(\Omega_{ij,t})$	-1.35
σ^2_Ω	Var of $\log(\Omega_{ij,t})$	0.84
μ_{e_k}	Mean of ER	0
$\sigma^2_{e_k}$	Var of ER	1
$\mu_{\varphi_{ij,t}}$	Mean of $\log(\varphi_{ij,t})$	-2.62
$\sigma^2_{\varphi_{ij,t}}$	Var of $\log(\varphi_{ij,t})$	1.72
$\lambda_{\xi_{k,ij,t}}$	Scale Par of Exp($\lambda_{\xi_{k,ij,t}}$)	1

Note: Table 6 reports the externally calibrated parameters. J and M_j are directly calibrated using ENIA data. The parameters governing the productivity and import intensity distributions are estimated via maximum likelihood. N_k, the exchange rate distribution, and the quality parameter distribution are externally set based on model assumptions.

Internally Estimated Parameters Similarly, Table 7 lists the internally estimated parameters. I estimate the optimal model parameter vector, $\Theta = \rho, \eta, \delta, \theta$, using a two-step Simulated Method of Moments (SMM) procedure. The optimal vector $\widehat{\theta_{SMM}}$ solves:

$$\widehat{\theta_{SMM}} = \arg\min_\theta \left(\frac{\hat{m}(\tilde{x}|\theta) - m(x)}{m(x)}\right)' W \left(\frac{\hat{m}(\tilde{x}|\theta) - m(x)}{m(x)}\right),$$

where $m(x)$ is the vector of data moments, $\hat{m}(\tilde{x}|\theta)$ is the vector of average simulated moments, and W is the optimal weighting matrix estimated in the first step. The estimation procedure follows these steps. For each simulated economy and a given guess of the model parameters, compute the model-based equivalents of β, γ, aggregate markup, and aggre-

[22] The simplifying assumption that import intensity is exogenous and equal to the share of intermediate inputs in production is without loss of generality and does not affect the theoretical results of the model.

gate markdown. Then, take the average across 50 simulated economies and compute the weighted percentage difference relative to the corresponding data moments. Repeat this process until convergence. [23] The estimation is exactly identified, with four parameters matched to four moments: $m(x) = \gamma, \beta, \mathcal{M}_t, \mu_t$. The targeted moments for β and γ are -0.18 and 0.42, respectively.

Table B.10 in Appendix B reports the estimated coefficients from Equations (18) and (21), which are statistically significant at the 1% level. The targeted aggregate markup $\mathcal{M}_t$ is 1.22, and the aggregate markdown μ_t is 0.68. Table B.11 shows summary statistics, while Figures B.4 and B.4 illustrate their time series evolution.

Table 7: **Estimated Parameters**

Parameter	Description	Value	Targeted Moment	Model Moment
ρ	Within Sector Substitutability	12	$\mathcal{M}_t = 1.22$	1.21
η	Cross Sector Substitutability	1.8	$\beta = -0.18$	-0.20
δ	Within Labor Market Substitutability	8	$\mu_t = 0.68$	0.72
θ	Cross Labor Market Substitutability	0.48	$\gamma = 0.42$	0.55

Note: Table 7 reports the internally calibrated parameters.

The estimation procedure produces the following results. The elasticity of substitution across sectors is low, with a point estimate of 1.8, while the elasticity of substitution across goods within sectors is 12. The parameters governing labor market dynamics indicate an elasticity of 8 within local labor markets and 0.48 across labor markets.

7 Quantification & Aggregate Implications

In this section, I evaluate the model's ability to replicate the heterogeneous exchange rate pass-through to prices and wages documented in Section 5. I then interpret these findings through the lens of the model, which allows me to quantify the role of variable markdowns in explaining cross-sectional differences in firms' sensitivity of prices and wages. I conclude the section by deriving new aggregate predictions and test them against the data.

Variable Markdown: Firm Heterogeneity Here, I assess the model's ability to quantitatively replicate the type of cross-sectional heterogeneity in exchange rate pass-through to export prices and domestic wages documented in Section 5. To do so, I use the model calibrated with the parameters estimated in Section 6 to generate a simulated panel of firms and estimate the model-based equivalent of the empirical specifications in Equations (16) and (15). Specifically, the model is calibrated using both the externally set parameters reported in Table 6 and the estimated parameters in Table 7. I then simulate an exchange rate series

[23] Consistent with the production function assumptions, each firm belongs to only one industry. While I estimate production functions for nine industries, in the estimation procedure I limit the number of industries to four, as computation time increases sharply with the number of industries.

over a 10-period horizon to mirror the 1997–2007 period in the data. This generates a simulated firm-level panel that can be used to estimate the model-based analogues of Equations (16) and (15). [24]

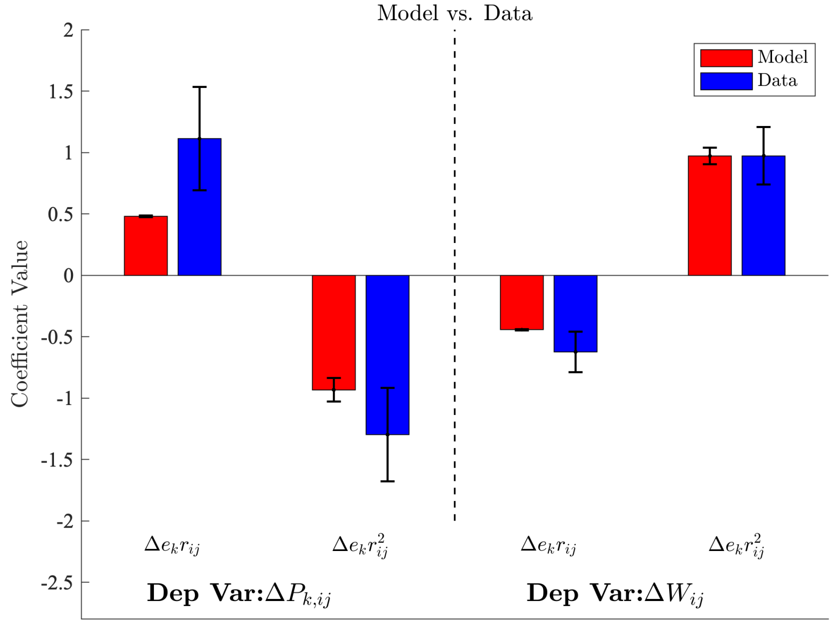

Figure 7: Exchange Rate Pass-Through Coefficients: Model vs Data.

Note: Figure 7 compares the exchange rate pass-through coefficients to export prices and domestic wages as a function of the firm's payroll share, r_{ij}, estimated in the data and reported in Column (4) of Tables 3 and 2, respectively. The model implied coefficients are obtained by estimating a specification equivalent to Equations (16) and (15) on a simulated panel spanning 10 time periods.

The results are reported in Figure 7, which compares the exchange rate pass-through coefficients to export prices and domestic wages as a function of the firm's payroll share, r_{ij}, estimated in the data and reported in Column (4) of Tables 3 and 2, respectively. The model matches both qualitatively and quantitatively the type of heterogeneity observed in the data.

Specifically, it replicates the U-shaped relationship between the sensitivity of domestic wages and the firm's payroll share, as well as the hump-shaped relationship between the sensitivity of export prices and the payroll share. This serves as an initial validation of both the model and the estimated parameters, as the exchange rate pass-through coefficients are untargeted moments. Next, I use the model to quantify the role of variable markdowns in generating the cross-sectional heterogeneity observed in the data and matched by the calibrated model.

[24] It is important to note two key differences between the model and the empirical data-generating process for the exchange rate pass-through coefficients. First, the empirical coefficients are estimated using within-sector–destination-LLM variation across firms, while the model is calibrated to a single representative sector and exploits firm-level variation within that sector. Second, for computational reasons, I reduce the number of destination markets from the empirical average of seven to three in the simulation. Again, these simplifications do not affect identification, since the coefficients are estimated using variation across firms within each sector–destination-LLM for prices and within LLM for wages.

Table 8: Firm Level ERPT Decomposition: Role of Variable Markdown

	Large Employer		Small Employer	
Component	Change	Contribution	Change	Contribution
Δw_{ij}	1.30%	25%	1.50%	36.5%
$\Delta \mu_{ij}$	-1.90%	36.5%	-0.65%	15.8%
ΔMPL_{ij}	-1.65%	31.7%	-1.91%	46.5%
$\Delta \mathcal{M}_{ij}$	-0.35%	6.7%	-0.04%	0.97%
ΔP_{ij}	4.50%	100%	4.02%	100%

Note: Table 8 reports the price decomposition following an exchange rate depreciation of 10%. A large employer is defined as a firm whose individual payroll share is between 20-30%. A small employer is defined as a firm individual payroll shares is between 0.01% and 5%. Note that: $\Delta P_{ij} = \Delta \mathcal{M}_{ij} + \Delta w_{ij} - \Delta \mu_{ij} - \Delta \text{MPL}_{ij}$, $\text{Contribution}_i = 100 \times |\text{Contribution}_i| / |\sum_i \text{Contribution}_i|$.

Table 8 presents the results of the price decomposition exercise illustrated in Figure 2. It reports the components of the resulting price change following an exchange rate shock of 10%, and their relative contributions for different types of employers. Any change in prices can be decomposed into four components, listed in the rows of Table 8: changes in markdowns, wages, markups, and the marginal product of labor.

The first two columns report the decomposition for a large employer: a firm whose individual payroll share in its local labor market is roughly 20–30 percent. The last two columns show the same exercise for a small employer, which hold on average 0.01–5 percent of payroll.[25]

Table 8 highlights how variable markdowns mediate the transmission of an exchange-rate depreciation to prices and domestic wages. Large employers exhibit an exchange rate pass-through to wages of about 13 percent, roughly 12 percentage points lower than that of small employers. This gap is driven primarily from the greater markdown elasticity of large firms: they cut markdowns by 1.90 percent, versus 0.65 percent for small firms. Diminishing returns of labor yields a milder decrease in the marginal product of labor (MPL) for large firms. Markups respond differently as well. Large firms, who also have significant product market power, reduce markups by 0.35 percent, compared with 0.04 percent for small firms. Combining all four components, the pass-through to export prices is 45 percent for large employers and a little above 40 percent for small ones. Moreover, Table 8 quantifies the relative contribution of product and labor market imperfections. Variable markdowns play an important quantitative role in explaining incomplete ERPT to export prices for both types of employers, but their contribution is relatively larger for large employers. Specifically, variable markdowns account for about 36% of incomplete ERPT to export prices among large employers, compared to roughly 16% for small employers.

This decomposition illustrates the key mechanism driving the model's results and pro-

[25]The comparison between large and small employers refers to firms whose payroll share lies below the inflection point. In other words, I focus on the decreasing segment of the U-shaped relationship between ERPT to wages and payroll share, and the corresponding hump-shaped relationship between ERPT to prices and payroll share. The same but reverse intuition applies to the other segment of the relationship.

vides a lens through which to interpret the empirical findings. Before the exchange rate depreciation, large employers were already employing most of the workers in their local labor markets. As a result, they face steeper marginal cost of labor curves. When the exchange rate shock occurs, marginal costs increase due to higher prices of intermediate inputs. In turn, this change affects firms' first-order condition for labor. Large firms respond by expanding labor input through higher wages and lower markdowns. The combined effect of these two adjustments leads to a larger increase in the marginal cost of labor for large firms. This is a direct consequence of their originally steeper labor supply curves. To absorb the higher marginal cost, driven by both more expensive imports and rising labor costs, large firms also reduce markups more aggressively. The net effect is that large firms require a larger price adjustment compared to smaller firms.

Variable Markdown: Local Labor Market Heterogeneity In what follows, I show the effect of an exchange rate shock to aggregate domestic wages and to aggregate export prices. The level of aggregation is at the local labor market level. To do so, I repeat an exercise similar to the one exposed in the previous section. That is, I use the model to obtain a simulated panel of firms after generating a time series of exchange rate shocks over 10 time periods. Then, I aggregate the firm level variables at the local labor market level.

At the firm level, the model is tractable and, as shown in Section 2, yields closed-form solutions for the desired exchange rate pass-through to export prices and domestic wages. These are functions of key endogenous variables: export market shares, payroll shares, and import intensity. Aggregation to the labor market level remains tractable, but the resulting closed-form expressions for prices and wages are difficult to interpret. Appendix A.9 details the system of equations used for aggregation.[26]

Thus, to derive testable predictions, I solve this system using closed-form expressions for aggregate wages and prices, calibrated to the parameters reported in Tables 6 and 7. The aim is to illustrate how two labor markets with identical distributions of export shares and import intensities across firms, but different distributions of payroll shares, display different sensitivities of aggregate export prices and wages to exchange rate shocks. This setup isolates the role of payroll share concentration and it simplifies the analysis by holding two endogenous distributions constant across labor markets.

The model delivers clear predictions: i) aggregate wage sensitivity is decreasing in the level of concentration in the labor market, ii) aggregate price sensitivity is increasing in the level of concentration in the labor market. I proxy labor market concentration using the HHI based on payroll shares.

Figure 8 visualizes the relationship between aggregate wages, export prices, and the pay-

[26]The system of two equations reported in Appendix A.9 determines two unknowns: aggregate wage and aggregate price at the local labor market level. Given a set of parameters, the system is pinned down by the distribution of export market shares, payroll shares, and import intensity. It generalizes the result in Amiti et al. (2019). Unlike Amiti et al. (2019), labor input is endogenously chosen, and thus wages are endogenous as well. The system in Appendix A.9 nests the one in Amiti et al. (2019) as a special case under perfect competition in the labor market.

roll share HHI, conditional on a fixed distribution of import intensity and export market shares. The x-axis measures the aggregate cumulative payroll share of the top 10 firms in a labor market. Each line in Figure 8 shows the response of aggregate prices and wages across local labor markets, holding constant the local payroll share $r_j = \frac{w_j l_j}{\sum_j w_j l_j}$ in the aggregate economy. As labor market j becomes more important in the aggregate economy, $r_j \to 1$, the line becomes a darker shade of red. This captures equilibrium effects across labor markets. Holding local labor market concentration fixed, when a labor market accounts for a larger share of the aggregate wage bill, both aggregate wages and aggregate prices become less responsive.

