Testing the Production Approach to Markup Estimation*

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Abstract

Under the production approach to markup estimation, any flexible input should recover the markup. I test this implication using four manufacturing censuses and store-level data from a US retailer, and overwhelmingly reject that markups estimated using labor and materials have the same distribution. For every dataset, markups estimated using labor are negatively correlated with markups using materials, exhibit greater dispersion, and have opposite time trends. Non-neutral productivity differences can reconcile these findings. I develop a flexible cost share estimator to model such heterogeneity. Using this estimator, markups estimated with different inputs are positively correlated in the cross-section and time series.

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Measuring the markup of price over cost is central to recent debates on whether market power has been rising for the US and the world economy (Basu, 2019; Berry et al., 2019; De Loecker et al., 2018; Syverson, 2019). Additionally, markups are crucial to evaluate the effects of mergers and changes in trade barriers. Because it is crucial to get good estimates of markups to answer these questions, a growing literature has studied markup estimation.

The *production approach* to markup estimation (Hall, 1988; De Loecker and Warzynski, 2012) has allowed economists to measure changes in aggregate markups by estimating firm level markups across industries. The production approach uses flexible input choice to identify the markup as a variable input's output elasticity divided by its share of revenue.[1]

This approach requires one to know the production function. In practice, economists using the approach have typically assumed that productivity is Hicks neutral. However, when productivity is labor augmenting, more productive firms will have different output elasticities of labor and materials than less productive firms. Ignoring such heterogeneity will lead to systematically different markups estimated using different inputs.

Because *any* flexible input identifies the markup, the markup is overidentified with multiple flexible inputs. I thus compare markups estimated using labor, materials, or, mirroring cost of goods sold in De Loecker et al. (2018), a composite of both.[2] I conduct these comparisons using manufacturing censuses and surveys from Chile, Colombia, India, and Indonesia,

[1]Given competitive input markets, a cost minimizing firm sets the additional revenue from a marginal increase in a flexible input equal to the marginal cost of the input multiplied by the markup.

[2]In the literature, De Loecker and Warzynski (2012) and Blonigen and Pierce (2016) use labor, De Loecker et al. (2016) materials, De Loecker and Scott (2017) both, De Loecker and Eeckhout (2018) cost of goods sold, and De Loecker et al. (2018) cost of goods sold (Compustat) and labor (Economic Census).

as well as unique data on individual stores from a nationwide US retailer.

Because the production approach requires estimates of the production function, these comparisons jointly test the assumptions of the production approach itself and auxiliary assumptions on production technology. For my baseline tests, I follow De Loecker and Warzynski (2012) and estimate production functions using the Ackerberg et al. (2015) control function approach. The control function estimator assumes productivity is Hicks neutral.

Assuming Hicks neutral productivity, I strongly reject that different inputs estimate the same markup in all five datasets. In addition to multiple statistical tests, I focus on three major features of the markup distribution. Labor markups are much more dispersed than materials markups. Markup measures using labor and materials are *negatively* correlated in the cross-section. Finally, their time trends are negatively correlated as well.

My findings of conflicting correlations when estimating markups with different inputs are also robust to several estimation approaches that assume only neutral productivity differences, estimating production functions at the subindustry or product level, estimating quantity rather than revenue production functions, and controls for local labor markets.

Non-neutral technology can explain these findings. When labor and materials are complements, higher labor augmenting productivity would both lower labor's output elasticity relative to materials' output elasticity and labor costs relative to materials costs. By ignoring such productivity differences when estimating output elasticities, markups based upon alternative inputs would have opposing time trends and negative correlations.

To test this possibility, I develop an estimator that accounts for differences in labor augmenting productivity. Labor augmenting productivity is proportional to the ratio of labor to materials costs; I group plants into bins with similar labor augmenting productivities based upon this ratio and estimate output elasticities as input cost shares within each group. This flexible cost share estimator does not require data on output quantities, which are typically not observed, and so avoids biases from estimating output elasticities based upon revenue production functions. Across all five datasets, as well as in Monte Carlo simulations, markups estimated with different inputs using this approach are positively correlated, have similar time trends, and similar dispersion.

I then assess the performance of the flexible cost share estimator by examining stylized facts for markups. Using the flexible cost share estimator, I consistently find that markups are positively correlated with size, exporting, and profit shares, as would be expected from theory. For the retailer, I find little relationship between company provided classifications of the degree of competition faced by a retail store and markups. Using the control function estimators that do not control for labor augmenting productivity, I find many estimates contrary to theoretical predictions and conflicting evidence across datasets and input measures.

This article is most similar to work that examines differences between markup estimates using the production approach. De Loecker et al. (2018), Karabarbounis and Neiman (2018), and Traina (2018) debate how using different inputs from Compustat affects the aggregate trend in US markups, while Bridgman (2019) examines the same question using the National

Accounts. De Loecker and Scott (2017) find similar average markup estimates using the demand approach, as in Berry et al. (1995), to those from the production approach using data on US breweries.

This article is also related to the literature on non-neutral productivity. Raval (2019) and Oberfield and Raval (2020) document growth in labor augmenting productivity and labor augmenting productivity differences for US manufacturing; Doraszelski and Jaumandreu (2018) and Zhang (2019) do the same using Spanish manufacturing and Chinese steel data.

Two additional papers examine markup estimation given non-neutral technology. Doraszelski and Jaumandreu (2019) provide a dynamic panel estimator for markups given labor augmenting productivity differences, and apply it to the effect of exporting on markups using Spanish manufacturing data.[3] Demirer (2020) develops a non-parametric control function approach to estimate output elasticities given non-neutral productivity and then applies this approach to estimate markups.

Section 1 lays out the production approach to estimating markups. Section 2 and Section 3 detail the data and control function estimators. Section 4 tests the production approach. Section 5 shows that labor augmenting technology differences can explain the failure of the tests and provides a new estimator to account for such differences. Section 6 applies this estimator to examine several stylized facts on markups. Section 7 concludes.

[3]They show that labor markups and materials markups estimated assuming neutral productivity provide opposing estimates of the effect of exporting on markups; with the dynamic panel approach, exporters and non-exporters have similar markups.

1 Production Approach

The key assumptions for the production approach are that the firm cost minimizes in each period with respect to a variable input, and that the firm is a price taker in the input market for that input. Below, I derive the estimator for the markup under these assumptions following De Loecker and Warzynski (2012).

Take a firm with production function $F_{it}(K_{it}, L_{it}, M_{it})$, where K_{it} is capital for firm i and time t, L_{it} is labor, and M_{it} is materials. The firm receives price P_{it} for its output and faces input prices p_{it}^X for input X. A cost minimizing firm sets marginal products equal to factor prices. This implies, for variable input X_{it},

$$P_{it} \frac{\partial F_{it}}{\partial X_{it}} = \frac{P_{it}}{\lambda_{it}} p_{it}^X, \tag{1}$$

where λ_{it} is the firm's marginal cost.[4] The left hand side is the marginal revenue product of increasing input X_{it}. The right hand side is the marginal cost of increasing X_{it} – its price, p_{it}^X – multiplied by the markup $\frac{P_{it}}{\lambda_{it}}$. Thus, the markup is a wedge between the marginal revenue product of an input and the marginal cost of an input.

Converting this expression to elasticity form[5], the output elasticity for input X, β_{it}^X, is

[4] The marginal cost is the Lagrange multiplier on the production function in the cost minimization problem.

[5] Formally, multiply each side by $\frac{X_{it}}{F_{it}}$ and divide each side by the price P_{it}.

equal to the markup μ_{it} multiplied by input X's share of revenue s_{it}^X:

$$
\begin{aligned}
\frac{\partial F_{it}}{\partial X_{it}} \frac{X_{it}}{F_{it}} &= \frac{P_{it}}{\lambda_{it}} \frac{p_{it}^X X_{it}}{P_{it} F_{it}} && (2) \\
\beta_{it}^X &= \mu_{it} s_{it}^X. && (3)
\end{aligned}
$$

The markup μ_{it} is then the output elasticity of input X divided by X's share of revenue:

$$
\mu_{it} = \frac{\beta_{it}^X}{s_{it}^X}. \tag{4}
$$

This expression for markups holds for *all* variable inputs at the firm level. Thus, I can test the production approach by examining whether the markup recovered using one input is the same as the markup recovered using another.

2 Data

I use production level datasets on manufacturing for four countries: Chilean plants from 1979-1996, Colombian plants from 1978-1991, Indian plants from 1998-2014, and Indonesian firms from 1991-2000. These data are yearly censuses, except for India which is part census and part sample (for which I use the provided sampling weights). These datasets have between 5,000 to 30,000 establishments per year. I summarize the characteristics of these datasets in Table I and include further details on data construction in Appendix D.

In addition, I also use retail store-level data from an anonymous major US nationwide retailer ("Retailer") for three years. This retailer has thousands of stores across the United States. This dataset allows me to examine a different industry than manufacturing, in the spirit of De Loecker et al. (2018) who examine all US industries, as I have similar data on inputs and output at the store level as in the manufacturing datasets. Unlike in the manufacturing datasets, any differences in markups across stores for the retailer will be purely *within* firm differences.

Table I Datasets

Dataset	Unit of Observation	Time Period	No. Establishments	No. Industries Used
Chile	Manufacturing Plant	1979-1996	5,000 / year	16
Colombia	Manufacturing Plant	1978-1991	7,000 / year	21
India	Manufacturing Plant	1998-2014	30,000 / year	23
Indonesia	Manufacturing Firm	1991-2000	14,000 / year	22
Retailer	Retail Store	3 years	Thousands / year	1

For each dataset, I have data on capital, labor, materials, and sales at the establishment-year level. An establishment is a manufacturing plant for the Chilean, Colombian, and Indian data, a firm for the Indonesian data, and a retail store for the retailer. I use capital, materials, and output deflators in order to construct consistent measures of inputs and outputs over time, and drop any observations with zero or negative capital, labor, materials, sales, or labor costs. I also drop observations in the bottom 1% and top 1% of labor's share of revenue, materials's share of revenue, and the composite variable input share of revenue for each industry to remove outliers.

For labor, I use the number of workers for Chile, Colombia, and Indonesia, and the number of manufacturing worker-days for India. For the retailer, I use the total number of hours worked by all workers. Labor costs are the total of salaries and worker benefits.

For materials, I include expenses for raw materials, electricity, and fuels for the manufacturing datasets. For the retailer, I have data on the cost of goods sold for separate parts of the store; materials is the sum of the cost of goods sold. The composite variable input is the sum of materials and labor costs.[6]

For capital, I construct a perpetual inventory measure of capital for each type of capital. I then construct rental rates of capital based on an average real interest rate over time plus depreciation for that type of capital, and sum capital stocks times their rental rates, plus any rental payments for capital, as my measure of capital.[7]

For the manufacturing datasets, I estimate production functions at the industry level. I define industries at a similar level to two digit US SIC (i.e., Chilean Food Products).[8] I only include industries with at least 1,000 observations over the entire dataset, and so use between 16 and 23 industries for each manufacturing dataset. For the retailer, I estimate a single production function across all retail outlets.

[6]I deflate this input using the output deflator to match De Loecker et al. (2018)'s treatment of cost of goods sold.

[7]This provides an approximation to a Divisia index for capital given different types of capital. See Diewert and Lawrence (2000) and Harper et al. (1989) for details on capital rental rates and aggregation. For the retailer, I use BLS rental rates for retail trade. See Appendix D for more details on capital construction.

[8]For Chile, Colombia, and Indonesia this is at the three digit ISIC (Rev.2) level, and for India at the two digit NIC 08 level. Estimating production functions at this level of aggregation is consistent with the production function literature, such as Levinsohn and Petrin (2003) or Gandhi et al. (forthcoming).

3 Estimation

Given (4), estimating the markup requires the input share of revenue and the output elasticity of that input. The input share of revenue, defined as costs for input X divided by total firm revenue, is observed. However, the production function has to be estimated to recover output elasticities. I describe below how De Loecker and Warzynski (2012), and subsequent papers using the production approach such as De Loecker et al. (2018), address this estimation challenge using a control function approach that assumes productivity is Hicks neutral.

3.1 Production Functions

I estimate Cobb-Douglas and translog production functions. In one specification, inputs are capital, labor, and materials; in another, inputs are capital and a composite variable input of labor and materials.

All lower case variables are in logged form, so k_{it} is capital, l_{it} labor, and m_{it} materials. For the Cobb Douglas production function with labor and materials, the (logged) production function excluding the Hicks neutral productivity term is:

$$f_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}$$

and so the output elasticity for input X is simply β_X. For the translog production function, the production function is:

$$f_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it}$$

and so the output elasticity for each input will depend upon the level of all inputs. For example, the firm's output elasticity for materials would be $\beta_m + 2\beta_{mm} m_{it} + \beta_{km} k_{it} + \beta_{lm} l_{it}$.

For both the Cobb-Douglas and translog production functions, the production function coefficients are not time-varying. However, for the translog, output elasticities can vary over time due to changes in factors.

3.2 Control Function Estimation

I follow De Loecker and Warzynski (2012) and use the Ackerberg et al. (2015) (ACF) estimator for my baseline estimates. The ACF estimator imposes substantial additional assumptions on productivity, including that productivity is Hicks neutral and evolves following a Markov process. In addition, it requires a set of timing assumptions where at least one input is decided at the time the firm learns its productivity shock. I discuss problems with this estimator, and alternative estimation approaches using neutral productivity, in Section A.3.

The control function approach assumes that observed revenue includes additive measurement error ϵ_{it}. Thus, given log productivity ω_{it}, measured log revenue y_{it} is:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it}. \tag{5}$$

Let materials be the flexible input decided at the time the firm learns its productivity shock. Materials is then a function of the observed inputs and productivity $m_{it} = g(k_{it}, l_{it}, \omega_{it})$. It can then be inverted for productivity, so $\omega_{it} = g^{-1}(k_{it}, l_{it}, m_{it})$.[9]

The first stage of the ACF estimator controls for a flexible form of the inputs to recover the additive measurement error ϵ_{it}. Formally, measured log revenue y_{it} is:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + g^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} = h(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \tag{6}$$

Since both the production function and productivity are functions of the inputs, they cannot be separated in the first stage. Instead, the nonparametric function h includes both productivity ω_{it} and the production function f. The measurement error in sales ϵ_{it} is a residual in the first stage equation after controlling for h.[10]

The second major assumption of the ACF approach is that productivity follows a first order Markov process. In my implementation, I further assume an AR(1) process. Formally,

$$\omega_{it} = \rho\omega_{it-1} + \nu_{it} \tag{7}$$

[9]The g() function can include other determinants of materials as well, such as materials prices.

[10]In practice, I use a third order polynomial in inputs for the function h, and also control for year effects.

with AR(1) coefficient ρ and productivity innovation ν_{it}. In that case, given knowledge of the production function coefficients β, one can recover the innovation in productivity ν_{it} as:

$$\nu_{it}(\beta) \quad = \quad \omega_{it} - \rho\omega_{it-1} \tag{8}$$

The innovation in productivity is a function of production coefficients β because $\omega_{it} = y_{it} - \epsilon_{it} - f_{it}(\beta)$, and ϵ_{it} was recovered in the first stage.

Because the innovation in productivity is, by construction, independent of inputs chosen before time t, moments of the innovations multiplied by inputs chosen before the productivity innovation, such as $E(\nu_{it}l_{it-1})$ or $E(\nu_{it}k_{it})$, identify the production function coefficients.

For the Cobb-Douglas production function, I use capital and the first lag of materials and labor as instruments. For the translog, I use capital and the first lag of materials and labor, as well as their interactions, as instruments.[11]

Finally, I follow De Loecker and Warzynski (2012) and correct the value of sales in the input share of revenue for the measurement error estimated in the first stage. Thus, for input X, the estimate of the markup is:

$$\hat{\mu_{it}} = \frac{\hat{\beta_i^X}}{s_{it}^X exp(\hat{\epsilon}_{it})}. \tag{9}$$

[11]For the specification with the composite variable input instead of labor and materials separately, I use the lag of the composite input and its interactions as instruments, symmetrically to the case above.

4 Empirical Tests

Under the production approach, any flexible input identifies the markup. I first test the production approach, implemented using the control function estimator described in Section 3, through formal statistical tests of whether the distribution of markups is the same using different inputs. I then examine how several features of the markup distribution vary using different inputs. For all of these tests, and in all the datasets, I strongly reject that different inputs estimate the same markup.

4.1 Implementation

For each dataset, I estimate industry-level production functions using the control function estimator. I estimate four specifications: either a Cobb-Douglas or translog production function, and either capital, labor, and materials or capital and a composite variable input as inputs. I then estimate markups at the establishment-year level using the resulting output elasticities. This process results in six markup estimates for each establishment-year. Each markup is estimated using one of three inputs (labor, materials, or the composite input) and one of two production functions to recover the output elasticity for that input (a Cobb-Douglas or translog).

4.2 Statistical Tests

I begin by conducting three statistical tests of equality: the paired t-test (mean), the Kolmogorov-Smirnov test (distribution), and the paired Wilcoxon signed-rank test (median). I conduct these tests for both the Cobb-Douglas and translog production functions comparing labor, materials, and composite variable input markups. I thus conduct 90 tests – 5 datasets, 2 production functions, 3 flexible inputs, and 3 statistical tests.