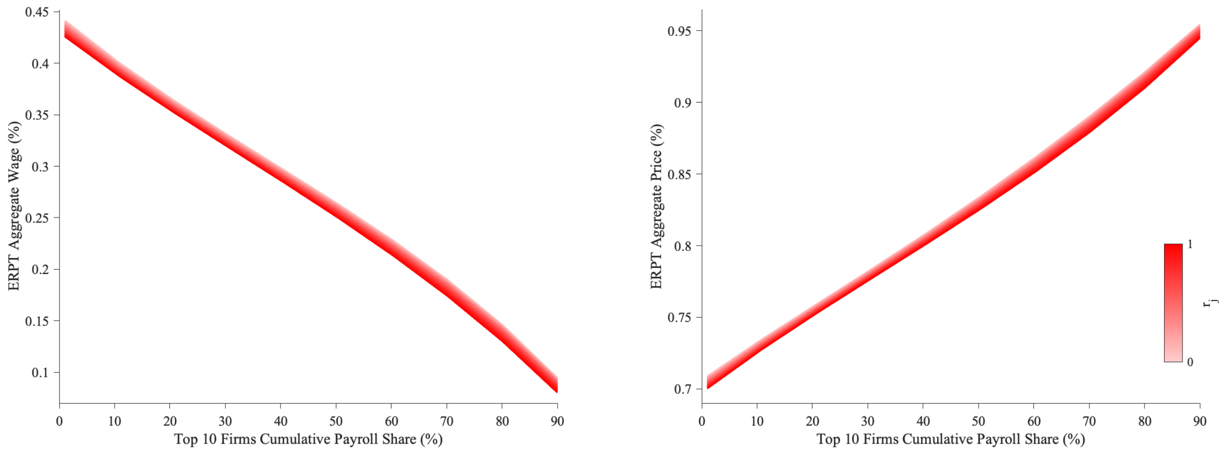

Figure 8: ERPT To Aggregate Wage and Price and Labor Market Power: Model Predictions

Note: Each line in Figure 8 shows the response of aggregate wages (left panel) and aggregate prices (right panel) across local labor markets, holding constant the local payroll share r_j in the aggregate economy. As labor market j becomes more important in the aggregate economy, $r_j \to 1$, the line becomes a darker shade of red (the line shifts downward). The x-axis measures the aggregate cumulative payroll share of the top 10 firms in a labor market. Parameters are set to those reported in Table 7 and Table 6. The distribution of φ_{ij} is drawn from a uniform distribution between 0.01 and 0.3. The distribution of $S_{k,ij}$ is drawn from a Dirichlet distribution. Consistent with the theory, there is positive covariance between payroll share, export share, and import intensity.

Figure 8 also motivates the specifications used to relate aggregate wage and price sensitivity to local labor market concentration. Unlike the firm-level analysis presented in previous sections, the relationship between aggregate exchange rate pass-through to wages and prices is modeled as linear in labor market concentration and does not feature any quadratic terms. More precisely, let

$$\Psi^{P^\star}_{k,j,t} \equiv \sum_i S_{k,ij,t} \Delta \log P^\star_{k,ij,t}$$

be the aggregate export price change to destination k for labor market j at time t. Similarly, let

$$\Psi^{W}_{j,t} \equiv \sum_i r_{ij,t} \Delta \log W_{ij,t}$$

be the aggregate domestic wage change for labor market j at time t. Also, let the payroll-weighted average firm import intensity be defined as

$$\overline{\varphi}_{ij,t} \equiv \sum_i r_{ij,t}\varphi_{ij,t},$$

which captures the average import intensity of firms located in labor market j, weighted by their respective payroll shares in that market. Therefore, the specification for aggregate wage sensitivity is:

$$\begin{aligned}\Psi^W_{j,t} = \alpha\,\Delta\log e_{k,t} + \beta\,\mathrm{HHI}^r_{ij,t} + \gamma\,\mathrm{HHI}^s_{ij,t} + \delta\,\overline{\varphi}_{ij,t} + \\ + \left(\varepsilon\,\mathrm{HHI}^r_{ij,t} + \zeta\,\mathrm{HHI}^s_{ij,t} + \eta\,\overline{\varphi}_{ij,t}\right)\Delta\log e_{k,t} + \theta_{jt},\end{aligned} \tag{27}$$

where $\mathrm{HHI}^r_{ij,t} = \sum_{i\in J} r^2_{ij,t}$ is the HHI of payroll shares of firms active in labor market j at time t, and $\mathrm{HHI}^s_{ij,t} = \sum_{i\in J} S^2_{ij,t}$ is the HHI of export market shares for firms that are active in labor market j at time t. The main coefficient of interest is ε, which captures the interaction between the proxy for labor market concentration, $\mathrm{HHI}^r_{ij,t}$, and the change in the bilateral exchange rate, $\Delta\log e_{k,t}$. Similarly, the specification for aggregate price sensitivity is:

$$\begin{aligned}\Psi^{P\star}_{k,j,t} = \iota\,\Delta\log e_{k,t} + \kappa\,\mathrm{HHI}^r_{ij,t} + \lambda\,\mathrm{HHI}^s_{k,ij,t} + \mu\,\overline{\varphi}_{ij,t} + \\ + \left(\nu\,\mathrm{HHI}^r_{ij,t} + \xi\,\mathrm{HHI}^s_{k,ij,t} + o\,\overline{\varphi}_{ij,t}\right)\Delta\log e_{k,t} + \pi_{kjt}.\end{aligned} \tag{28}$$

In this case, the main coefficient of interest is ν. I estimate Equations (27) and (28) using both aggregate data and the simulated aggregate data generated from the model. The aggregate data source is the same as that introduced in Section 3 and then used in Section 5 for the firm-level analysis.

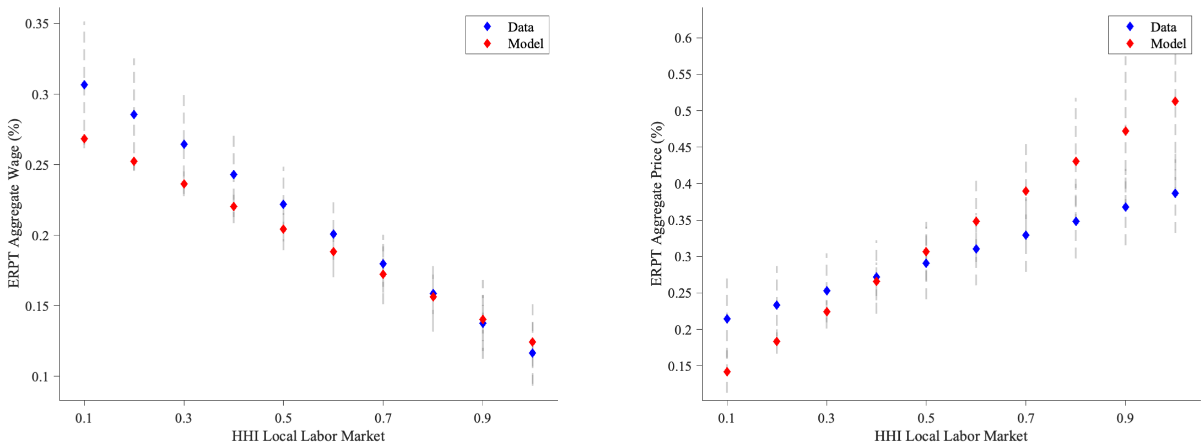

Figure 9: ERPT To Aggregate Wage and Price and Labor Market Power: Model vs Data

Note: Figure 9 plots the estimated exchange rate pass-through to aggregate wage (left panel) and to aggregate export prices (right panel) for different levels of local labor market concentration in the data (blue dots) and in the simulated data (red dots). More precisely, the right panel of Figure 9 plots the marginal effect of exchange rate changes on $\Psi^W_{j,t}$ by $\text{HHI}^r_{ij,t}$, evaluating $\text{HHI}^s_{ij,t}$ and $\overline{\varphi}_{ij,t}$ at their average values in the corresponding two samples. The coefficients are estimated by running Equation (27) in the data and in the simulated data. The left panel plots the equivalent object estimated from Equation (28). Dashed gray lines represent confidence intervals at the 95% level.

Figure 9 plots the results. Both panels validate the aggregate predictions of the model, both qualitatively and quantitatively. In particular, the right panel shows the marginal effect of exchange rate changes on $\Psi^W_{j,t}$ as a function of $\text{HHI}^r_{ij,t}$, evaluating $\text{HHI}^s_{ij,t}$ and $\overline{\varphi}_{ij,t}$ at their respective sample averages. For labor markets with a payroll share concentration $\text{HHI}^r_{ij,t}$ around 0.10, both the model and the data estimate an ERPT to aggregate wages between 26% and 31%. The corresponding sensitivity of aggregate prices ranges between 15% and 21%. By contrast, labor markets with $\text{HHI}^r_{ij,t}$ around 0.30, above the 0.25 threshold typically considered indicative of high concentration, display an aggregate wage sensitivity that is approximately 10 percentage points lower than in nearly perfectly competitive markets. In contrast, the sensitivity of aggregate prices is about 5 percentage points higher.

To interpret the negative correlation between aggregate wage sensitivity and labor market concentration I turn to my last theoretical result. I shut down imperfect competition in the product market to make analytically tractable the system of equations that pins down aggregate wages and prices in Appendix A.9.

Proposition 6 *If the product market is perfectly competitive, then pass-through of a bilateral exchange rate shock to the aggregate domestic wages $\Psi^W_{j,t}$ in labor market j is equal to:*

$$\Psi^W_{j,t} = 1 - \overline{\varphi}_{ij,t} + \frac{\text{Cov}\left(sc^\ell_{ij},\, \varphi_{ij,t}\right)}{1 - \overline{sc}^\ell_{ij}},$$

where $\overline{\varphi}_{ij,t} \equiv \sum r_{ij}\varphi_{ij,t}$, $\text{Cov}\left(sc^\ell_{ij},\, \varphi_{ij,t}\right) \equiv \sum r_{ij}(sc^l_{ij} - \overline{sc}^l_{ij})\varphi_{ij,t}$, $sc^l_{ij} \equiv -\frac{\eta_{ij}}{(1-\eta_{ij}-r_{ij})} \in [0,1)$, $\overline{sc}^\ell_{ij} \equiv \sum_{i\in J} r_{ij} sc^l_{ij}$. [27]

[27] This result exactly mirrors the result in Amiti et al. (2019) but for the labor market.

Proof: *See Appendix A.10*

Proposition 6 offers insight into the observed negative correlation between aggregate wage sensitivity and labor market concentration. In the absence of import intensity, firms are only exposed to the export price channel discussed in Proposition 1, which leads to complete ERPT to aggregate wages, regardless of the presence of strategic complementarities in wage setting. However, when firms do rely on imported inputs, the import cost channel becomes relevant (again, per Proposition 1), and higher aggregate import intensity reduces ERPT to wages, dampening the overall wage response.

Moreover, the elasticity of an individual firm's wage with respect to the local wage index, denoted by sc^l_{ij}, is increasing in the firm's payroll share r_{ij}. This elasticity captures the strength of strategic complementarities in wage setting: as other firms raise wages, a firm must also raise wages to attract workers. Since more import-intensive firms also tend to exhibit higher sc^l_{ij}, the covariance between import intensity and wage elasticity is expected to be positive. This term increases aggregate wage sensitivity because it amplifies wage adjustments in response to labor market conditions. Despite this, the negative correlation between aggregate wage sensitivity and labor market concentration suggests that the dampening effect of aggregate import intensity outweighs the amplifying role of strategic wage complementarities. In more concentrated labor markets, where large firms dominate and are often more import-intensive, the negative effect on ERPT to wages is stronger, resulting in lower overall wage sensitivity.

Table 9: Decomposition of Aggregate Wage ERPT Across Local Labor Markets

	High Concentration LLM			**Low Concentration LLM**		
Perfect Labor Market	✓	×	×	✓	×	×
Perfect Product Market	✓	✓	×	✓	✓	×
$1-\overline{\varphi}_{ij,t}$	0.72	0.72	0.72	0.80	0.80	0.80
$\text{Cov}(sc^{\ell}_{ij},\, \varphi_{ij,t})/(1-\overline{sc}^{\ell}_{ij})$	0	0.09	0.06	0	0.04	0.05
Product Market Wedge $\omega_{j,t}$	0	0	0.03	0	0	0.01
$\Psi^W_{j,t}$	0.72	0.81	0.81	0.80	0.84	0.86

Note: Table 9 reports the decomposition of the ERPT to aggregate wage across local labor markets with high and low concentration. Each column corresponds to a different combination of product market and labor market imperfections. A check-mark (✓) indicates perfectly competitive markets, while a cross (×) indicates the absence of perfect competition. The decomposition includes (i) the import share channel $1-\overline{\varphi}_{ij,t}$, (ii) the covariance term $\text{Cov}(sc^{\ell}_{ij},\, \varphi_{ij,t})/(1-\overline{sc}^{\ell}_{ij})$, and (iii) the residual product market wedge ω_j capturing deviations from perfect competition or monopolistic competition in the product market.

Table 9 reports the decomposition of aggregate wages following a bilateral exchange rate depreciation according to Proposition 6 across two types of local labor markets: a highly concentrated labor market in terms of payroll distribution and a less concentrated one. The decomposition is shown under three scenarios: (i) both product and labor markets are perfectly competitive (ii) only the labor market is oligopolistic as in the benchmark model while the product market is perfectly competitive, and (iii) the benchmark case in which both product and labor markets are imperfectly competitive, as modeled in the main text. Proposition 6 applies strictly to perfectly competitive product markets, therefore, deviations from the formula in scenario (iii) are captured by the wedge ω_j, representing the effect of product market imperfections.[28]

Turning to the results, when both markets are perfectly competitive, aggregate wage sensitivity depends solely on the average import intensity of firms. As expected, more concentrated labor markets, which tend to have larger and more productive firms with higher import intensity, exhibit lower wage sensitivity. When only the labor market is imperfect, strategic complementarities in wages, captured by the covariance term, influence aggregate wage sensitivity. Here, concentrated markets again display stronger effects, as large employers react more to competitors' wage adjustments and the correlation between import intensity and wage response is higher. Finally, in the benchmark scenario, product market imperfections contribute positively through ω_j in concentrated markets. Intuitively, large exporting firms reduce markups by more, raising the marginal revenue product of labor and this induces higher wage responses. This intuition enters clearly the F.O.C for labor input. Overall, the decomposition highlights that both wage complementarities and product market imperfections have quantitatively similar effects on shaping aggregate wage sensitivity.

These results have clear policy implications and applications. The key implication is that they challenge the traditional view that exchange rate changes are solely transmitted to prices. Instead, they provide evidence that wages, and therefore household income, are also affected, with potential welfare consequences. The policy application is also straightforward: policymakers can estimate the specifications in Equations (27) and (28) using readily available data on aggregate export market shares, wage bills, import intensity, and custom level data. Additionally, the approach grants policymakers an extra degree of flexibility, as they must define what constitutes a local labor market, that is the market in which labor demand and supply interact. For instance, one can run Equations (27) and (28) at the sectoral level and identify those sectors whose aggregate wages and prices are most exposed to exchange rate shocks.

[28]Formally, perfect competition in the product market arises as $\eta \to \infty$, which implies unit markups. Similarly, perfect competition in the labor market obtains as $\delta \to \infty$, yielding unit markdowns. In both limits, markups and markdowns become constant, eliminating their variability, the key factor determining how firms absorb real shocks. One would obtain qualitative similar results as those in Table 9 if firms are assumed to be infinitesimal in the product and/or labor market, which also implies constant (though not necessarily unitary) markups and markdowns pinned down by η and δ, respectively. What matters for the decomposition is that their variability is again zero.

8 Conclusion

This paper studies the role of labor market power in shaping the transmission of exchange rate shocks to both domestic wages and export prices. By introducing variable markdowns into a model of international pricing with imperfect competition in product and labor markets, I show that firms' labor market power fundamentally alters the mechanisms driving ERPT. While traditional models emphasize markup adjustments as the key source of incomplete ERPT, my framework demonstrates that markdown variability plays an equally, if not more, important role.

Empirically, using matched employer–exporter data from Chile, I find that large employers display lower ERPT to domestic wages but higher ERPT to export prices expressed in producer currency. These results are consistent with the model's predictions: firms with greater labor market power face a smaller direct cost of labor adjustment but a larger scale effect as employment expands, amplifying the price response to exchange rate shocks. Quantitatively, variable markdowns explain roughly twice as much of the incomplete ERPT to prices as variable markups, highlighting the relevance of labor market power for international transmission of shocks.

At the aggregate level, I show that local labor market concentration reduces wage sensitivity to exchange rate movements, primarily because concentrated markets are dominated by large, import-intensive firms that amplify the cost channel. However, strategic wage complementarities and variable markups offset this effect by raising the marginal revenue product of labor, thereby amplifying aggregate wage responses.

Taken together, the findings suggest that understanding international price and wage dynamics requires accounting for heterogeneity in firms' labor market power. Incorporating markdown behavior into open-economy models provides a richer and more realistic view of exchange rate transmission, one in which both markets for goods and for labor shape the aggregate consequences of external shocks.

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A Theoretical Appendix

A.1 Proof of Proposition 1

The elasticity of the firm's markdown $\mu_{i,j}$ with respect to the firm's own wage $w_{i,j}$, without holding constant the local labor market level wage index $\mathbf{w}_j$, takes the following form:

$$\frac{\partial \log \mu_{ij}}{\partial \log w_{ij}} = \frac{\partial \log \mu_{ij}}{\partial \log \epsilon_{ij}} \frac{\partial \log \epsilon_{ij}}{\partial \log r_{ij}} \frac{\partial \log r_{ij}}{\partial \log w_{ij}}.$$

The first term, $\frac{\partial \log \mu_{ij}}{\partial \log \epsilon_{ij}}$, is the elasticity of the markdown with respect to the labor supply elasticity and it is equal to:

$$\frac{\partial \log \mu_{ij}}{\partial \log \epsilon_{ij}} = \frac{\mu_{ij}}{\epsilon_{ij}},$$

the second term, $\frac{\partial \log \epsilon_{ij}}{\partial \log r_{ij}}$, is the elasticity of the elasticity with respect to the payroll share and it is equal to:

$$\frac{\partial \log \epsilon_{ij}}{\partial \log r_{ij}} = -\left(\frac{1}{\delta} - \frac{1}{\theta}\right) \epsilon_{ij} r_{ij},$$

lastly, the third term, $\frac{\partial \log r_{ij}}{\partial \log w_{ij}}$, is the elasticity of the payroll share with respect to the wage and it is equal to:

$$\frac{\partial \log r_{ij}}{\partial \log w_{ij}} = (1+\delta)(1-r_{ij}).$$

Combining the three expression above yields the expression in the main text. That is,

$$\eta_{ij}(r_{ij}) \equiv \frac{\partial \log \mu_{ij}}{\partial \log w_{ij}} = (r_{ij}^2 - r_{ij})\mu_{ij}\left(\frac{1}{\theta} - \frac{1}{\delta}\right)(1+\delta) \leq 0 \qquad \blacksquare$$

A.2 Firm Marginal Cost

The firm minimizes total cost $\mathrm{TC}_{ij}^{\star}$ in producer currency:

$$\min_{\substack{x_{ij},\{x_{ij,a},z_{ij,a}\} \\ \{m_{ij,a}\},l_{ij}}} \quad \mathrm{TC}_{ij}^{\star}(y_{ij} \mid A_{0,ij}) = \underbrace{w(l_{ij}, \bar{l}_{-ij}, \mathbf{L}_t, \mathbf{W}_t) l_{ij}}_{\text{Labor Cost}} + \underbrace{\int_0^1 V_a^{\star} z_{ij,a} da}_{\text{Local Intermediate Cost}} + \underbrace{\int_{A_{0,ij}} e_k U_a m_{ij,a} da}_{\text{Foreign Intermediate Cost}}$$

subject to:

$$y_{ij} = \Omega_{ij} x_{ij}^{\phi} l_{ij}^{1-\phi}, \qquad \phi \in [0,1] \tag{A.1}$$

$$x_{ij} = \exp\left\{\int_0^1 \gamma_a \log x_{ij,a} da\right\}, \qquad \int_0^1 \gamma_a da = 1 \tag{A.2}$$

$$x_{ij,a} = \left[z_{ij,a}^{\frac{\zeta}{1+\zeta}} + g_a^{\frac{1}{1+\zeta}} m_{ij,a}^{\frac{\zeta}{1+\zeta}}\right]^{\frac{1+\zeta}{\zeta}}, \qquad \zeta > 0 \tag{A.3}$$

where I plugged into the objective function the labor supply displayed in Equation (5). Let λ, ψ and χ be the Lagrangian multiplier associated with Equation (A.1), Equation (A.2), and Equation (A.3), respectively. The F.O.Cs can be re-written as:

$$w_{ij}l_{ij} = \mu_{ij}\lambda(1-\phi)y_{ij} \tag{A.4}$$

$$V_a^{\star}x_{ij,a} = \lambda\phi\gamma_a y_{ij}\left(\frac{x_{ij,a}}{z_{ij,a}}\right)^{1/(1+\zeta)} \qquad a \in [0,1] \tag{A.5}$$

$$m_{ij,a} = z_{ij,a}\left(\frac{e_k U_a}{V_a^{\star}}\right)^{-(1+\zeta)} \qquad a \in A_{0,ij} \tag{A.6}$$

with $x_{ij,a} = z_{ij,a}$ and $m_{ij,a} = 0$ for $a \in \tilde{A}_{0,ij} \equiv [0,1] \setminus A_{0,ij}$. Substituting Equation (A.6) into Equation (10), I obtain

$$x_{ij,a} = z_{ij,a}\left[1 + \left(\frac{e_k U_a}{V_a^{\star}}\right)^{-\zeta}\right]^{\frac{1+\zeta}{\zeta}} \qquad a \in A_{0,ij}$$

which together with Equation (A.5) yields:

$$V_a^{\star}x_{ij,a} = \begin{cases} \lambda\phi\gamma_a y_{ij} b_{ij,a} & a \in A_{0,ij} \\ \lambda\phi\gamma_a y_{ij} & a \in \tilde{A}_{0,ij} \end{cases}$$

where $b_{ij,a} \equiv \left[1 + \left(\frac{e_k U_a}{V_a^{\star}}\right)^{-\zeta}\right]^{\frac{1}{\zeta}}$. The marginal cost of the firm is derived by inserting the two different values of $x_{ij,a}$ into Equation (A.2):

$$\begin{aligned}
x_{ij} &= \exp\left\{\int_0^1 \gamma_a \log x_{ij,a} da\right\} \\
&= \exp\left\{\int_{A_{0,ij}} \gamma_a \log \frac{\lambda\phi\gamma_a y_{ij} b_{ij,a}}{V_a^{\star}} da + \int_{\tilde{A}_{0,ij}} \gamma_a \log \frac{\lambda\phi\gamma_a y_{ij}}{V_a^{\star}} da\right\} \\
&= \exp\left\{\int_{A_{0,ij}} \gamma_a \log b_{ij,a} da + \int_{A_{0,ij}} \gamma_a \log \lambda\phi y_{ij} da + \int_{A_{0,ij}} \gamma_a \log \frac{\gamma_a}{V_a^{\star}} da + \right. \\
&\left. + \int_{\tilde{A}_{0,ij}} \gamma_a \log \frac{\gamma_a}{V_a^{\star}} da + \int_{\tilde{A}_{0,ij}} \gamma_a \log \lambda\phi y_{ij} da\right\} \\
&= \exp\left\{\int_{A_{0,ij}} \gamma_a \log b_{ij,a} da + \int_0^1 \gamma_a \log \frac{\gamma_a}{V_a^{\star}} da + \log \lambda\phi y_{ij}\right\}.
\end{aligned} \tag{A.7}$$

Solving Equation (A.4) for l_{ij} and plugging the resulting expression in Equation (A.1) together with Equation (A.7) and solving for λ yields:

$$\text{MC}^{\star}_{ij} = \lambda_{ij} = \frac{1}{\Omega_{ij}} \left[\frac{\exp\left\{ \int_0^1 \gamma_a \log \frac{V_a^{\star}}{\gamma_a} da \right\}}{\phi \exp\left\{ \int_{A_{0,ij}} \gamma_a \log b_{ij,a} da \right\}} \right]^{\phi} \left[\frac{w_{ij}}{\mu_{ij}(1-\phi)} \right]^{1-\phi} = \frac{\text{C}^{\star}_{ij}}{\text{B}^{\phi}_{ij} \Omega_{ij}}.$$

where the definitions of $\text{C}^{\star}_{ij}$ and B_{ij} are those reported in the main text.

A.3 Proof of Proposition 2

Start from the full log differential of the optimal price setting equation:

$$d\log P^{\star}_{k,ij} = d\log \mathcal{M}_{k,ij} + d\log \text{MC}^{\star}_{k,ij}. \tag{A.8}$$

Total log differentiation of markup yields:

$$d\log \mathcal{M}_{k,ij} = -\Gamma_{k,ij}(d\log P_{k,ij} - d\log P_k) + \Gamma_{k,ij}\frac{d\log \xi_{k,ij}}{\rho - 1}. \tag{A.9}$$

Total log differentiation of marginal cost yields:

$$d\log \text{MC}^{\star}_{k,ij} = d\log \text{C}^{\star}_{ij} - \phi d\log \text{B}_{ij} - d\log \Omega_{ij}. \tag{A.10}$$

Note that:

$$\begin{aligned}
d\log b_{ij,a} &= -(1 - b^{\zeta}_{ij,a}) d\log \frac{e_k U_a}{V_a^{\star}}, \\
\phi d\log \text{B}_{ij} &= \phi \int_{A_{0,ij}} \gamma_a d\log b_{ij,a} da \\
&= -\varphi_{ij} d\log \frac{e_k \overline{U}}{\overline{V}^{\star}} - \phi \int_{A_{0,ij}} \gamma_a (1 - b^{\zeta}_{ij,a}) \left[d\log \frac{U_a}{\overline{U}} - d\log \frac{V_a^{\star}}{\overline{V}^{\star}} \right] da,
\end{aligned} \tag{A.11}$$

with $d\log \overline{V}^{\star} = \int_0^1 \gamma_a d\log V_a^{\star} dada$ and $d\log \overline{U} = \int_0^1 \gamma_a d\log U_a dada$. Also,

$$\log \text{C}^{\star}_{ij} = \phi \left(\int_0^1 \gamma_a \log \frac{V_a^{\star}}{\gamma_a} da - \log \phi \right) + (1-\phi)\left(\log w_{ij} - \log \mu_{ij} - \log(1-\phi)\right) \tag{A.12}$$

$$d\log \text{C}^{\star}_{ij} = (1-\phi)[1-\eta_{ij}] d\log w_{ij} + \nu_{ij} \tag{A.13}$$

where ν_{ij} is the full log differential of the first term of Equation (A.12). Note that the full log differentiation of the marginal cost is derived under the assumption that $d\log W_k = 0$. I relax this assumption below where I study the aggregate sensitivity of prices and wages to exchange rate shocks. Inserting Equation (A.11) and (A.13) into Equation (A.10) and plugging the resulting equation into Equation (A.8) together with Equation (A.9) yields:

$$
\begin{aligned}
d\log P^{\star}_{k,ij} = -\Gamma_{k,ij}(d\log P_{k,ij} - d\log P_k) + \varphi_{ij} d\log \frac{e_k\overline{U}}{\overline{V}^{\star}} + \\
+ (1-\phi)[1-\eta_{ij}]d\log w_{ij} + \epsilon_{k,ij}
\end{aligned}
\tag{A.14}
$$

where $\epsilon_{k,ij}$ collects all the residual terms. I assume that $\epsilon_{k,ij}$ is mean zero and independent and $d\log e_k$. Substituting $d\log P_{k,ij} = d\log P^{\star}_{k,ij} - d\log e_k$ into Equation (A.14), I obtain the following expression:

$$
\begin{aligned}
d\log P^{\star}_{k,ij} = \frac{\Gamma_{k,ij}}{1+\Gamma_{k,ij}}(d\log e_k + d\log P_k) + \frac{\varphi_{ij}}{1+\Gamma_{k,ij}} d\log \frac{e_k\overline{U}_s}{\overline{V}^{\star}_s} + \\
+ \frac{(1-\phi)[1-\eta_{ij}]}{1+\Gamma_{k,ij}} d\log w_{ij} + \epsilon_{k,ij}.
\end{aligned}
\tag{A.15}
$$