I overwhelmingly reject that markups estimated using different flexible inputs have the same distributions. Across the 90 tests, the largest p-value was 1.8×10^{-4}, with all of the other p-values an order of magnitude or more smaller.[12]

Because my datasets are large, it is unclear whether these rejections reflect economically meaningful differences. Therefore, I examine specific features of the markup distribution: dispersion, time series correlations, and cross-sectional correlations.[13]

4.3 Dispersion in Markup Estimates

Under the production approach, the degree of markup dispersion should be the same using different flexible inputs. Instead, I find very different levels of dispersion using different inputs. As an example, I plot the distribution of each markup across manufacturing plants in the Chilean Food Products industry in 1996 using the translog estimates in Figure 1. The

[12]The second highest p-value is 6.1×10^{-17}. I would continue to reject all tests given a Bonferroni correction for multiple hypothesis testing.

[13]I also examine average markups in Appendix B.3.

red solid lines are the labor markup, the blue dashed lines the materials markup, and the green dash-dot lines the combined variable input markup. The labor markups are much more dispersed than the materials markups, which are in turn more dispersed than the composite input markups. Because of its greater dispersion, a large fraction of labor markups are below one, which might be considered a lower bound on markups (Flynn et al., 2019).

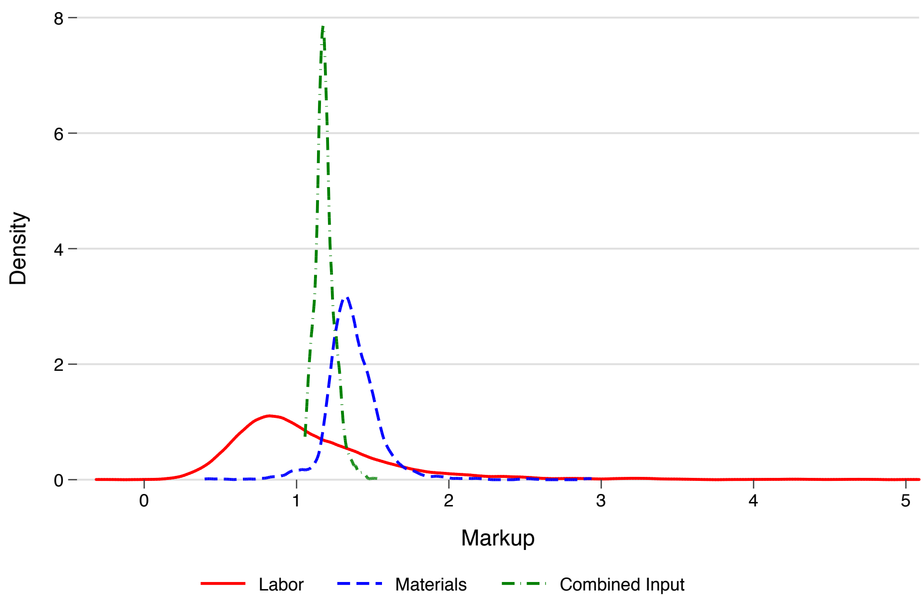


Figure 1 Distribution of Translog Markups for Chilean Food Products, 1996

I find a similar pattern in all the datasets. I measure dispersion by calculating the 90/50 ratio of the markup estimates, which I report in Table II.[14] Just as in Figure 1, labor markups are more disperse than materials markups, which are more disperse than composite input markups, for each dataset and production function. For example, using the translog

[14] I report the 75/25 and 90/10 ratios in Appendix B.2.

estimates, the 90th percentile markup is 103% higher than the median markup for Chile using labor, 39% higher using materials, and 17% using the composite input.

For the retailer, there is hardly any dispersion in materials markups – the 90th percentile markup is only 3% higher than the median and 6% higher than the 10th percentile – but substantial dispersion in the labor markup. For the labor markup, the 90th percentile is 30% higher than the median markup and 76% higher than the 10th percentile under the translog estimates.

Table II 90/50 Ratio of Markup Estimates

	Labor		Materials		Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	2.67	2.03	1.53	1.39	1.17	1.17
	(0.013)	(0.008)	(0.003)	(0.004)	(0.001)	(0.001)
Colombia	2.88	1.82	1.82	1.43	1.16	1.17
	(0.016)	(0.005)	(0.008)	(0.004)	(0.001)	(0.001)
India	4.04	2.95	1.38	1.29	1.14	1.14
	(0.013)	(0.007)	(0.001)	(0.001)	(0.000)	(0.000)
Indonesia	4.06	3.12	1.66	1.46	1.15	1.16
	(0.025)	(0.019)	(0.004)	(0.003)	(0.001)	(0.001)
Retailer	1.23	1.30	1.02	1.03	1.02	1.02
	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)

Note: CD is Cobb-Douglas and TL translog. Estimates use all establishments and years. Standard errors are based on 20 bootstrap simulations. For India, these estimates ignore the sample weights.

4.4 Time Trends

Under the production approach, the time path in markups should be the same using different flexible inputs. To test this, I estimate the following specification:

$$\log(\mu_{it}^X) = \alpha + \gamma_t + \delta_n + \epsilon_{it} \tag{10}$$

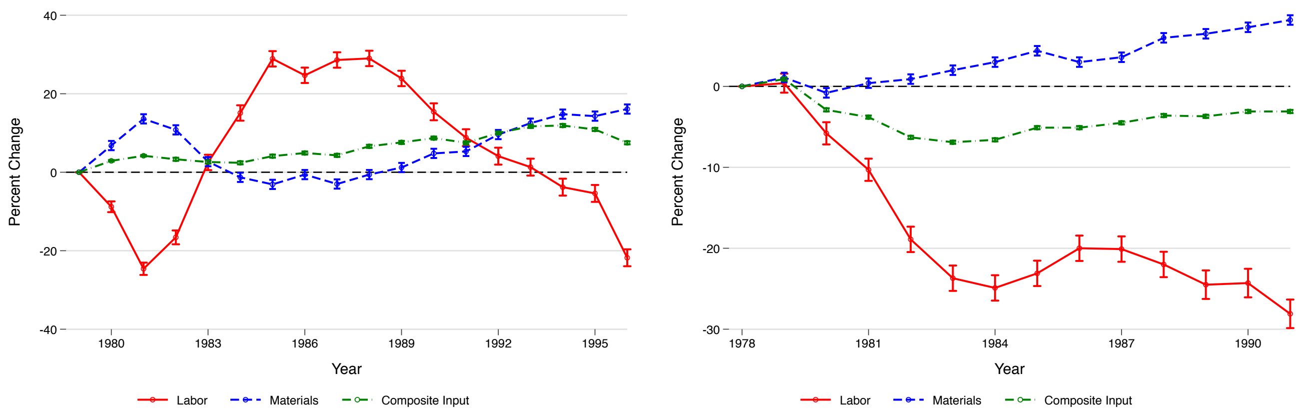
where μ_{it}^X is the markup using input X for establishment i in year t, and γ_t and δ_n are year and industry fixed effects. I then plot the year effects using the translog estimates in Figure 2 and Figure 3, with the first year normalized to zero. The red solid lines are the labor markup, the blue dashed lines the materials markup, and the green dash-dot lines the composite input markups.[15]

For all of the datasets, I find *opposing* patterns over time using labor compared to materials to measure the markup. The time trend for composite input markups lie between the two, but much closer to materials, and exhibit less extreme movements.

For example, for Colombia, the average labor markup falls by 28% lower over the sample, while the average materials markup rises by 8% and the composite input markup declines by 3%. For India, the average labor markup is 39% lower at the end of the sample, while the materials markup exhibits little change and the composite input markup declines by 5%. For Indonesia, the Asian financial crisis strikes in 1998. The average labor markup rises by 17% in 1998, while the average materials markup declines by 4% and the composite input markup remains unchanges.

[15] I include the Cobb-Douglas trends in Figure 19 and Figure 20 in Appendix B.1. I always find significantly different markup trends using different inputs.

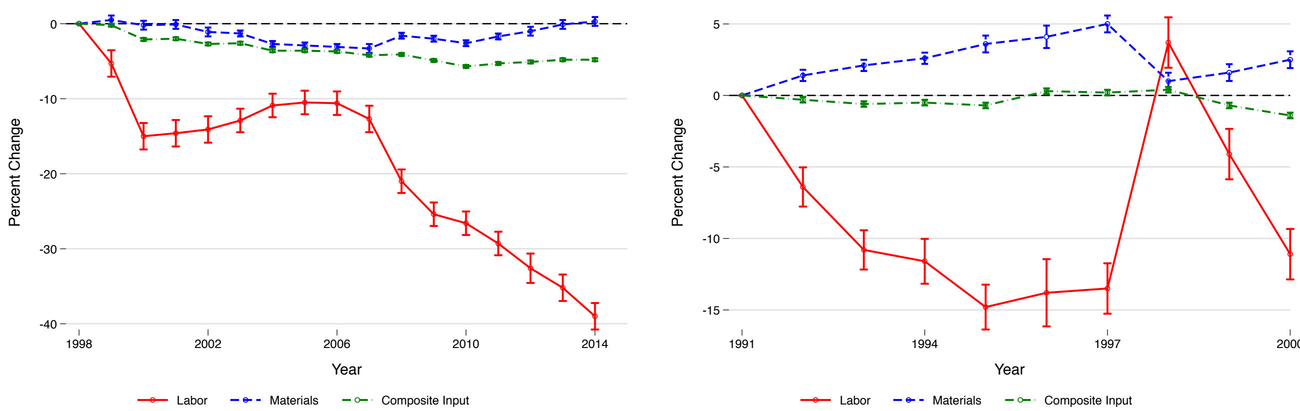
Figure 2 Markup Time Trends using Translog Estimates: Chile and Colombia



(a) Chile (b) Colombia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 3 Markup Time Trends using Translog Estimates: India and Indonesia



(a) India (b) Indonesia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

4.5 Correlations of Markup Estimates

Under the production approach, markup estimates using different inputs for the same establishment should be highly correlated with each other. Instead, I find negative correlations between labor and materials markups. For example, in Figure 4, I plot the materials markup on the x-axis against the labor markup on the y-axis for all plants in the Chilean Food Products industry in 1996 using the translog estimates. Each a point is a different manufacturing plant with the best linear fit as a solid black line. There is a slight negative relationship between the labor markup and materials markup.