Use the following identities:

$$
d\log w_{ij} = \varepsilon_{ij}^{-1} d\log l_{ij}, \tag{A.16}
$$

$$
d\log y_{ij} = \phi d\log x_{ij} + (1-\phi)d\log l_{ij} + d\log \Omega_{ij}, \tag{A.17}
$$

$$
d\log x_{ij} = (1-\eta_{ij})d\log w_{ij} + d\log l_{ij}. \tag{A.18}
$$

Plug Equation (A.18) in Equation (A.17) and solve for $d\log l_{ij}$. Then, plug the resulting expression into Equation (A.16) and solve $d\log w_{ij}$ as a function of $d\log y_{ij}$ to obtain:

$$
d\log w_{ij} = \frac{\varepsilon_{ij}^{-1}}{1+\phi\varepsilon_{ij}^{-1}(1-\eta_{ij})} d\log y_{ij}, \tag{A.19}
$$

where the expression above is obtained under the assumption that $d\log W_k = 0$. Total log differentiate the demand function that the firm faces:

$$
d\log y_{ij} = -\rho(d\log P^{\star}_{k,ij} - d\log e_k) + (\rho - \eta)d\log P_k
$$

Plug Equation (A.15) into the expression above and solve for $d\log y_{ij}$. Then, plug the resulting expression into Equation (A.19), assume that $d\log P_k = 0$, and solve for $d\log w_{ij}$ to obtain the expression in Proposition 2:

$$
\begin{aligned}
\frac{d\log w_{ij}}{d\log e_k} = \frac{\rho\varepsilon_{ij}^{-1}}{(1+\phi\varepsilon_{ij}^{-1}(1-\eta_{ij}))(1+\Gamma_{k,ij}) + \rho(1-\phi)\varepsilon_{ij}^{-1}(1-\eta_{ij})} - \\
+ \frac{\rho\varepsilon_{ij}^{-1}}{(1+\phi\varepsilon_{ij}^{-1}(1-\eta_{ij}))(1+\Gamma_{k,ij}) + \rho(1-\phi)\varepsilon_{ij}^{-1}(1-\eta_{ij})} \times \varphi_{ij},
\end{aligned}
$$

where f_{ij} reported in the main text corresponds to the coefficient above. In addition, one can show that $f_{ij} > 0$ always holds. Moreover, $f_{ij} < 1$ if the condition $\frac{-\eta_{ij}}{1-\eta_{ij}} > \phi\left(1-\frac{1}{\rho}\right)$ is satisfied, which is true for conventional parameter values. Intuitively, $f_{ij} > 1$ only when a firm is a monopsony in its local labor market and when the substitutability across products ρ within industry approaches very low values which are not empirically supported. Proving symbolically that the function is convex in the firm's payroll share r_{ij} is analytically intractable. Therefore, I verify this property numerically by calibrating the model parameters to empirically relevant values. See Section 2 for details. ■

A.4 Proof of Proposition 3

Plug Equation (A.19) into Equation (A.15) and obtain:

$$
\begin{aligned}
d\log P^{\star}_{k,ij} = {} & \frac{\Gamma_{k,ij}}{1+\Gamma_{k,ij}}\left(d\log e_k + d\log P_k\right) + \frac{\varphi_{ij}}{1+\Gamma_{k,ij}} d\log\frac{e_k \overline{U}_s}{\overline{V}^{\star}_s} + \\
& + \frac{(1-\phi)[1-\eta_{ij}]}{1+\Gamma_{k,ij}} \times \frac{\varepsilon_{ij}^{-1}}{1+\phi\varepsilon_{ij}^{-1}(1-\eta_{ij})} d\log w_{ij} + \epsilon_{k,ij},
\end{aligned}
$$

and let $z_{ij} \equiv \frac{(1-\phi)(1-\eta_{ij})\varepsilon_{ij}^{-1}}{1+\phi\varepsilon_{ij}^{-1}(1-\eta_{ij})}$ be the coefficient reported in Proposition 3. Then, plug the expression above in the total log differentiation of firm demand function, assume $d\log P_k = 0$, and solve for $d\log P^{\star}_{k,ij}$ to obtain the expression reported in Proposition 3. Clearly, $z_{ij} > 0$ as long as the firm uses labor input in production ($\phi > 0$). Similarly as shown above, proving symbolically that the function is concave in the firm's payroll share r_{ij} is analytically intractable. Therefore, I verify this property numerically by calibrating the model parameters to empirically relevant values. See Section 2 for additional details. ■

A.5 Proof of Proposition 4

Start from:

$$
d\log w_{ij} = \frac{\rho\varepsilon_{ij}^{-1}}{\Omega_{ij}} d\log e_k + \frac{\left[\rho - \eta(1+\Gamma_{k,ij})\right]\varepsilon_{ij}^{-1}}{\Omega_{ij}} d\log P_k + \frac{\varphi_{ij}\varepsilon_{ij}^{-1}[(1+\Gamma_{k,ij})-\rho]}{\Omega_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}^{\star}_s]
$$

where $\Omega_{ij} = (1-\phi)(1-\eta_{ij})\varepsilon_{ij}^{-1}\rho + (1+\Gamma_{k,ij})[1+\varepsilon_{ij}^{-1}\phi(1-\eta_{ij})]$. For notational convenience, let:

$$
\begin{aligned}
\mathbf{\Lambda} &\equiv (\rho, \eta, \delta, \eta, \phi), \\
\Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\rho\varepsilon_{ij}^{-1}}{\Omega_{ij}}, \\
\Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\left[\rho - \eta(1+\Gamma_{k,ij})\right]\varepsilon_{ij}^{-1}}{\Omega_{ij}}, \\
\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\varepsilon_{ij}^{-1}[(1+\Gamma_{k,ij})-\rho]}{\Omega_{ij}}.
\end{aligned}
$$

Thus, the equation above becomes:

$$d\log w_{ij} = \Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log e_k + \Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log P_k + \varphi_{ij}\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}].$$

Next, perform a second-order Taylor approximation around φ_{ij}, $S_{k,ij}$ and r_{ij}. Let $\overline{\Theta}_{ij} = \Theta_{ij}(\overline{S}_{k,ij}, \overline{r}_{ij}, \mathbf{\Lambda})$, $\overline{S}_{k,ij}$ is some average statistics of the $S_{k,ij}$ distribution. Analogous definition applies to $\overline{\varphi}_{ij}$ and $\overline{r}_{ij}$. Moreover, let $\tilde{X} \equiv X - \overline{X}$, $\tilde{X}^2 \equiv 0.5(X - \overline{X})^2$.

$$\begin{aligned}
d\log w_{ij} \approx & \left[\overline{\Theta}_{ij} d\log e_k + \overline{\Upsilon}_{ij} d\log P_k + \overline{\varphi}_{ij}\overline{\Pi}_{ij} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] + \\
& + \tilde{S}_{k,ij}\left[\frac{\partial\Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial S_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial\Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial S_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right. \\
& \left. + \overline{\varphi}_{ij}\frac{\partial\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial S_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] + \\
& + \tilde{S}^2_{k,ij}\left[\frac{\partial^2\Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial S^2_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial^2\Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial S^2_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right. \\
& \left. + \overline{\varphi}_{ij}\frac{\partial^2\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial^2 S_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] + \\
& + \tilde{\varphi}_{ij}\left[\overline{\Pi}_{ij} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] + \\
& + \tilde{r}_{ij}\left[\frac{\partial\Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial r_{ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial\Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial r_{ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right. \\
& \left. + \overline{\varphi}_{ij}\frac{\partial\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial r_{ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] + \\
& + \tilde{r}^2_{ij}\left[\frac{\partial^2\Theta_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial r^2_{ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial^2\Upsilon_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial r^2_{k,ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right. \\
& \left. + \overline{\varphi}_{ij}\frac{\partial^2\Pi_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda})}{\partial^2 r_{ij}}\bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right].
\end{aligned}$$

Let $\Psi_k^P \equiv \mathbb{E}\left\{\frac{d\log P_k}{d\log e_k}\right\}$, $\Psi_{ij}^X \equiv \mathbb{E}\left\{\frac{d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}}{d\log e_k}\right\}$. Divide the equation above by $d\log e_k$ and take expectations to characterize the pass-through elasticity. Collecting terms yields the following final expression:

$$\Psi_{ij}^{W} \equiv \mathbb{E}\left\{\frac{d\log w_{ij}}{d\log e_k}\right\} \approx \kappa_{k,ij} + \xi_{k,ij}\varphi_{ij} + \pi_{k,ik}S_{k,ij} + p_{k,ij}S_{k,ij}^2 + \sigma_{k,ij}r_{ij} + o_{k,ij}r_{k,ij}^2$$

where the coefficients are functional forms of

$$\begin{aligned}
\kappa_{k,ij} &= \kappa(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\xi_{k,ij} &= \xi(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\pi_{k,ik} &= \pi(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
p_{k,ij} &= p(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\sigma_{k,i,j} &= \sigma(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
o_{k,ij} &= o(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}).
\end{aligned}$$

■

A.6 Proof of Proposition 4

Start from

$$d\log P_{k,ij}^{\star} = \frac{\Xi_{ij}\rho + \Gamma_{k,ij}\Sigma_{ij}}{\Omega_{ij}} d\log e_k + \frac{\Xi_{ij}(\rho-\eta) + \Gamma_{k,ij}\Sigma_{ij}}{\Omega_{ij}} d\log P_k + \frac{\varphi_{ij}\Sigma_{ij}}{\Omega_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}],$$

where $\Xi_{ij} = (1-\phi)(1-\eta_{ij})\varepsilon_{ij}^{-1}$, $\Sigma_{ij} = [1+\varepsilon_{ij}^{-1}\phi(1-\eta_{ij})]$. Similarly, let:

$$\begin{aligned}
A_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\Xi_{ij}\rho + \Gamma_{k,ij}\Sigma_{ij}}{\Omega_{ij}},\\
B_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\Xi_{ij}(\rho-\eta) + \Gamma_{k,ij}\Sigma_{ij}}{\Omega_{ij}},\\
C_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) &\equiv \frac{\Sigma_{ij}}{\Omega_{ij}}.
\end{aligned}$$

Thus, the equation above becomes:

$$d\log P_{k,ij}^{\star} = A_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log e_k + B_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log P_k + \varphi_{ij}C_{ij}(S_{k,ij}, r_{ij}, \mathbf{\Lambda}) d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]$$

Next, perform a second-order Taylor approximation around φ_{ij}, $S_{k,ij}$ and r_{ij}. Let $\overline{A}_{ij} = A_{ij}(\overline{S}_{k,ij}, \overline{r}_{ij}, \mathbf{\Lambda})$, $\overline{S}_{k,ij}$ is some average statistics of the $S_{k,ij}$ distribution. Analogous definition applies to $\overline{\varphi}_{ij}$ and $\overline{r}_{ij}$. Moreover, let $\tilde{X} \equiv X - \overline{X}$, $\tilde{X}^2 \equiv 0.5(X-\overline{X})^2$.

$$d\log w_{ij} \approx \left[\overline{A}_{ij} d\log e_k + \overline{B}_{ij} d\log P_k + \overline{\varphi}_{ij}\overline{C}_{ij} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right] +$$

$$
\begin{aligned}
&+\tilde{S}_{k,ij}\left[\frac{\partial A_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial S_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial B_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial S_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right.\\
&\left. + \overline{\varphi}_{ij}\frac{\partial C_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial S_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right]+\\
&+\tilde{S}^2_{k,ij}\left[\frac{\partial^2 A_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial S^2_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial^2 B_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial S^2_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right.\\
&\left. + \overline{\varphi}_{ij}\frac{\partial^2 C_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial^2 S_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right]+\\
&+\tilde{\varphi}_{ij}\left[\overline{\Pi}_{ij} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right]+\\
&+\tilde{r}_{ij}\left[\frac{\partial A_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial r_{ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial B_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial r_{ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right.\\
&\left. + \overline{\varphi}_{ij}\frac{\partial C_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial r_{ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right]+\\
&+\tilde{r}^2_{ij}\left[\frac{\partial^2 A_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial r^2_{ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log e_k + \frac{\partial^2 B_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial r^2_{k,ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log P_k + \right.\\
&\left. + \overline{\varphi}_{ij}\frac{\partial^2 C_{ij}(S_{k,ij},r_{ij},\mathbf{\Lambda})}{\partial^2 r_{ij}}\Bigg|_{\overline{S}_{k,ij},\overline{r}_{ij}} d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]\right].
\end{aligned}
$$

Let $\Psi_k^{P^*} \equiv \mathbb{E}\left\{\frac{d\log P_k}{d\log e_k}\right\}$, $\Psi_{ij}^{X} \equiv \mathbb{E}\left\{\frac{d\log[(e_k\overline{U}_s)/\overline{V}_s^{\star}]}{d\log e_k}\right\}$. Divide the equation above by $d\log e_k$ and take expectations to characterize the pass-through elasticity. Collecting terms yields the following final expression:

$$
\Psi_{k,ij}^{P^*} \equiv \mathbb{E}\left\{\frac{d\log P^{\star}_{k,ij}}{d\log e_k}\right\} \approx \alpha_{k,s,ij} + \beta_{k,s,ij}\varphi_{ij} + \gamma_{k,s,ij}S_{k,s,ij} + j_{k,s,ij}S^2_{k,s,ij} + \delta_{k,s,ij}r_{ij} + z_{k,s,ij}r^2_{ij}
$$

where the coefficients are functional forms of

$$
\begin{aligned}
\alpha_{k,s,ij} &= \alpha(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\beta_{k,s,ij} &= \beta(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\gamma_{k,s,ij} &= \gamma(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
j_{k,s,ij} &= j(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
\delta_{k,s,ij} &= \delta(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}),\\
z_{k,s,ij} &= z(\Psi_k^P, \Psi_{ij}^X, \mathbf{\Lambda}).\blacksquare
\end{aligned}
$$

A.7 Implementation of Production Function Estimation

In what follows, I outline the methodology used to estimate the output elasticities. In particular, I show the most general case which consists in the use of a translog production function specification. The Cobb-Douglas case is nested in the translog case as the latter is a second-order approximation to any arbitrary, differentiable production function (De Loecker and Warzynski (2012)). Also, I perform robustness checks in which I do not include the use of energy inputs to estimate elasticities. Robustness checks are reported in **??**.

Let $y_{i,t}$ be log output and $\mathbf{I}_{i,t}$ be a vector of log inputs used in production. $\mathbf{I}_{i,t} = (k_{i,t}, l_{i,t}, m_{i,t}, e_{i,t})$ stores the first-order, second-order and cross-product terms of capital, labor, material, and energy. Let $\mathbf{Z}_{i,t}$ it be the vector which contains the instruments for endogenous inputs $\mathbf{I}_{i,t}$. Instruments are needed because of the unobserved productivity parameter. As in De Loecker and Warzynski (2012), $\mathbf{Z}_{i,t}$ contains the lag of each variable contained in $\mathbf{I}_{i,t}$ with the exception of $k_{i,t}$. $f(\mathbf{I}_{i,t}, \omega_{i,t})$ is the log of the production function. Because of productivity is Hicks-neutral, I can write the following relationship:

$$y_{i,t} = f(\mathbf{I}_{i,t}; \boldsymbol{\beta}) + \omega_{i,t} + \epsilon_{i,t},$$

where $\epsilon_{i,t}$ is a measurement error term. Clearly, the goal is to estimate the vector of parameters $\boldsymbol{\beta}$. I follow a three-step process as in Ackerberg et al. (2015) and estimate the production function by 2-digit ISIC code using the Chilean Survey of Manufacturing (ENIA) between the years 1995 and 2015.

STEP 1: I estimate non-parametrically log output $\psi_{i,t}$ and $\epsilon_{i,t}$ by fitting a third-order polynomial regression of $y_{i,t}$ on the vector $\mathbf{I}_{i,t}$. Also, the estimate of log output $\psi_{i,t}$ is free of measurement error. The set of independent variables to estimate log output is:

$$\mathbf{I}_{i,t} = (k_{i,t}, l_{i,t}, m_{i,t}, e_{i,t}, k_{i,t}l_{i,t}, k_{i,t}m_{i,t}, k_{i,t}e_{i,t}, l_{i,t}m_{i,t}, l_{i,t}e_{i,t}, m_{i,t}e_{i,t}, k_{i,t}^2, l_{i,t}^2, m_{i,t}^2, e_{i,t}^2)'.$$

STEP 2: Assume $\omega_{i,t}$ follows a Markov process. Then, first construct a measure of firm productivity $\omega_{i,t}(\hat{\boldsymbol{\beta}})$:

$$\omega_{i,t}(\hat{\boldsymbol{\beta}}) = \psi_{i,t} - f(\mathbf{I}_{i,t}; \hat{\boldsymbol{\beta}}).$$

Second, run a third-order polynomial of $\omega_{i,t}(\hat{\boldsymbol{\beta}})$ on $\omega_{i,t-1}(\hat{\boldsymbol{\beta}})$ to construct a proxy for the innovation in productivity $\vartheta_{i,t}(\hat{\boldsymbol{\beta}})$:

$$\omega_{i,t}(\hat{\boldsymbol{\beta}}) = \sum_{p=0}^{3} \rho_p \omega_{i,t-1}^p(\hat{\boldsymbol{\beta}}) + \vartheta_{i,t},$$

and then construct $\vartheta_{i,t}(\hat{\boldsymbol{\beta}})$ as a residual.

STEP 3: Assume firm chooses capital at time $t-1$, thus $k_{i,t}$ is orthogonal to innovation in productivity in the current period. Similarly, input decisions made at time t are orthogonal to innovation that will happen in the future. Thus, one can write the following moment conditions to identify the coefficient $\boldsymbol{\beta} \in \mathbb{R}^Z$:

$$\mathbb{E}(\vartheta_{i,t}(\boldsymbol{\beta})\mathbf{z}_{i,t}) = 0_{\mathbf{Z}\times 1}$$

where $\mathbf{z}_{i,t}$ contains lagged values of one-period lagged values of every polynomial term containing $l_{i,t}, m_{i,t}, e_{i,t}$ in the production technology $f(\mathbf{I}_{i,t};\boldsymbol{\beta})$ but with capital preserved at its current value $k_{i,t}$. Estimate of output elasticities is based on the following minimization:

$$\hat{\hat{\beta}} = \arg\min_{\beta\in\mathbb{R}^Z} \sum_{m=1}^{Z}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\vartheta_{i,t}(\boldsymbol{\beta})z_{i,t}^{m}\right]^2 \quad \text{where} \quad z_{it} = (z_{1,it},\ldots,z_{Z,it})'.$$

A.8 Derivations of Markups and Markdowns

I derive markups and markdowns following the production approach originally developed by Hall (1988), De Loecker (2011), and De Loecker and Warzynski (2012). In what follows, I drop the subscript j and use only the subscript i to identify a firm. Suppose a firm minimizes total cost:

$$TC^*_{i,t} = \min_{\mathbf{I}_{i,t}\in\mathbb{R}^k_+} \sum_{k=1}^{K} P^k_{i,t}(I^k_{i,t})I^k_{i,t} + \Xi^k_t(I^k_{i,t}, I^k_{i,t-1}) \quad \text{s.t.} \quad F(\mathbf{I}_{i,t};\omega_{i,t}) \geq Q_{it},$$

where $I_{i,t}$ is the firm's vector which contains $K>1$ production inputs. Let $P^k_{i,t}$ be the price for input $I^k_{i,t}$. $\Xi^k_t(\cdot)$ be the adjustment cost function for *some* of the input k. $F(\mathbf{I}_{i,t};\omega_{it})$ is the production function used by the firm, $\omega_{i,t}$ is the firm's productivity. Assume that I) $F(\mathbf{I}_{i,t};\omega_{it})$ is continuous and twice differentiable, and II) that there is at least one input $\hat{k}$ which is not subject to adjustments cost and which price is exogenous to the firm. Then, the F.O.C the flexible input $\hat{k}$ yields:

$$\frac{\partial F(\mathbf{I}_{i,t};\omega_{it})}{\partial I^{\hat{k}}_{i,t}}\lambda_{i,t} = P^{\hat{k}}_{i,t} \tag{A.20}$$

where $\lambda_{i,t}$ is the marginal cost of firm i. After using the definition of markup and manipulating Equation (A.20), I obtain the expression for firm i markup $\mathcal{M}_{i,s,t}$ in the main text:

$$\mathcal{M}_{i,s,t} = \frac{\epsilon^{\hat{k}}_{i,t}}{\alpha^{\hat{k}}_{i,t}},$$

where $\epsilon^{\hat{k}}_{i,t} \equiv \frac{\partial F(\mathbf{I}_{i,t};\omega_{i,t})}{\partial I^{\hat{k}}_{i,t}}\frac{I^{\hat{k}}_{i,t}}{Q_{i,t}}$ is the output elasticity with respect to flexible input $\hat{k}$, $\alpha^{\hat{k}}_{i,t} \equiv \frac{P^{\hat{k}}_{i.t}X^{\hat{k}}_{i,t}}{Z_{i,t}Q_{i,t}}$ is the revenue share of flexible input $\hat{k}$.

Now, turn to the conditional cost minimization problem:

$$\min_{l_{i,t}\geq 0} w_{i,t}(l_{i,t})l_{i,t} \quad \text{s.t.} \quad F(l_{i,t}, \mathbf{I}^*_{-l,it}; \omega_{i,t}) \geq Q_{i,t},$$

where $\mathbf{I}^*_{-l,it}$ contains the optimal cost minimizing level of inputs for all inputs except for labor. The F.O.C can therefore be written as:

$$\begin{aligned}
\left[\frac{w'_{i,t}(l_{i,t})l_{i,t}}{w_{i,t}(l_{i,t})} + 1\right] &= \lambda_{it}\frac{\partial F(l_{i,t}, \mathbf{I}^*_{-l_{i,t}}; \omega_{it})}{\partial l_{i,t}} \\
&= \frac{Z_{i,t}Q_{it}}{w_{i,t}l_{i,t}}\frac{\partial F(l_{i,t}, \mathbf{I}^*_{-l_{i,t}}; \omega_{it})}{\partial l_{i,t}}\frac{l_{i,t}}{Q_{i,t}}\frac{\lambda_{i,t}}{Z_{i,t}} \\
&= \frac{\epsilon^L_{i,t}}{\alpha^L_{i,t}} \times \frac{1}{\mathcal{M}_{i,t}} \equiv \mu_{i,t}.
\end{aligned}$$

A.9 Derivation of Aggregate Prices and Wages

Start from:

$$\begin{aligned}
d\log P^\star_{k,ij,t} = \frac{1}{1+\Gamma_{k,ij,t}}&\left[\varphi_{ij,t} + \frac{(1-\phi)(1-\eta_{ij}-r_{ij})}{(1-r_{ij})}d\log w_{ij,t} + \frac{(1-\phi)\eta_{ij}}{(1-r_{ij})}\Psi^W_{j,t}\right] + \\
&+ \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}\left[d\log e_{k,t} + \Psi^P_{k,-ij,t}\right]
\end{aligned}$$

Where I assumed that $\Gamma_{k,ij,t} = \Gamma_{k,-ij,t}$ and from:

$$d\log w_{ij,t} = \frac{k_{ij,t}(1-r_{ij})}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})}d\log y_{ij,t} - \frac{\phi k_{ij,t}\eta_{ij}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})}\Psi^W_{j,t}$$

Plug the latter above, simplify and obtain:

$$\begin{aligned}
d\log P^\star_{k,ij,t} = \frac{1}{1+\Gamma_{k,ij,t}}&\left[\varphi_{ij,t} + \frac{(1-\phi)(1-\eta_{ij}-r_{ij})k_{ij,t}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})}d\log y_{ij,t} + \right. \\
&\left. + \frac{(1-\phi)\eta_{ij}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})}\Psi^W_{j,t}\right] + \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}\left[d\log e_{k,t} + \Psi^P_{k,-ij,t}\right]
\end{aligned}$$

Let:

$$\begin{aligned}
k_{ij,t} &\equiv \frac{\varepsilon^{-1}_{ij,t}}{1-r_{ij,t}r_{j,t}} - \frac{r_{ij,t}r_{j,t}}{\theta(1-r_{ij,t}r_{j,t})} \\
z_{ij,t} &\equiv \frac{(1-\phi)(1-\eta_{ij}-r_{ij})k_{ij,t}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})} \\
f_{ij,t} &\equiv \frac{(1-\phi)\eta_{ij}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij}) + (1-r_{ij})}
\end{aligned}$$

Rewrite above as:

$$d\log P^{\star}_{k,ij,t} = \frac{1}{1+\Gamma_{k,ij,t}}\left[\varphi_{ij,t} + z_{ij,t} d\log y_{ij,t} + f_{ij,t}\Psi^{W}_{j,t}\right] + \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}\left[d\log e_{k,t} + \Psi^{P}_{k,-ij,t}\right]$$

Use:

$$d\log y_{ij,t} = -\rho\left(d\log P^{\star}_{k,ij,t} - d\log e_{k,t}\right) + (\rho-\eta)\Psi^{P}_{k,-ij,t}$$

Plug above and simplify:

$$\begin{aligned} d\log P^{\star}_{k,ij,t} = & \frac{\rho z_{ij,t}+\Gamma_{k,ij,t}}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}} d\log e_{k,t} + \frac{1}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}}\varphi_{ij,t} + \frac{f_{ij,t}}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}}\Psi^{W}_{j,t} + \\ & + \frac{(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}}\Psi^{P}_{k,-ij,t} \end{aligned}$$

Let:

$$SC_{ij,t} \equiv \frac{1}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}}$$