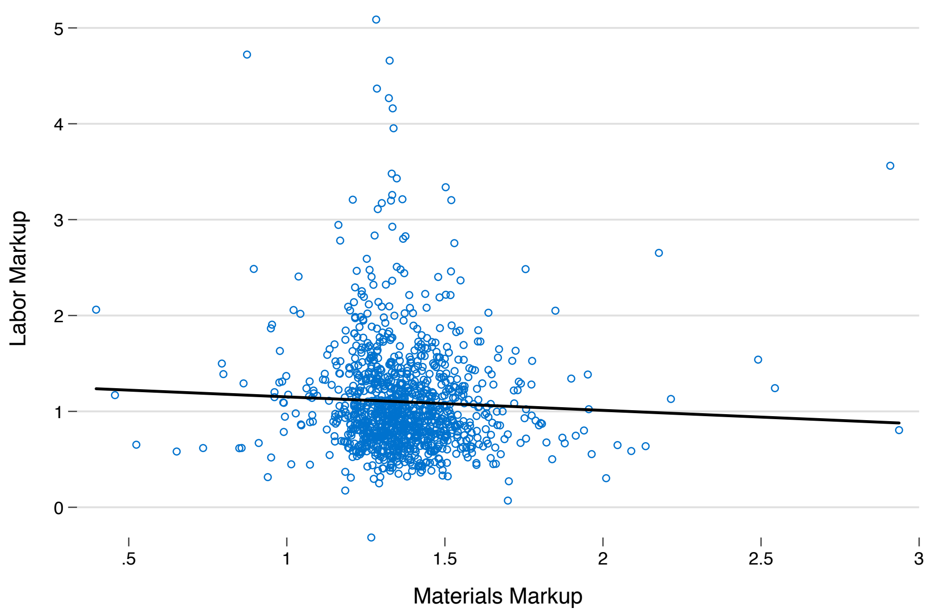


Figure 4 Correlation of Markups for Chilean Food Products, 1996

Note: Each point is the translog markup for a manufacturing plant in Chilean Food Products in 1996; the x-axis is the materials markup and the y-axis is the labor markup. Solid black line is the the best linear fit.

I examine the correlation between markup estimates for all the datasets by estimating the following regression:

$$\log(\mu_{it}^{L}) = \alpha + \beta \log(\mu_{it}^{M}) + \gamma_t + \delta_n + \epsilon_{it} \tag{11}$$

where μ_{it}^{L} and μ_{it}^{M} are the markups using labor and materials for establishment i in year t. I also include controls γ_t and δ_n, which are year and industry fixed effects, so estimated correlations do not reflect the yearly trends discussed in the previous section. In this specification, β represents the elasticity of the markup using labor with respect to the markup using materials.

I report these correlations between markup measures in Table III. The labor and materials markups are *negatively* correlated with each other, the opposite of the relationship implied by the production approach. Under the translog estimates, an establishment with a 100% higher materials markup has, on average, a 16% lower labor markup for Chile, 28% lower for Colombia, 53% lower for India, 48% lower for Indonesia, and 1008% lower for the Retailer. In general, the magnitude of the negative correlation is even higher using the Cobb-Douglas estimates.[16]

[16] The large magnitude of the elasticities for the retailer is due to the measurement error correction to the input share of revenue as in (9), because the estimated measurement error in sales is negatively correlated with the materials share of revenue. If I ignore this correction, the elasticity between the labor and materials markup is -1 for the Cobb-Douglas case and -2.3 for the translog case.

Table III Relationship between Markup Estimates

Dataset	CD	TL
Chile	-0.66	-0.16
	(0.017)	(0.014)
Colombia	-0.99	-0.28
	(0.015)	(0.021)
India	-1.73	-0.53
	(0.012)	(0.009)
Indonesia	-0.97	-0.48
	(0.018)	(0.021)
Retailer	-7.51	-10.08
	(0.143)	(0.102)

Note: Estimates based on (11) where the labor markup is the dependent variable and materials markup the independent variable. CD is Cobb-Douglas and TL translog. Standard errors are clustered at the establishment level.

4.6 Robustness

In Appendix A, I show that the large, substantive differences between markups estimated with different inputs demonstrated in this section are robust to several additional specifications. First, I find similar patterns looking at two non-labor inputs by splitting materials into raw materials and energy, so these results are not specific to labor as an input. In addition, I control for local labor markets through MSA fixed effects for the retailer and find similar patterns as before.

Second, these patterns are robust to using several alternative production function estimators assuming neutral productivity, including a dynamic panel approach (Blundell and Bond, 2000), an alternative control function approach (Flynn et al., 2019), and a industry-level cost share approach. Third, these patterns continue to hold estimating production functions at the subindustry or product level. Fourth, I find similar patterns estimating quantity rather than revenue production functions using a set of Indian homogenous products. Finally, the data patterns are not consistent with measurement error explanations.

5 Non-Neutral Productivity and Markups

In this section, I show that non-neutral productivity differences across plants can explain my findings. I then develop an estimator to account for labor augmenting productivity differences. Using this estimator, markups estimated using different inputs have similar cross-sectional correlations, time series correlations, and dispersion.

5.1 Theory

In order to allow productivity to be non-neutral, I assume a CES production function with elasticity of substitution σ, neutral productivity A_{it}, labor augmenting productivity B_{it}, and distribution parameters α_l and α_m:

$$F_{it} = A_{it}((1-\alpha_l-\alpha_m)K_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_l(B_{it}L_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_m M_{it}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}. \tag{12}$$

Input shares of revenue are equal to the output elasticity of that input divided by the markup μ_{it}:

$$\frac{w_{it}L_{it}}{P_{it}F_{it}} = \frac{1}{\mu_{it}}(\frac{w_{it}}{\lambda_{it}A_{it}})^{1-\sigma}(\alpha_l)^{\sigma}(B_{it})^{\sigma-1} \tag{13}$$

$$\frac{p^m_{it}M_{it}}{P_{it}F_{it}} = \frac{1}{\mu_{it}}(\frac{p^m_{it}}{\lambda_{it}A_{it}})^{1-\sigma}(\alpha_m)^{\sigma} \tag{14}$$

where λ_{it} is the marginal cost, w_{it} the wage, and p^m_{it} the price of materials. An increase in neutral productivity A_{it} does not affect input shares of revenue, as the marginal cost λ_{it} falls to exactly compensate.

Labor augmenting productivity, in contrast, does affect input shares of revenue. In this model, an increase in B_{it} is akin to more labor. Thus, after an increase in B_{it}, a firm will increase materials M_{it} to exactly match the increase in effective labor $B_{it}L_{it}$. However, the increase in B_{it} also reduces the cost of an efficient unit of labor, which is $\frac{w_{it}}{B_{it}}$. The plant will then substitute towards relatively cheaper labor, with the ratio of effective labor to materials $\frac{B_{it}L_{it}}{M_{it}}$ changing by σ given the change in the ratio of prices $(w_{it}/B_{it})/p^m_{it}$. Hence the labor cost to materials cost ratio $w_{it}L/p^m_{it}M_{it}$ decreases 1 by a direct effect and increases σ by a substitution effect when B_{it} increases.

When inputs are gross complements, as estimated in Doraszelski and Jaumandreu (2018) and Raval (2019), σ is less than one and so the direct effect is stronger than the substitution effect. A plant with higher labor augmenting productivity will then have a lower labor share, higher materials share, and lower labor cost to materials cost ratio.

Thus, changes in labor augmenting productivity B_{it} move the output elasticities of labor and materials in different directions. In the case when σ is less than one, improvements in B_{it} decrease labor's output elasticity, but increase materials's output elasticity as the marginal cost of production λ falls. If production function estimates ignore labor augmenting productivity differences, a plant with a higher B_{it} would have a lower labor share and higher materials share, and so a higher labor markup and lower materials markup. Estimated markups estimated using different inputs would be negatively correlated.