Then:

$$\begin{aligned} d\log P^{\star}_{k,ij,t} = & SC_{ij,t}\left(\rho z_{ij,t}+\Gamma_{k,ij,t}\right) d\log e_{k,t} + SC_{ij,t}\varphi_{ij,t} + SC_{ij,t} f_{ij,t}\Psi^{W}_{j,t} + \\ & + SC_{ij,t}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]\Psi^{P}_{k,-ij,t} \\ d\log P^{\star}_{k,ij,t} = & SC_{ij,t}\left(\rho z_{ij,t}+\Gamma_{k,ij,t}\right) d\log e_{k,t} + SC_{ij,t}\varphi_{ij,t} + SC_{ij,t} f_{ij,t}\Psi^{W}_{j,t} + \\ & + SC_{ij,t}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]\left[\frac{1}{1-S_{k,ij,t}}\left(\sum_{-i} S_{k,-ij,t} d\log P^{\star}_{k,-ij,t} + \right.\right. \\ & \left.\left. + S_{k,ij,t} d\log P^{\star}_{k,ij,t} - S_{k,ij,t} d\log P^{\star}_{k,ij,t}\right)\right] \\ d\log P^{\star}_{k,ij,t} = & SC_{ij,t}\left(\rho z_{ij,t}+\Gamma_{k,ij,t}\right) d\log e_{k,t} + SC_{ij,t}\varphi_{ij,t} + SC_{ij,t} f_{ij,t}\Psi^{W}_{j,t} + \\ & + \frac{SC_{ij,t}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]}{1-S_{k,ij,t}}\left[\Psi^{P}_{j,t} - S_{k,ij,t} d\log P^{\star}_{k,ij,t}\right] \end{aligned}$$

Solve for $d\log P^{\star}_{k,ij,t}$, multiply both sides $S_{k,ij,t}$, sum over firms and solve for $\Psi^{P}_{j,t}$:

$$\Psi^{P}_{j,t} = \frac{1}{1-\sum \frac{\widetilde{SC}_{ij}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]}{1-S_{k,ij,t}}} \times \left[\sum \widetilde{SC}_{ij}\left[\rho z_{ij,t}+\Gamma_{k,ij,t}\right] + \sum \widetilde{SC}_{ij}\varphi_{ij,t} + \sum \widetilde{SC}_{ij} f_{ij,t}\Psi^{W}_{j,t}\right]$$

where

$$\widetilde{SC}_{ij} = \frac{SC_{ij,t}S_{k,ij,t}(1-S_{k,ij,t})}{1-S_{k,ij,t}+SC_{ij,t}S_{k,ij,t}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]}$$

Start from again:

$$d\log P^{\star}_{k,ij,t} = \frac{1}{1+\Gamma_{k,ij,t}}\left[\varphi_{ij,t} + \frac{(1-\phi)(1-\eta_{ij}-r_{ij})}{(1-r_{ij})}d\log w_{ij,t} + \frac{(1-\phi)\eta_{ij}}{(1-r_{ij})}\Psi^{W}_{j,t}\right] + \\ + \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}d\log e_{k,t} + \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}\frac{1}{(1-S_{k,ij,t})}\Psi^{P}_{k,j,t} - \frac{\Gamma_{k,ij,t}}{1+\Gamma_{k,ij,t}}\frac{S_{k,ij,t}}{(1-S_{k,ij,t})}d\log P^{\star}_{k,ij,t}$$

Solve for $d\log P^{\star}_{k,ij,t}$

$$d\log P^{\star}_{k,ij,t} = \frac{1-S_{k,ij,t}}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}\left[\varphi_{ij,t} + \frac{(1-\phi)(1-\eta_{ij}-r_{ij})}{(1-r_{ij})}d\log w_{ij,t} + \frac{(1-\phi)\eta_{ij}}{(1-r_{ij})}\Psi^{W}_{j,t}\right] + \\ + \frac{\Gamma_{k,ij,t}(1-S_{k,ij,t})}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}d\log e_{k,t} + \frac{\Gamma_{k,ij,t}}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}\Psi^{P}_{k,j,t}$$

Use:

$$d\log y_{ij,t} = -\rho\left(d\log P^{\star}_{k,ij,t} - d\log e_{k,t}\right) + \frac{(\rho-\eta)}{1-S_{k,ij,t}}\left(\Psi^{P}_{k,j,t} - S_{k,ij,t}d\log P^{\star}_{k,ij,t}\right)$$

Simplify $d\log P^{\star}_{k,ij,t}$:

$$d\log y_{ij,t} = \frac{S_{k,ij,t}\eta-\rho}{1-S_{k,ij,t}}d\log P^{\star}_{k,ij,t} + \rho d\log e_{k,t} + \frac{(\rho-\eta)}{1-S_{k,ij,t}}\Psi^{P}_{k,j,t}$$

Plug $d\log P^{\star}_{k,ij,t}$ from above and obtain:

$$d\log y_{ij,t} = \frac{(S_{k,ij,t}\eta-\rho)}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}\varphi_{ij,t} + \frac{(S_{k,ij,t}\eta-\rho)}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}\frac{(1-\phi)(1-\eta_{ij}-r_{ij})}{(1-r_{ij})}d\log w_{ij,t} + \\ + \frac{(S_{k,ij,t}\eta-\rho)}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}\frac{(1-\phi)\eta_{ij}}{(1-r_{ij})}\Psi^{W}_{j,t} + \frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+\rho(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}d\log e_{k,t} + \\ + \frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+(\rho-\eta)(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{(1-S_{k,ij,t}+\Gamma_{k,ij,t})(1-S_{k,ij,t})}\Psi^{P}_{k,j,t}$$

Plug this in the expression for $d\log w_{ij,t}$ and let:

$$B_{ij,t} = \frac{k_{ij,t}(1-r_{ij})}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij})+(1-r_{ij})} \times \frac{(S_{k,ij,t}\eta-\rho)}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}$$
$$F_{ij} = \frac{1-S_{k,ij,t}+\Gamma_{k,ij,t}}{S_{k,ij,t}\eta-\rho} \times \frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+\rho(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{1-S_{k,ij,t}+\Gamma_{k,ij,t}}$$
$$D_{ij} = \frac{1-S_{k,ij,t}+\Gamma_{k,ij,t}}{S_{k,ij,t}\eta-\rho} \times \frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+(\rho-\eta)(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{(1-S_{k,ij,t}+\Gamma_{k,ij,t})(1-S_{k,ij,t})}$$

Thus one can rewrite the expression for $d\log w_{ij,t}$ as:

$$d\log w_{ij,t} = B_{ij,t}\varphi_{ij,t} + B_{ij,t}\frac{(1-\phi)(1-\eta_{ij}-r_{ij})}{(1-r_{ij})}d\log w_{ij,t} + B_{ij,t}\frac{(1-\phi)\eta_{ij}}{(1-r_{ij})}\Psi^{W}_{j,t} + \\ + B_{ij,t}F_{ij}d\log e_{k,t} + B_{ij,t}D_{ij}\Psi^{P}_{k,j,t}$$

Solve for $d\log w_{ij,t}$:

$$
\begin{aligned}
d\log w_{ij,t} = & \frac{(1-r_{ij})}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}\left[B_{ij,t}\varphi_{ij,t}+B_{ij,t}F_{ij}d\log e_{k,t}+B_{ij,t}D_{ij}\Psi^P_{k,j,t}\right]+ \\
& +\frac{B_{ij,t}(1-\phi)\eta_{ij}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}\Psi^W_{j,t}
\end{aligned}
$$

Multiply both sides by r_{ij} and sum across firms, then solve for $\Psi^W_{j,t}$ which eventually yields:

$$
\Psi^W_{j,t} = \frac{1}{1-\sum\frac{r_{ij}B_{ij,t}(1-\phi)\eta_{ij}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}} \times \left[\sum G_{ij,t}B_{ij,t}\varphi_{ij,t}+\sum G_{ij,t}B_{ij,t}F_{ij}+\sum G_{ij,t}B_{ij,t}D_{ij}\Psi^P_{k,j,t}\right]
$$

where

$$
G_{ij,t} = \frac{r_{ij}(1-r_{ij})}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}
$$

Thus, I end up with the following system of equations:

$$
\begin{aligned}
\Psi^P_{j,t} &= \frac{1}{1-\sum\frac{\widetilde{SC}_{ij}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]}{1-S_{k,ij,t}}} \times \left[\sum \widetilde{SC}_{ij}\left[\rho z_{ij,t}+\Gamma_{k,ij,t}\right]+\sum \widetilde{SC}_{ij}\varphi_{ij,t}+\sum \widetilde{SC}_{ij}f_{ij,t}\Psi^W_{j,t}\right] \\
\Psi^W_{j,t} &= \frac{1}{1-\sum\frac{r_{ij}B_{ij,t}(1-\phi)\eta_{ij}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}} \times \left[\sum G_{ij,t}B_{ij,t}F_{ij}+\sum G_{ij,t}B_{ij,t}\varphi_{ij,t}+\sum G_{ij,t}B_{ij,t}D_{ij}\Psi^P_{k,j,t}\right]
\end{aligned}
$$

Let

$$
\begin{aligned}
\widetilde{SC}_{ij} &\equiv \frac{SC_{ij,t}S_{k,ij,t}(1-S_{k,ij,t})}{1-S_{k,ij,t}+SC_{ij,t}S_{k,ij,t}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]} \\
SC_{ij,t} &\equiv \frac{1}{1+\rho z_{ij,t}+\Gamma_{k,ij,t}} \\
k_{ij,t} &\equiv \frac{\varepsilon^{-1}_{ij,t}}{1-r_{ij,t}r_{j,t}}-\frac{r_{ij,t}r_{j,t}}{\theta(1-r_{ij,t}r_{j,t})} \\
z_{ij,t} &\equiv \frac{(1-\phi)(1-\eta_{ij}-r_{ij})k_{ij,t}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij})+(1-r_{ij})} \\
f_{ij,t} &\equiv \frac{(1-\phi)\eta_{ij}}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij})+(1-r_{ij})} \\
B_{ij,t} &\equiv \frac{k_{ij,t}(1-r_{ij})}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij})+(1-r_{ij})}\times\frac{(S_{k,ij,t}\eta-\rho)}{1-S_{k,ij,t}+\Gamma_{k,ij,t}} \\
F_{ij} &\equiv \frac{1-S_{k,ij,t}+\Gamma_{k,ij,t}}{S_{k,ij,t}\eta-\rho}\times\frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+\rho(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{1-S_{k,ij,t}+\Gamma_{k,ij,t}} \\
D_{ij} &\equiv \frac{1-S_{k,ij,t}+\Gamma_{k,ij,t}}{S_{k,ij,t}\eta-\rho}\times\frac{(S_{k,ij,t}\eta-\rho)\Gamma_{k,ij,t}+(\rho-\eta)(1-S_{k,ij,t}+\Gamma_{k,ij,t})}{(1-S_{k,ij,t}+\Gamma_{k,ij,t})(1-S_{k,ij,t})} \\
Z_{ij} &\equiv \frac{\widetilde{SC}_{ij}\left[(\rho-\eta)z_{ij,t}+\Gamma_{k,ij,t}\right]}{1-S_{k,ij,t}} \\
H_{ij} &\equiv \frac{r_{ij}B_{ij,t}(1-\phi)\eta_{ij}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}
\end{aligned}
$$

$$G_{ij,t} \equiv \frac{r_{ij}(1-r_{ij})}{(1-r_{ij}) - B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})}$$

System above becomes:

$$\begin{aligned}
\Psi^P_{j,t} &= \frac{1}{1-\sum Z_{ij}} \times \left[\sum \widetilde{SC}_{ij}\left[\rho z_{ij,t} + \Gamma_{k,ij,t}\right] + \sum \widetilde{SC}_{ij}\varphi_{ij,t} + \sum \widetilde{SC}_{ij} f_{ij,t}\Psi^W_{j,t}\right] \\
\Psi^W_{j,t} &= \frac{1}{1-\sum H_{ij}} \times \left[\sum G_{ij,t}B_{ij,t}F_{ij} + \sum G_{ij,t}B_{ij,t}\varphi_{ij,t} + \sum G_{ij,t}B_{ij,t}D_{ij}\Psi^P_{k,j,t}\right]
\end{aligned}$$

Plug $\Psi^W_{j,t}$ into $\Psi^P_{j,t}$ and solve for it:

$$\begin{aligned}
\Psi^P_{j,t} = \frac{1}{1-\sum Z_{ij}} \times \Bigg[& \sum \widetilde{SC}_{ij}\left[\rho z_{ij,t} + \Gamma_{k,ij,t}\right] + \sum \widetilde{SC}_{ij}\varphi_{ij,t} + \\
& + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{1-\sum H_{ij}} \times \sum G_{ij,t}B_{ij,t}F_{ij} + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{1-\sum H_{ij}} \times \sum G_{ij,t}B_{ij,t}\varphi_{ij,t} + \\
& + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{1-\sum H_{ij}} \times \sum G_{ij,t}B_{ij,t}D_{ij}\Psi^P_{k,j,t}\Bigg]
\end{aligned}$$

Or:

$$\begin{aligned}
\Psi^P_{j,t} = \frac{1}{1-\sum Z_{ij}} \times \Bigg[& \sum \widetilde{SC}_{ij}\left[\rho z_{ij,t} + \Gamma_{k,ij,t}\right] + \sum \widetilde{SC}_{ij}\varphi_{ij,t} + \\
& + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{1-\sum H_{ij}} \times \sum G_{ij,t}B_{ij,t}F_{ij} + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{1-\sum H_{ij}} \times \sum G_{ij,t}B_{ij,t}\varphi_{ij,t}\Bigg] + \\
& + \frac{\sum \widetilde{SC}_{ij} f_{ij,t}}{(1-\sum H_{ij})(1-\sum Z_{ij})} \times \sum G_{ij,t}B_{ij,t}D_{ij}\Psi^P_{k,j,t}
\end{aligned}$$

Solve for $\Psi^P_{j,t}$:

$$\begin{aligned}
\Psi^P_{j,t} = & \frac{(1-\sum H_{ij})(1-\sum Z_{ij})}{(1-\sum H_{ij})(1-\sum Z_{ij}) - \sum \widetilde{SC}_{ij} f_{ij,t} \sum G_{ij,t}B_{ij,t}D_{ij}} \times \\
& \times \left[\frac{\sum \widetilde{SC}_{ij}\left[\rho z_{ij,t} + \Gamma_{k,ij,t}\right]}{1-\sum Z_{ij}} + \frac{\sum \widetilde{SC}_{ij} f_{ij,t} \sum G_{ij,t}B_{ij,t}F_{ij}}{(1-\sum H_{ij})(1-\sum Z_{ij})} + \right. \\
& \left. + \frac{\sum \widetilde{SC}_{ij}\varphi_{ij,t}}{1-\sum Z_{ij}} + \frac{\sum \widetilde{SC}_{ij} f_{ij,t} \sum G_{ij,t}B_{ij,t}\varphi_{ij,t}}{(1-\sum H_{ij})(1-\sum Z_{ij})}\right]
\end{aligned}$$