5.2 Flexible Cost Share Estimator

To explore whether accounting for non Hicks neutral productivity can explain my findings, I develop a variant of the cost share method of production function estimation to estimate output elasticities given labor augmenting productivity differences. The traditional cost share method has been used in productivity analysis (Foster et al., 2001, 2008), and markup estimation (De Loecker et al., 2018). The cost share estimator requires two major assumptions:

Assumption 1 (Cost Minimization Conditions) *On average, first order cost minimization conditions hold for all inputs:*

$$E[p_{it}^X X_{it}] = \beta^X E[\lambda_{it} F_{it}]$$

Assumption 2 (Returns to Scale) *Returns to scale are constant.*

A sufficient condition for Assumption 1 to hold is that all inputs, including capital, are flexibly determined. However, Assumption 1 also holds if capital faces time to build adjustment conditions, under which the capital first order condition will hold on average. Assumption 2 implies that the marginal cost is equal to the average cost, so one can use data on input costs to compute $\lambda_{it} F_{it}$. For capital, a measure of the rental rate of capital r_{it} would be required. An estimate for the output elasticity of labor is then:

$$\beta^L = \frac{E(w_{it} L_{it})}{E(r_{it} K_{it} + w_{it} L_{it} + p^m_{it} M_{it})}. \tag{15}$$

While Assumption 1 and Assumption 2 are strong, the cost share estimator relaxes other assumptions of the control function estimator. First, the cost share estimator does not require data on firm quantities, which are typically unobserved in production datasets. Thus, it is robust to criticism that estimating revenue production functions can lead to biased output elasticities when markups vary across plants (Flynn et al., 2019; Doraszelski and Jaumandreu, 2019; Bond et al., 2020). When markups are the primary interest of analysis, it is important to not use an estimator that is biased in the presence of markups.

Second, this estimator only requires data on labor costs and not on labor input. When workers vary in quality, measures of labor input such as the number of workers may not reflect labor efficiency units. Finally, since only expectations of input costs enter, it is robust to measurement errors in inputs, which might be particularly important for capital.

I adapt the cost share estimator to the model in Section 5.1 in which labor augmenting productivity varies across plants. As (13) and (14) demonstrate, the output elasticities of labor and materials both depend upon B_{it} (for labor directly, and for both labor and materials through the marginal cost λ_{it}).

I estimate cost shares within groups based on their level of labor augmenting productivity. After dividing (13) and (14), labor augmenting productivity B_{it} is proportional to the labor to materials cost ratio $\frac{w_{it}L_{it}}{p^m_{it}M_{it}}$:

$$B_{it} = (\frac{w_{it}}{p^m_{it}})(\frac{\alpha_l}{\alpha_m})^{\frac{-\sigma}{\sigma-1}}(\frac{w_{it}L_{it}}{p^m_{it}M_{it}})^{\frac{1}{\sigma-1}}. \tag{16}$$

Given exogenous variation in input prices, one could estimate σ, as in Raval (2019), and therefore recover B_{it} directly.

Instead, I use the fact that plants with a similar labor to materials cost ratio have similar values of B_{it}, and so similar output elasticities of labor and materials. I divide plants into groups based upon their labor cost to materials cost ratio in order to create groups with a similar value of B_{it}. I then estimate output elasticities as the input share of total cost within each group. The output elasticities for labor and materials for a plant in group g would be:

$$\beta_g^L = \frac{E(w_{it}L_{it}|G=g)}{E(r_{it}K_{it} + w_{it}L_{it} + p_{it}^m M_{it}|G=g)} \tag{17}$$

$$\beta_g^M = \frac{E(p_{it}^m M_{it}|G=g)}{E(r_{it}K_{it} + w_{it}L_{it} + p_{it}^m M_{it}|G=g)}. \tag{18}$$

For example, by using quintiles, five groups approximate the differences in B_{it} across plants. In that case, output elasticities would be the input share of total cost within the industry quintile.

The standard cost share approach, as implemented in Foster et al. (2001) and Foster et al. (2008), is equivalent to only one group. On the other hand, having every observation be its own group would set the markup using all inputs to the revenue to cost ratio. By averaging across groups, I allow for (mean-zero) measurement errors in capital, as well as for less strict assumptions on the flexibility of capital such as time to build adjustment frictions, while still accounting for differences in labor augmenting technology.

These two polar cases – one group or each plant-year as its own group – illustrate a major advantage of the grouping approach. The econometrician can easily vary the size of the group to examine sensitivity to this tuning parameter. In addition, one can easily estimate production functions at the subindustry or product level at which the number of plants is small.

A potential concern is that wages and materials prices may also vary across plants, as the equation for B includes the ratio of factor prices as well. Such differences in factor prices could misclassify plants into the wrong groups. A simple solution to this problem would be to construct groups based on factor prices, or variables correlated with factor price differences, as well as the labor to materials cost ratio. For example, if the wage to materials price ratio is likely to change over time, groups could be constructed based on quantiles of the labor to materials cost ratio within year. If factor prices vary across local labor markets, plant location could be included in the grouping.

An alternative reason why production functions might vary across plants is due to different production distribution parameters. For example, some plants could produce parts of the production process internally with labor, or outsource their production and purchase them as materials (Giannoni and Mertens, 2019), so insourcing plants would have a higher labor output elasticity and lower materials output elasticity than outsourcing plants. In that case, given (16), changes in the labor and materials distribution parameters would also affect the labor to materials cost ratio. Thus, the groups in the flexible cost share estimator based upon this ratio would approximate differences in the distribution parameters.

5.3 Monte Carlo

Through a Monte Carlo exercise, I show that labor augmenting productivity differences can cause a negative correlation between markups estimated using labor and materials as flexible inputs. However, with the flexible cost share estimator, markups using different inputs are positively correlated with each other and with the true markup.

I simulate an economy in which markups and labor augmenting productivity differences vary across plants. In this economy, 1000 cost minimizing plants produce for 10 years. All plants have a common CES production function, as in (12), with substitution elasticity 0.5. The logarithm of neutral productivity A and labor augmenting productivity B evolve over time through an autoregressive process with a productivity persistence parameter of 0.9 and jointly normal shocks. Productivity is thus distributed as a joint lognormal. I then calibrate the parameters of this lognormal to match moments from data on factor shares and productivity from US manufacturing plants.[17]

Plants face CES demand with an elasticity of demand drawn from a uniform distribution between 2 and 6. Because demand is CES, the markup plants choose is a simple inversion of the demand elasticity; markups range between 1.2 and 2. Plants then set all inputs flexibly given the factor prices they face and their productivity draws.

[17] I initialize productivities in their first year to the stationary distribution given the persistence process. I normalize the mean of the stationary distribution of $\log A$ to 1, and calibrate the mean of the stationary distribution of $\log B$ and the variances and covariance of $\log A$ and $\log B$ through moment-matching. I match the following six moments: an aggregate capital share of capital and labor cost of 0.3, a value of the weighted variance of capital shares of capital and labor of 0.1, and the aggregate materials share of total cost of 0.55 (all from Oberfield and Raval (2020)) the 90-10 ratio of marginal cost across plants to 2.7 (from Syverson (2004)), the coefficient of a regression of the capital cost to labor cost ratio on the log of the plant's total cost of capital and labor (weighting by the plant's total cost of capital and labor) of 0.08 from Raval (2019), and a log of total industry cost of $\log(10,000)$ (to keep the same size industry across simulations). Distribution parameters are 0.1 for capital, 0.3 for labor, and 0.6 for materials.

I estimate the relationship between markup estimates using the following regressions:

$$\log(\mu_{it}^{L}) = \alpha + \beta \log(\mu_{it}^{M}) + \epsilon_{it} \tag{19}$$

$$\log(\mu_{it}^{True}) = \alpha + \beta \log(\mu_{it}^{X}) + \epsilon_{it}. \tag{20}$$

First, I compare the labor markup to the materials markup using (19). Second, I examine how the true markup based on the demand elasticity the plant faces is correlated with different production based markups for input X using (20). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table IV, I report the average of β across 200 Monte Carlo simulations, with standard deviations across simulations in parentheses. I first examine three estimators that ignore labor augmenting productivity: the Cobb Douglas and translog control function estimators, as well as industry-wide cost shares, i.e., the traditional cost share approach, in the first three rows.[18] With all three of these estimators, B is assumed not to vary across plants.

As I found in the previous section, labor markups are negatively correlated with materials markups. A 100% increase in the materials markup decreases the labor markup on average by 115% using the Cobb-Douglas control function estimator, 8% using the translog control function estimator, and 14% using the industry wide cost share estimator.

[18] The Cobb Douglas estimates are based on 114 of 200 simulations for labor and materials, and 197 of 200 simulations for the composite input, as in some simulations the coefficient on labor or materials was negative.

In addition, both labor and materials markups are only slightly correlated with the true markup using the control function estimators; on average, the true markup is only 12% higher using the Cobb-Douglas estimator, or 5% higher using the translog estimator, after a 100% increase in the labor markup. The true markup is 36% higher using the Cobb-Douglas estimator, or 3% lower using the translog estimator, after a 100% increase in the materials markup. For the industry wide cost share estimator, the true markup is 36% higher on average with a 100% increase in the labor markup, and 65% higher with a 100% increase in the materials markup.

Table IV Relationship between Markup Estimates: Monte Carlo Estimates

Estimator	Labor on Materials	True Markup on Labor	True Markup on Materials	True Markup on Composite Input
Cobb-Douglas CF	-1.15	0.12	0.36	0.79
	(0.97)	(0.16)	(0.33)	(0.23)
Translog CF	-0.08	0.05	-0.03	0.27
	(0.33)	(0.10)	(0.02)	(0.21)
Industry-Wide CS	-0.14	0.36	0.65	0.94
	(0.95)	(0.32)	(0.33)	(0.08)
Quintile CS	0.59	0.61	0.80	0.99
	(0.44)	(0.31)	(0.27)	(0.01)
Decile CS	0.74	0.72	0.84	0.996
	(0.32)	(0.27)	(0.23)	(0.004)

Note: Estimates based on 200 Monte Carlo simulations, using (19) and (20). For example, True Markup on Materials indicates a regression where the true markup is the dependent variable and materials markup the independent variable. True markup is the actual markup set by the firm based on its demand elasticity in the Monte Carlo simulations. For the first two rows, markups estimates are based on ACF control function estimators. For the last three rows, markup estimates are based on the flexible cost share approach, using either one group (industry wide), five groups (quintiles), or ten groups (deciles). Standard deviation across 200 bootstrap estimates in parentheses.

However, the correlation between the labor and materials markup is positive once I use the flexible cost share estimator. I estimate output elasticities as cost shares within quintiles (fourth row) and deciles (fifth row) of the labor cost to materials cost ratio. A 100% increase in the materials markup increases the labor markup by 59% using quintiles and 74% using deciles.

In addition, both labor and materials markups have much higher correlations with the true markup. A 100% increase in the labor markup increases the true markup by 61% using quintiles and 72% using deciles. A 100% increase in the materials markup increases the true markup by 80% using quintiles and 84% using deciles. Thus, although imperfect, estimates using the flexible cost share estimator are much more correlated with each other and with the true markup.[19]

In all specifications, the composite input markup is more highly correlated with the true markup than labor or materials, as might be expected as the composite input combines two negatively correlated inputs. A 100% increase in the composite input markup increases the true markup by 99% using quintiles or deciles.

As discussed earlier, the grouping procedure would potentially assign plants to the wrong group with differences in input prices. I examine this scenario in Appendix C.1 by introducing plant specific input prices, and find that the flexible cost share estimator continues to perform well. In addition, in Appendix C.2, I examine an alternative scenario with heterogeneity in production technology through different Cobb-Douglas production parameters instead of

[19] While I have not focused on the average markup in this paper, the flexible cost share estimator also delivers similar average markups. On average across plants, the true markup is 1.4. Using the flexible cost share estimator, the average markup is 1.45 using labor and 1.44 using materials with quintiles, and 1.42 using labor and 1.42 using materials with deciles.

labor augmenting productivity differences. I also allow time to build adjustment frictions on capital, so capital is not flexibly chosen. Using the flexible cost share estimator, I continue to find positively correlated markups using different inputs, and high correlations with the true markup.

5.4 Production Datasets

I then estimate markups using the flexible cost share estimator on all five datasets, using output elasticities that are the cost share for each industry quintile. These quintiles are based on the entire panel (i.e they are not within year). I first examine the same statistical tests as in Section 4.2. I conduct 45 tests – 5 datasets, 3 flexible inputs (labor, materials, or the composite input), and 3 statistical tests (paired t-test, Kolmogorov-Smirnov test, and the paired Wilcoxon signed-rank test). With the cost share quintile estimator, I fail to reject the null of no difference at the 5% level for 6 out of 45 tests.[20]

I next examine several important features of the markup distribution. First, in Table V, I measure markup dispersion through the ratio of the 90th percentile markup to the 50th percentile markup. Dispersion in the markup is quite similar across inputs using the flexible cost share estimator. For example, the 90th percentile markup is 54% higher than the median markup for Chile using labor, 52% higher using materials, and 47% using the composite input. While labor markups continue to be more disperse than materials markups, the

[20]With a Bonferroni correction to adjust for multiple hypothesis testing, I would fail to reject in 9 of 45 tests.

magnitude of the difference in dispersion is much smaller. In addition, markup dispersion is much smaller across retail stores for the retailer compared to the manufacturing datasets.

Table V 90/50 Ratio of Markup Estimates: Cost Share Quintile Estimates

	Labor	Materials	Composite Input
Chile	1.54	1.52	1.47
	(0.004)	(0.005)	(0.003)
Colombia	1.47	1.47	1.38
	(0.004)	(0.005)	(0.002)
India	1.51	1.39	1.36
	(0.001)	(0.001)	(0.001)
Indonesia	1.74	1.59	1.54
	(0.004)	(0.003)	(0.005)
Retailer	1.07	1.05	1.05
	(0.001)	(0.000)	(0.000)

Note: Estimates use all establishments and years. Standard errors are based on 20 bootstrap simulations. For India, these estimates ignore the sample weights.

Second, in Table VI, I report correlations between markup measures estimating using (11) using cost share quintiles. Unlike what I previously found in Section 4, the labor and materials markups are very correlated with each other, the opposite of the relationship found in the baseline approach. An establishment with a 100% higher materials markup has, on average, a 75% higher labor markup for Chile, 34% higher for Colombia, 68% higher for India, 72% higher for Indonesia, and 89% higher for the retailer under the cost share quintile estimates.

Finally, I examine time trends estimated using (10) for markups estimated using cost share quintiles in Figure 5 and Figure 6. I keep the same scale as in the previous graphs in Section 4.4.

Table VI Correlation between Markup Estimates: Cost Share Quintile Estimates

Chile	0.75
	(0.007)
Colombia	0.34
	(0.011)
India	0.68
	(0.004)
Indonesia	0.72
	(0.005)
Retailer	0.89
	(0.012)

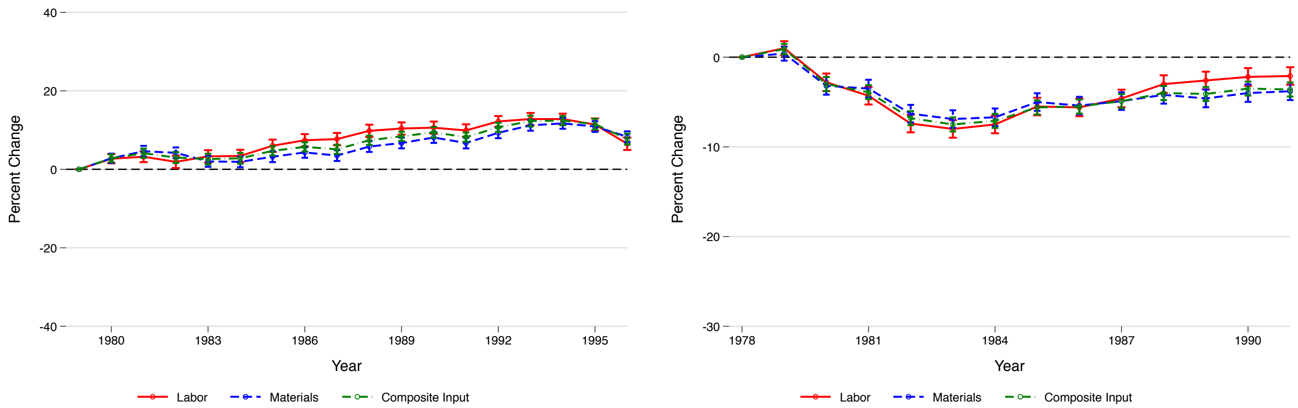
Note: Estimates based on (11) for markups from two flexible inputs, so Labor on Materials indicates a regression where the labor markup is the dependent variable and materials markup the independent variable. Standard errors are clustered at the establishment level.

Across all of the datasets, the time trends in markups are very similar. For example, for India, the average labor markup declines by 4.8% over the sample, compared to 4.1% for the average materials markup and 4.6% for the average composite input markup. With the 1998 Asian financial crisis, average markups in Indonesia using all inputs now increase. The largest difference in markup trends between labor and materials for any year is 4.2 percentage points for Chile, 2.0 percentage points for Colombia, 1.2 percentage points for India, and 2.3 percentage points for Indonesia.

The magnitude of changes are also much smaller than in the baseline estimates. For India, the average labor markup declines over the sample by 5.6%, compared to 39% in the baseline estimates. With the 1998 Asian financial crisis, Indonesian labor markups now rise by 3%, compared to 17% in the baseline estimates.

Thus, after accounting for non-neutral productivity differences through the flexible cost share estimator, markups estimating using different inputs have similar levels of dispersion, cross-sectional correlations, and time series correlations.