Plug above in the expression for $\Psi^W_{j,t}$ to obtain the final solution for $\Psi^W_{j,t}$. ∎

A.10 Proof of Proposition 6

Suppose product market is perfectly competitive $\eta \to \rho$ and $\eta \to \infty$, then:

$$\begin{aligned} B_{ij,t} &= \frac{k_{ij,t}(1-r_{ij})}{k_{ij,t}\phi(1-\eta_{ij}-r_{ij})+(1-r_{ij})} \times (-\rho) \\ F_{ij} &= -1 \\ D_{ij} &= 0 \end{aligned}$$

Then expression for $\Psi^W_{j,t}$ becomes:

$$\begin{aligned} B_{ij,t} &\to -\infty \\ G_{ij,t} \times B_{ij,t} &= \frac{r_{ij}(1-r_{ij})B_{ij,t}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})} \end{aligned}$$

Divide numerator and denominator by $B_{ij,t}$ and get:

$$\begin{aligned} B_{ij,t} &\to -\infty \\ G_{ij,t} \times B_{ij,t} &= \frac{r_{ij}(1-r_{ij})}{\frac{(1-r_{ij})}{B_{ij,t}}-(1-\phi)(1-\eta_{ij}-r_{ij})} \end{aligned}$$

Then,

$$\begin{aligned} B_{ij,t} &\to -\infty \\ G_{ij,t} \times B_{ij,t} &= -\frac{r_{ij}(1-r_{ij})}{(1-\phi)(1-\eta_{ij}-r_{ij})} \end{aligned}$$

Also:

$$\frac{r_{ij}B_{ij,t}(1-\phi)\eta_{ij}}{(1-r_{ij})-B_{ij,t}(1-\phi)(1-\eta_{ij}-r_{ij})} = \frac{r_{ij}(1-\phi)\eta_{ij}}{\frac{(1-r_{ij})}{B_{ij,t}}-(1-\phi)(1-\eta_{ij}-r_{ij})} = -\frac{r_{ij}\eta_{ij}}{(1-\eta_{ij}-r_{ij})}$$

Let:

$$sc^l_{ij} \equiv -\frac{\eta_{ij}}{(1-\eta_{ij}-r_{ij})}$$

Thus:

$$\begin{aligned} \Psi^W_{j,t} &= \frac{\sum r_{ij}(1-sc^l_{ij})(1-\varphi_{ij,t})}{1-\sum r_{ij}sc^l_{ij}} \\ &= \frac{1}{1-\sum r_{ij}sc^l_{ij}} \times \left[\sum r_{ij}(1-sc^l_{ij}) - \sum r_{ij}(1-sc^l_{ij})\varphi_{ij,t}\right] \\ &= \frac{\sum r_{ij}(1-sc^l_{ij})}{1-\sum r_{ij}sc^l_{ij}} - \frac{\sum r_{ij}(1-sc^l_{ij})\varphi_{ij,t}}{1-\sum r_{ij}sc^l_{ij}} \end{aligned}$$

$$
\begin{aligned}
&= 1 - \frac{\sum r_{ij}(1 - sc_{ij}^{l})\varphi_{ij,t}}{1 - \sum r_{ij} sc_{ij}^{l}} \\
&= 1 - \left[\frac{\sum r_{ij}\varphi_{ij,t} - \sum r_{ij} sc_{ij}^{l}\varphi_{ij,t}}{1 - \sum r_{ij} sc_{ij}^{l}} \right] \\
&= 1 - \left[\frac{\sum r_{ij}\varphi_{ij,t}}{1 - \sum r_{ij} sc_{ij}^{l}} - \frac{\sum r_{ij} sc_{ij}^{l}\varphi_{ij,t}}{1 - \sum r_{ij} sc_{ij}^{l}} \right] \\
&= 1 - \left[\frac{\sum r_{ij}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} - \frac{\sum r_{ij} sc_{ij}^{l}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} + \frac{\sum r_{ij} \overline{sc}_{ij}^{l}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} - \frac{\sum r_{ij} \overline{sc}_{ij}^{l}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} \right] \\
&= 1 - \left[\overline{\varphi_{ij,t}} - \frac{\sum r_{ij} sc_{ij}^{l}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} + \frac{\sum r_{ij} \overline{sc}_{ij}^{l}\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} \right] \\
&= 1 - \left[\overline{\varphi_{ij,t}} - \frac{\sum r_{ij}(sc_{ij}^{l} - \overline{sc}_{ij}^{l})\varphi_{ij,t}}{1 - \overline{sc}_{ij}^{l}} \right] \\
&= 1 - \overline{\varphi_{ij,t}} + \frac{\operatorname{Cov}\left(sc_{ij}^{\ell},\, \varphi_{ij,t}\right)}{1 - \overline{sc}_{ij}^{\ell}}
\end{aligned}
$$

■

B Empirical Appendix

Table B.1: Summary Statistics for Payroll Share

	Median	**Mean**	**IQR**	**SD**
Payroll Share r_{ij}	0.28%	2.29%	0.0130	0.0891
Observations	10798			

Table B.2: Distribution of Local Labor Markets and Average Payroll Share r_{ij}

Region	**Industry Label**	**Payroll Share r_{ij}**
5th Percentile		
Metropolitana (Santiago)	Food, Beverages, and Tobacco	0.0081%
25th Percentile		
Maule	Food, Beverages, and Tobacco	0.0742%
75th Percentile		
Los Lagos	Wood and Furniture	1.38%
90th Percentile		
Maule	Metal Products, Machinery, and Equipment	6.79%
99th Percentile		
Valparaíso	Wood and Furniture	47.45%

Table B.3: **ERPT to Prices and Labor Market Power: Non-Parametric Regression**

	(1)	(2)	(3)
	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$
$Q_1 \Delta e_{k,t}$	0.277***	0.282***	0.239***
	(0.065)	(0.070)	(0.083)
$Q_2 \Delta e_{k,t}$	0.296***	0.301***	0.290***
	(0.092)	(0.097)	(0.099)
$Q_3 \Delta e_{k,t}$	0.447***	0.451***	0.435***
	(0.071)	(0.077)	(0.078)
$Q_4 \Delta e_{k,t}$	0.265***	0.271***	0.259***
	(0.050)	(0.057)	(0.057)
$Q_5 \Delta e_{k,t}$	0.216**	0.224**	0.183*
	(0.090)	(0.107)	(0.111)
$S_{k,s,i,t-1} \Delta e_{k,t}$		-0.023	-0.006
		(0.102)	(0.104)
$\varphi_{k,i,t-1} \Delta e_{k,t}$			0.772***
			(0.196)
p-value Q_1 vs Q_5	0.586	0.614	0.650
p-value Q_3 vs Q_5	0.030**	0.039**	0.026**
p-value Q_3 vs Q_4	0.021**	0.021**	0.025**
Observations	112502	112502	112502

Note: Table B.3 reports the coefficients plotted in Figure (6). Firm, product, destination, and year observations split into five equal-sized bins by value of the payroll share r_{ij}. Where Q_q, $q \in [1, 5]$ denotes an indicator variable for the respective quintiles. Column (2) controls for the level of $S_{k,s,i,t-1}$ while Column (3) controls also for the level of $\varphi_{k,i,t-1}$. No fixed effects included in the nonparametric specifications. The table reports the p-values of the Wald test of equality of the coefficients for Bin 1 vs Bin 5, Bin 3 vs Bin 5, and Bin 3 vs Bin 4. Standard errors are clustered at the Year $\times$ Destination $\times$ LLM level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: **ERPT to Wages and Labor Market Power: Non-Parametric Regression**

	(1)	(2)	(3)
	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$
$Q_1 \Delta e_{ij,t}$	0.052***	0.052***	0.048***
	(0.015)	(0.015)	(0.015)
$Q_2 \Delta e_{ij,t}$	0.024*	0.023	0.020
	(0.014)	(0.014)	(0.015)
$Q_3 \Delta e_{ij,t}$	0.010	0.009	0.007
	(0.013)	(0.013)	(0.013)
$Q_4 \Delta e_{ij,t}$	0.046***	0.044***	0.042***
	(0.014)	(0.014)	(0.014)
$Q_5 \Delta e_{ij,t}$	0.058***	0.054***	0.052***
	(0.013)	(0.013)	(0.013)
$S_{ij,t-1} \Delta e_{ij,t}$		0.292*	0.297*
		(0.166)	(0.166)
$\varphi_{ij,t-1} \Delta e_{ij,t}$			0.060
			(0.047)
p-value Q_1 vs Q_5	0.760	0.910	0.837
p-value Q_3 vs Q_5	0.007***	0.014**	0.013**
p-value Q_3 vs Q_4	0.058*	0.065*	0.062*
Observations	86250	86247	86247

Note: Table B.4 reports the coefficients plotted in Figure (6). Firm, local labor market, and year observations split into five equal-sized bins by value of the payroll share r_{ij}. Where Q_q, $q \in [1, 5]$ denotes an indicator variable for the respective quintiles. Column (2) controls for the level of $S_{ij,t-1}$ while Column (3) controls also for the level of $\varphi_{ij,t-1}$. No fixed effects included in the nonparametric specifications. The table reports the p-values of the Wald test of equality of the coefficients for Bin 1 vs Bin 5, Bin 3 vs Bin 5, and Bin 3 vs Bin 4. Standard errors are clustered at the Year $\times$ LLM level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: **ERPT to Wage and Labor Market Power: Import-Weighted Exchange Rate**

	(1)	(2)	(3)	(4)
	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$	$\Delta w_{ij,t}$
$\Delta e_{ij,t}$	0.088***	0.115***	0.111***	0.113***
	(0.001)	(0.002)	(0.002)	(0.002)
$r_{ij,t-1}\Delta e_{ij,t}$		-0.114***	-0.096**	-0.143***
		(0.043)	(0.041)	(0.043)
$r^2_{ij,t-1}\Delta e_{ij,t}$		0.253***	0.225***	0.287***
		(0.066)	(0.064)	(0.067)
$S_{ij,t-1}\Delta e_{ij,t}$				-0.666***
				(0.173)
$S^2_{ij,t-1}\Delta e_{ij,t}$				0.559***
				(0.133)
$\varphi_{ij,t-1}\Delta e_{ij,t}$				0.022*
				(0.013)
Year X LLM	YES	YES	NO	YES
Year + LLM	NO	NO	YES	NO
Observations	86854	86204	86844	86201

Note: Table B.5 reports the estimated exchange rate pass-through coefficients to domestic wages. The dependent variable is the log annual change in the average firm wage. The explanatory variables are: the exchange rate $\Delta e_{ij,t}$ which is a firm level import-weighted exchange computed as the log annual change in the weighted average bilateral exchange rate between the Chilean Peso and origin-k whose weights are given by the firm level import share from origin-k, II) $r_{ij,t-1}$, $S_{ij,t-1}$, and $\varphi_{ij,t-1}$ are defined as in the main text. The local labor markets are defined as region $\times$ 2-digit industry. Standard errors are clustered at the Year $\times$ LLM level measures the firm level payroll share in local labor market j at year $t-1$. The local labor markets are defined as region $\times$ 2-digit industry. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: **ERPT to Price and Labor Market Power: Import-Weighted Exchange Rate**

	(1)	(2)	(3)	(4)
	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$	$\Delta P^{\star}_{k,g,i,t}$
$\Delta e_{ij,t}$	0.018***	0.011**	0.014***	0.017***
	(0.001)	(0.004)	(0.005)	(0.005)
$r_{ij,t-1}\Delta e_{ij,t}$		0.402***	0.372***	0.321***
		(0.081)	(0.058)	(0.056)
$r^2_{ij,t-1}\Delta e_{ij,t}$		-0.272***	-0.254***	-0.223***
		(0.050)	(0.046)	(0.045)
$S_{k,s,i,t-1}\Delta e_{ij,t}$			-0.026	-0.026
			(0.028)	(0.027)
$S^2_{k,s,i,t-1}\Delta e_{ij,t}$			0.034	0.028
			(0.030)	(0.029)
$\varphi_{k,i,t-1}\Delta e_{ij,t}$			0.102*	0.099*
			(0.057)	(0.055)
Year + Destination X HS4	YES	NO	NO	NO
Year + LLM X Destination X HS4	NO	YES	YES	NO
Year + LLM + Destination X HS4	NO	NO	NO	YES
Observations	112432	109430	112422	109430

Note: Table B.6 reports the estimated exchange rate pass-through coefficients to producer currency export prices. The dependent variable is the log annual change in the export price expressed in Chilean Peso. The explanatory variables are I) the exchange rate $\Delta e_{ij,t}$ which is a firm level import-weighted exchange computed as the log annual change in the weighted average bilateral exchange rate between the Chilean Peso and origin-k whose weights are given by the firm level import share from origin-k, II) $r_{ij,t-1}$ measures the firm level payroll share in local labor market j at year $t-1$, II) the market share of the firm $S_{k,ij,t-1}$ and its import intensity $\varphi_{k,ij,t-1}$. All specification include the level of the variables not interacted with the bilateral exchange rate. The local labor markets are defined as region $\times$ 2-digit industry. Standard errors are clustered at the Year $\times$ Destination $\times$ LLM. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B.7: **ERPT to Prices and Labor Market Power: Alternative Samples**