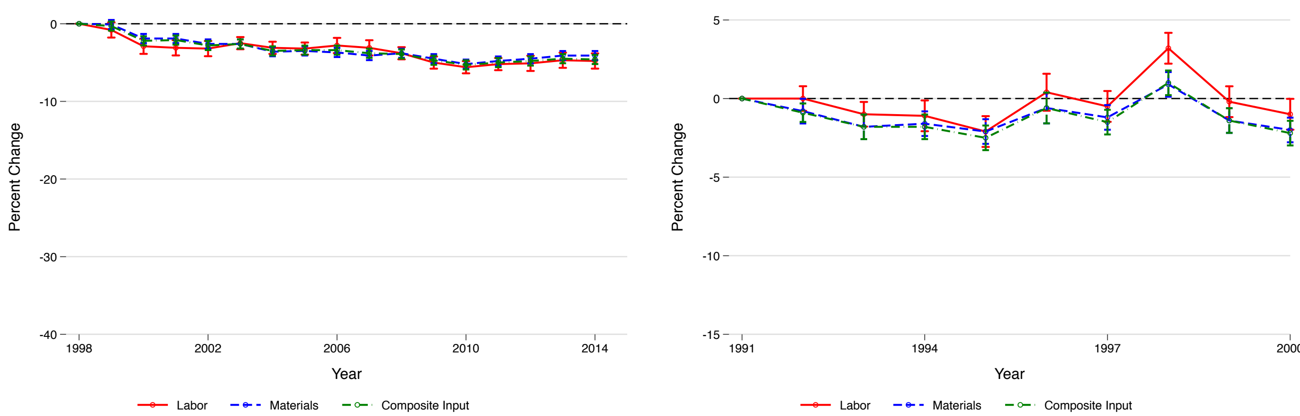
Figure 5 Markup Time Trends using Cost Share Quintile Estimates: Chile and Colombia



(a) Chile (b) Colombia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 6 Markup Time Trends using Cost Share Quintile Estimates: India and Indonesia



(a) India (b) Indonesia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

6 Markup Stylized Facts

In the previous sections, I have shown that the flexible cost share estimator leads to markup estimates that are more internally consistent than the baseline Cobb-Douglas and translog estimates. In this section, I show that it also provides more believable estimates for a set of stylized facts on markups.

I compare the flexible cost share and translog estimators using several stylized facts, including how markups correlate with size, competition, exporting behavior, and an alternative profit share based markup. For each variable Z_{it}, I estimate the following regression specification:

$$\log(\mu_{it}^X) = \alpha + \beta Z_{it} + \gamma_t + \delta_n + \epsilon_{it} \tag{21}$$

where μ_{it}^X is the markup estimate for establishment i in year t using input X, and γ_t and δ_n are year and industry fixed effects.

Below, I show that the flexible cost share estimator leads to estimates for each stylized fact across both inputs and datasets that are consistent with theoretical predictions as well as internally consistent. Estimates of all of the stylized facts, in contrast, vary in sign and magnitude across inputs and datasets using the control function estimator, and often conflict with predictions from theory.[21]

[21] I provide the equivalent stylized facts using the Cobb-Douglas control function estimator in Appendix B.5, and find similar conflicts with predictions from theory and variance in sign and magnitude across inputs and datasets.

6.1 Size

Multiple theories of variable markups (Atkeson and Burstein, 2008; Melitz and Ottaviano, 2008) predict markups increasing in firm size. I examine this prediction by estimating (21) regressing markups on the logarithm of deflated sales. I report these estimates in Table VII. I find a consistent, positive correlation between markups and size using the flexible cost share estimator. Across datasets and inputs, the markup increases, on average, between 2% and 9% with a 100% increase in sales. In contrast, using the translog baseline estimates, this correlation is negative for materials for all five datasets and negative for labor for two datasets.

Table VII Markups and Sales

	Translog			**Flexible Cost Share**		
	Labor	Materials	Composite	Labor	Materials	Composite
Chile	-0.03	-0.00	0.00	0.06	0.04	0.05
	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Colombia	-0.01	-0.00	0.01	0.04	0.02	0.03
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
India	0.05	-0.00	0.01	0.05	0.02	0.03
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	0.04	-0.03	0.01	0.07	0.05	0.06
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Retailer	0.09	-0.02	-0.04	0.09	0.06	0.07
	(0.008)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (21) where the independent variable is deflated sales. Markups are estimated using translog production functions in the first three columns, and industry cost share quintiles in the second three columns. Standard errors are clustered at the establishment level.

6.2 Exporting

Atkeson and Burstein (2008) and Melitz and Ottaviano (2008) also predict that exporters, being more productive than the typical firm, will have larger markups; De Loecker and Warzynski (2012) focused on this question. I examine this question using an indicator variable for whether the establishment exports.[22] Table VIII contains these estimates. The correlation of markups estimated using the flexible cost share estimator with exporting are always positive, with a 4 to 11 percentage point higher markup, on average, for exporters across inputs and datasets. Using the translog baseline estimates, this correlation is negative for labor for two of the four datasets, and positive with a much smaller magnitude for materials.

Table VIII Markups and Exporting

	Translog			**Flexible Cost Share**		
	Labor	Materials	Composite	Labor	Materials	Composite
Chile	-0.11	0.03	0.04	0.04	0.05	0.05
	(0.016)	(0.006)	(0.003)	(0.008)	(0.007)	(0.007)
Colombia	0.02	0.03	0.04	0.11	0.08	0.09
	(0.014)	(0.004)	(0.003)	(0.006)	(0.006)	(0.005)
India	-0.15	0.02	0.02	0.06	0.05	0.06
	(0.008)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)
Indonesia	0.05	0.01	0.03	0.09	0.08	0.09
	(0.011)	(0.004)	(0.001)	(0.004)	(0.004)	(0.004)

Note: Estimates are based on (21) where the independent variable is an indicator for whether the establishment exports. Markups are estimated using translog production functions in the first three columns, and industry cost share quintiles in the second three columns. Standard errors are clustered at the establishment level.

[22]For Chile, I only have exporter information for plants from 1990; for India, for plants from 2008.

6.3 Profit Share Markups

An alternative method to estimate markups has been to use data on profits to measure the markup. Returns to scale (RTS) are equal to the markup multiplied by one minus the share of profits s_π, or $RTS = \mu(1 - s_\pi)$. Thus, given constant returns to scale, one can invert the profit share to estimate the markup. We would expect this profit share based markup to be highly correlated with the production approach based markup.

I examine how production based markups correlate with the profit share based markup, estimating the profit share in two ways. First, as in Gutiérrez and Philippon (2016), I calculate the profit based markup as sales divided by total costs, where capital costs are measured through a user cost approach as the multiple of capital stocks and rental rates. Second, for the retailer, I have data on accounting profits measured as earnings before interest and taxes (EBIT) and so can calculate a profit based markup as sales divided by sales minus profits.

I then regress the log production based markup on the log profit share based markup using (21). I report these estimates in Table IX. Markups estimated using the flexible cost share estimator are always strongly positively correlated with the profit share based markup, with, on average, a 40% to 96% increase in the production markup with a 100% increase in the profit share based markup. In contrast, using the translog baseline estimates, this correlation is negative for materials for three of six datasets and negative for labor for five

Table IX Production Markup Estimates and Profit Based Markup

	Translog			Flexible Cost Share		
	Labor	Materials	Composite	Labor	Materials	Composite
Chile	-0.06	0.34	0.07	0.92	0.96	0.96
	(0.014)	(0.009)	(0.003)	(0.010)	(0.010)	(0.009)
Colombia	-0.22	0.02	-0.01	0.82	0.84	0.83
	(0.014)	(0.006)	(0.003)	(0.011)	(0.013)	(0.011)
India	-0.01	0.18	0.01	0.88	0.84	0.86
	(0.007)	(0.003)	(0.001)	(0.005)	(0.004)	(0.004)
Indonesia	-0.08	-0.09	-0.04	0.44	0.42	0.44
	(0.011)	(0.005)	(0.002)	(0.017)	(0.016)	(0.017)
Retailer	-0.03	-0.02	-0.19	0.80	0.56	0.60
	(0.042)	(0.003)	(0.003)	(0.012)	(0.007)	(0.006)
Retailer (EBIT)	0.90	-0.10	-0.18	0.82	0.58	0.62
	(0.045)	(0.004)	(0.003)	(0.012)	(0.007)	(0.007)

Note: Estimates are based on (21) where the independent variable is the profit share based markup. Markups are estimated using translog production functions in the first three columns, and industry cost share quintiles in the second three columns. Standard errors are clustered at the establishment level. All profit based markups are through a factor cost based profit measure, except for the last row which is an accounting profit (EBIT) based measure.

of six datasets.