Dep. Var.: $\Delta P^{\star}_{k,g,ij,t}$				
	(1)	(2)	(3)	(4)
	W/O US	Major Product HS8	Major Product HS4	W/O Copper
$\Delta e_{k,t}$	0.152***	0.135***	0.131***	0.140***
	(0.016)	(0.018)	(0.017)	(0.016)
$r_{ij,t-1}\Delta e_{k,t}$	0.777***	0.475*	0.418*	0.652***
	(0.221)	(0.254)	(0.251)	(0.218)
$r^2_{ij,t-1}\Delta e_{k,t}$	-0.908***	-0.693***	-0.566***	-0.765***
	(0.199)	(0.228)	(0.219)	(0.197)
Year + LLM + Destination X HS4	YES	YES	YES	YES
Observations	98725	104328	105757	99401

Note: Table B.7 reports the estimated exchange rate pass-through coefficients to producer currency export prices for four different alternative samples. The dependent variable is the log annual change in the export price expressed in Chilean Peso. I) Column (1) excludes exports to the US, II) Column (2) includes only products whose export share is above the HS8 product median export share for each firm, III) Column (3) includes only products whose export share is above the HS4 product median export share for each firm, IV) Column (4) excludes the HS2 74 category which contains "Copper and articles thereof". The explanatory variables are I) the bilateral exchange rate $\Delta e_{k,t}$, II) $r_{ij,t-1}$ measures the firm level payroll share in local labor market j at year $t-1$, II) the market share of the firm $S_{k,ij,t-1}$ and its import intensity $\varphi_{k,ij,t-1}$. All specification include the level of the variables not interacted with the bilateral exchange rate. The local labor markets are defined as region $\times$ 2-digit industry. Standard errors are clustered at the Year $\times$ Destination $\times$ LLM. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: **ERPT to Prices and Wages: Alternative Measure of Labor Market Power**

	$\Delta P^{\star}_{k,s,ij,t}$		$\Delta w_{ij,t}$	
	Municipality $\times$ 2-Industry	Region $\times$ 4-Industry	Municipality $\times$ 2-Industry	Region $\times$ 4-Industry
$\Delta e_{k,t}$	0.134***	0.105***	0.038**	0.021*
	(0.033)	(0.029)	(0.019)	(0.012)
$r_{ij,t-1}\Delta e_{k,t}$	0.105***	0.128***	-0.336***	-0.473***
	(0.036)	(0.034)	(0.021)	(0.022)
$r^2_{ij,t-1}\Delta e_{k,t}$	-0.149***	-0.106***	0.187***	0.314***
	(0.036)	(0.041)	(0.024)	(0.029)
Year + LLM X Destination X HS4	YES	YES	NO	NO
Year X LLM	NO	NO	YES	YES
Observations	107332	107532	86344	88248

Note: Table B.8 reports estimated exchange rate pass-through coefficients to producer-currency export prices and domestic wages under alternative definitions of local labor markets (LLMs). LLMs are defined either as Municipality $\times$ 2-Industry or as Region $\times$ 4-Industry. In Columns (1)–(2), the exchange rate corresponds to the bilateral rate between the Chilean Peso and the destination-k currency. In Columns (3)–(4), it corresponds to the firm-level trade-weighted bilateral exchange rate. All specifications include the level of each variable not interacted with the exchange rate. Standard errors are clustered at the Year $\times$ Destination $\times$ LLM level in Columns (1)–(2), and at the Year $\times$ LLM level in Columns (3)–(4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
.

Table B.9: **ERPT to Labor Input**

	Import-Weighted EXR	Trade-Weighted EXR
	(1)	(2)
	$\Delta l_{ij,t}$	$\Delta l_{ij,t}$
$\Delta e_{ij,t}$	0.011***	0.019***
	(0.002)	(0.002)
$r_{ij,t-1}\Delta e_{ij,t}$	-0.103***	-0.095***
	(0.011)	(0.011)
$S_{ij,t-1}\Delta e_{ij,t}$	0.007	0.125**
	(0.038)	(0.060)
$\varphi_{ij,t-1}\Delta e_{ij,t}$	-0.063**	-0.073**
	(0.030)	(0.030)
Year × LLM	YES	YES
Observations	84516	87483

Note: Table B.9 reports estimated exchange rate pass-through coefficients to labor input. The dependent variable is the log annual change in firm-level employment. Column (1) uses the import-weighted exchange rate constructed as in Table B.5, and Column (2) uses the trade-weighted exchange rate constructed as in Table 2. $r_{ij,t-1}$, $S_{ij,t-1}$, and $\varphi_{ij,t-1}$ are defined as in the main text. Local labor markets are defined as Region × 2-digit industry. Standard errors are clustered at the Year × LLM level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.1: Markups Robustness

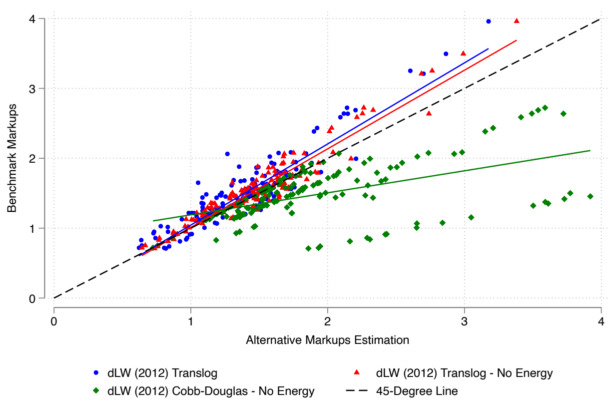
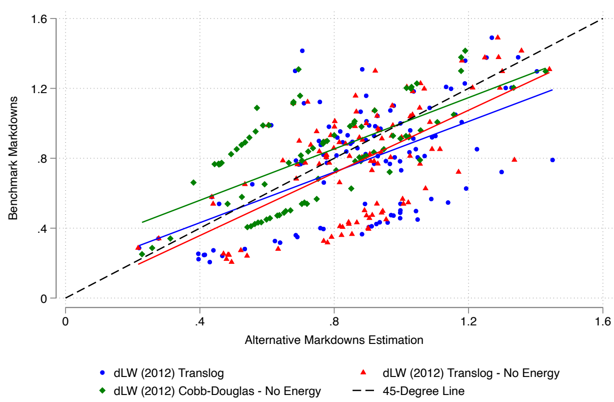


Figure B.2: Markdowns Robustness



Note: Figure (B.1) shows the correlation between the benchmark distribution of estimated markups and the distribution of markups obtained using three alternative methods. Figure (B.2) reports markdowns. The y-axis displays the obtained markups (Table 4) and markdowns (Table 5) using a Cobb-Douglas specification whose material input is the flexible input. Other inputs are capital, labor, and energy inputs. The x-axis reports the markups and markdowns recovered using three alternative specifications: I) translog specification with energy input, II) translog specification without energy input, and III) Cobb-Douglas specification without energy input. The black dashed line is the 45° degree line.

Figure B.3: Distribution of Local Labor Market Markdowns

Note: Figure (B.3) shows the distribution of the estimated local labor market markdowns $\mu_{j,t}$. Local labor market markdowns are estimated under the assumption of a Cobb-Douglas production function. Local labor market markdowns are the payroll share-weighted harmonic average of firm level markdowns.

Table B.10: Correlation between Markups & Market Share, Markdowns & Labor Share

(a) Markups and Market Shares

	$1/\mathcal{M}_{i,s,t}$
$S_{i,s,t}$	-0.187**
	(0.093)
Adjusted R^2	0.447
Firm Year X Industry	YES
Observations	27140

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Markdowns and Labor Shares

	$1/\mu_{ij,t}$
$r_{ij,t}$	0.424***
	(0.014)
Adjusted R^2	0.864
Firm Year X LLM	YES
Observations	26616

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Summary Statistics: Aggregate Markup & Aggregate Markdown

(a) Aggregate Markup

	Median	Mean	Max	Min
$\mathcal{M}_t$	1.22	1.23	1.43	1.05
Observations	19			

(b) Aggregate Markdowns

	Median	Mean	Max	Min
μ_t	0.68	0.68	0.72	0.65
Observations	19			

Figure B.4: Aggregate Markup

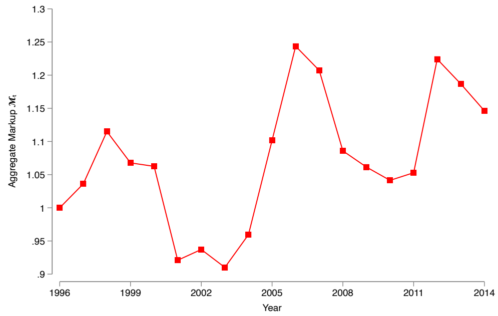
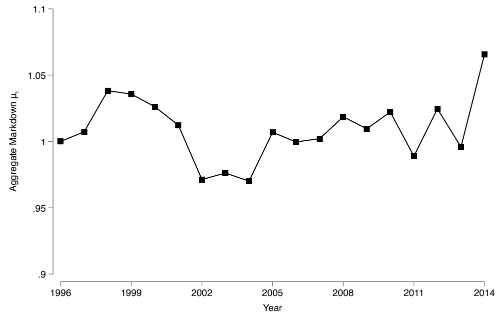


Figure B.5: Aggregate Markdown



Note: Figure (B.4) shows the time series of the aggregate markup for the Chilean manufacturing sector. Figure (B.5) shows the time series of the aggregate markdown for the Chilean manufacturing sector. Aggregate markup and aggregate markdown are estimated under the assumption of a Cobb-Douglas production function. Aggregate markup is the revenue-weighted harmonic average of sector level markups. Aggregate markdown is the payroll-weighted harmonic average of the local labor market level markdowns. Both aggregate markup and aggregate markdown are normalized relative to their initial values in 1996.

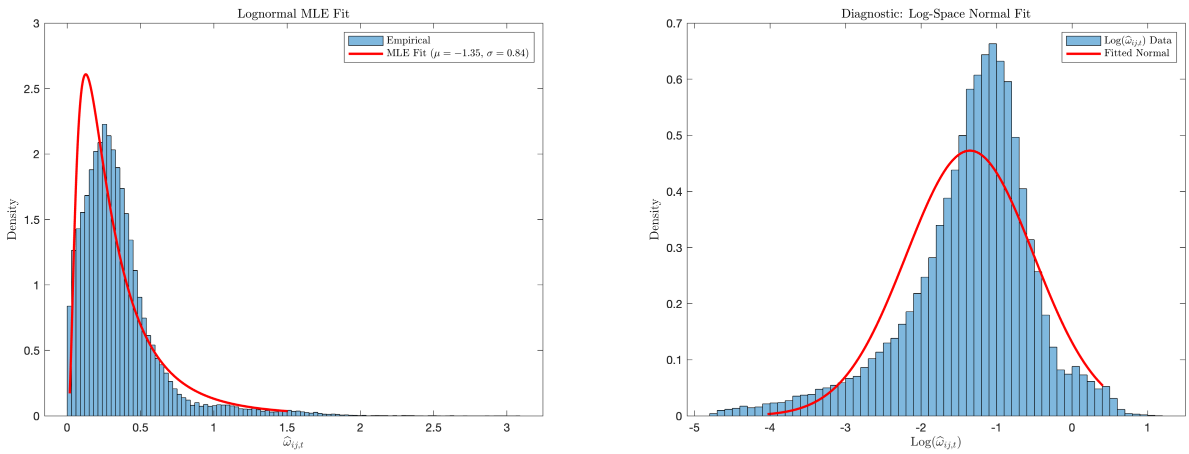


Figure B.6: MLE of Productivity Distribution Process

Note: The left panel of Figure B.6 shows the empirical distribution of firm level productivity $\widehat{\omega}_{ij,t}$ across firm-year observations along with the maximum likelihood log-normal fit. The right panel plots the same data in logarithmic space, where $\log(\widehat{\omega}_{ij,t})$ is approximately normally distributed.

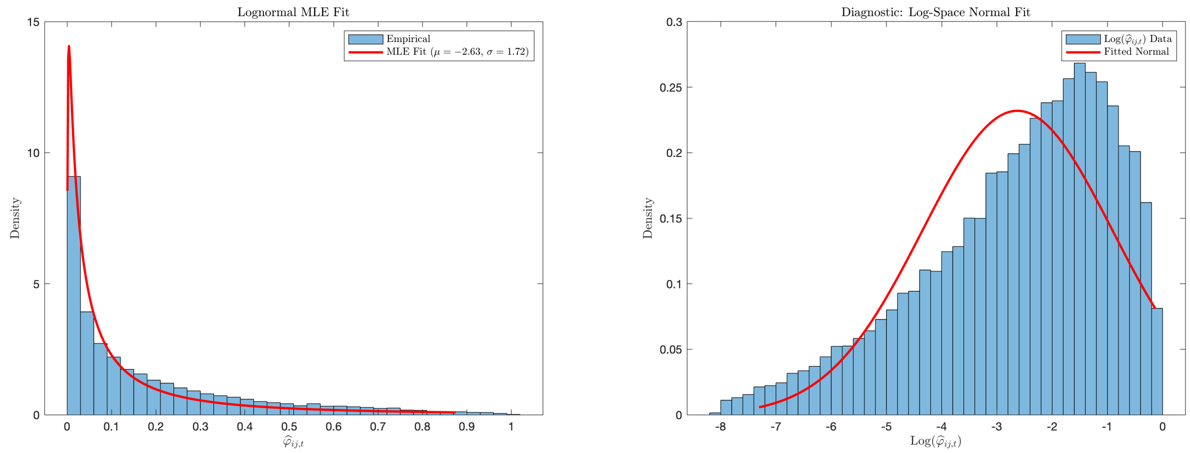


Figure B.7: MLE of Import Intensity Distribution Process

Note: The left panel of Figure B.7 shows the empirical distribution of import intensity $\widehat{\omega}ij, t$ across firm-year observations along with the maximum likelihood log-normal fit. The right panel plots the same data in logarithmic space, where $\log(\widehat{\omega}ij, t)$ is approximately normally distributed.