6.4 Competition

One explanation for high markups is less competition. I examine how markups correlate with competition for the retailer using its own classification of the degree of competition.[23] The retailer classifies each store as facing either Low, Medium, or High competition, and records the number of competitors for each store. I examine the competition band in this

[23] As in Bresnahan and Reiss (1991), any measures of the degree of competition are endogenous, and may reflect other underlying determinants of market structure such as market size. I examine correlations between competition and markups after controlling for market size through local area-year fixed effects in Appendix B.6, and continue to find sharp differences across markup measures using control function translog estimates. Using the flexible cost share estimator, the markup rises slightly with greater competition.

section in Table X, and a discretized number of competitors in Appendix B.6.

I find a consistent, statistically insignificant increase in the markup of 0.1% from moving from Low to High competition using the flexible cost share estimator across all three inputs. Thus, using the flexible cost share estimator, the retailer does not appear to have substantially different markups across stores facing different levels of competition. With the translog estimates, labor markups are substantially (9%) lower on average with competition, while materials markups rise slightly.

Here, theory is not as clear cut. On the one hand, we might expect from canonical models of competition that markups would decline with competition. On the other hand, these estimates are consistent with uniform or near-uniform pricing by many large retailers (DellaVigna and Gentzkow, 2017), and the retailer's own data shows that it uses only a small number of pricing zones.

Table X Markups and Competition

	Translog			**Flexible Cost Share**		
	Labor	Materials	Composite	Labor	Materials	Composite
Medium Competition	-0.016	-0.001	-0.004	-0.003	-0.002	-0.002
	(0.005)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
High Competition	-0.088	0.002	-0.014	0.001	0.001	0.001
	(0.009)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (21) where the independent variable is the company-derived measure of competition; all estimates are relative to a retail store facing Low Competition. Markups are estimated using translog production functions in the first three columns, and industry cost share quintiles in the second three columns. Standard errors are clustered at the establishment level.

7 Conclusion

A key advantage of the production approach to estimating markups is that it allows one to estimate markups across widely differing industries, and thus estimate the aggregate markup. However, the production approach, as currently implemented, delivers very different markups using alternative flexible inputs. Labor markups are negatively correlated with materials markups, have opposing time trends, and are much more disperse.

Non-neutral technological differences across plants can explain these findings. I developed a flexible cost share estimator to account for labor augmenting technology; using this estimator, markups estimated with different flexible inputs have similar time trends and cross-sectional correlations. In addition, the flexible cost share estimator provides more plausible estimates for several markup stylized facts.

The development of the parallel demand approach to markup estimation provides guidance on how to measure markups going forward. The demand approach focuses on modeling the heterogeneity in preferences across consumers; for example, Berry et al. (1995) estimate random coefficients that allow consumers to vary in their sensitivity to price. In order to use the production approach, economists will have to allow more heterogeneity in production technology.

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A Robustness to Section 4 (For Online Publication)

In this section, I show that the large, substantive differences between markups estimated with different inputs demonstrated in Section 4 are robust to several additional specifications. First, in Section A.1, I show similar patterns for two non-labor inputs: raw materials and energy. Second, in Section A.2, I show that these patterns continue to hold after controlling for local labor markets. Third, in Section A.3, I show that these patterns hold estimating production functions through several different estimation approach compared to the ACF approach in the main text. Fourth, in Section A.4, I show similar patterns estimating production functions at the subindustry or product level. Fifth, in Section A.5, I show similar patterns estimating quantity as opposed to revenue production functions using data on Indian homogeneous products. Finally, in Section A.6, I argue that measurement error is unlikely to explain the patterns that I find.

A.1 Additional Inputs

One potential explanation for my findings is labor-specific: that labor is not a flexible input. The literature suggests that violations of the static first order conditions are likely to be more severe for labor (Dobbelaere and Mairesse, 2013), either due to hiring and firing costs when adjusting labor (Petrin and Sivadasan, 2013), bargaining with unions, or labor monopsony power.[24]

However, I show that the patterns in Section 4 continue to hold for other inputs by including two non-labor flexible inputs in the production function; both should be robust to labor-specific violations of the static cost minimization conditions. I separate materials into raw materials and energy, where energy includes both electricity and fuel expenditure. I then estimate production functions with capital, labor, and both raw materials and energy as separate flexible inputs using the manufacturing datasets.

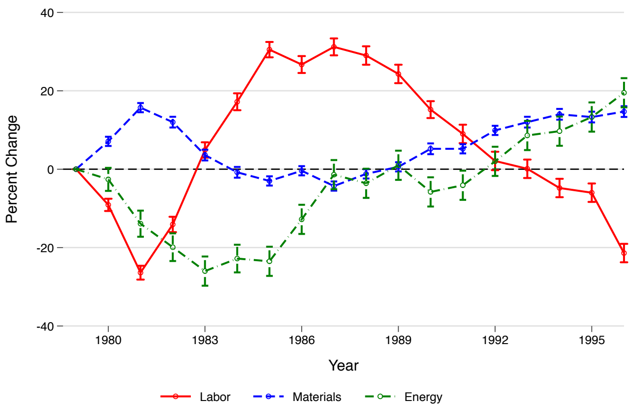
I examine time trends separating raw materials and energy estimated using (10). I depict the translog estimates in Figure 7 and Figure 8, and the Cobb-Douglas figures in Figure 9 and Figure 10. In all four datasets, the raw materials markup has a different time trend than the energy markup.

I report correlations between markup estimates using (11) in Table XI; for example, "Labor on Energy" indicates that the (logged) labor markup is the dependent variable and energy markup the independent variable.

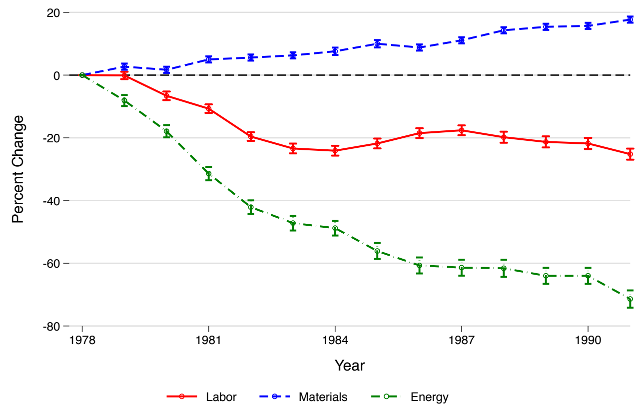
Neither the labor or raw materials markup is highly correlated with the energy markup. The raw materials markup is negatively correlated with the energy markup under the Cobb-Douglas estimates, with a 13% to 26% decline in the raw materials markup with a 100% increase in the energy markup. Under the translog estimates, the raw materials and energy markup are uncorrelated. The labor markup is positively correlated with the energy markup under the Cobb-Douglas estimates, with a 16% to 24% increase in the labor markup with a 100% increase in the energy markup. However, under the translog estimates, a 100% increase in the energy markup leads, on average, to

[24] Union bargaining under a "right to manage" model, in which bargaining is over the wage but the firm can freely choose the number of workers, does not violate my baseline approach. See Nickell and Andrews (1983) and Dobbelaere and Mairesse (2013).

Figure 7 Markup Time Trends using Translog Estimates, with Energy: Chile and Colombia



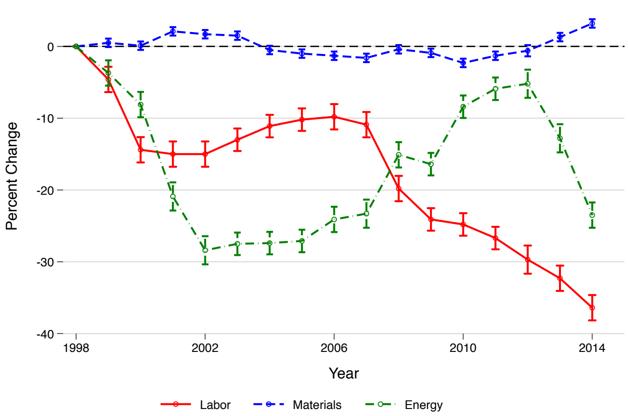
(a) Chile



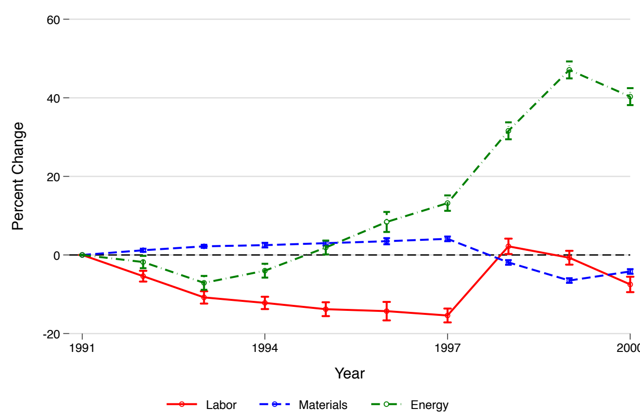
(b) Colombia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 8 Markup Time Trends using Translog Estimates, with Energy: India and Indonesia



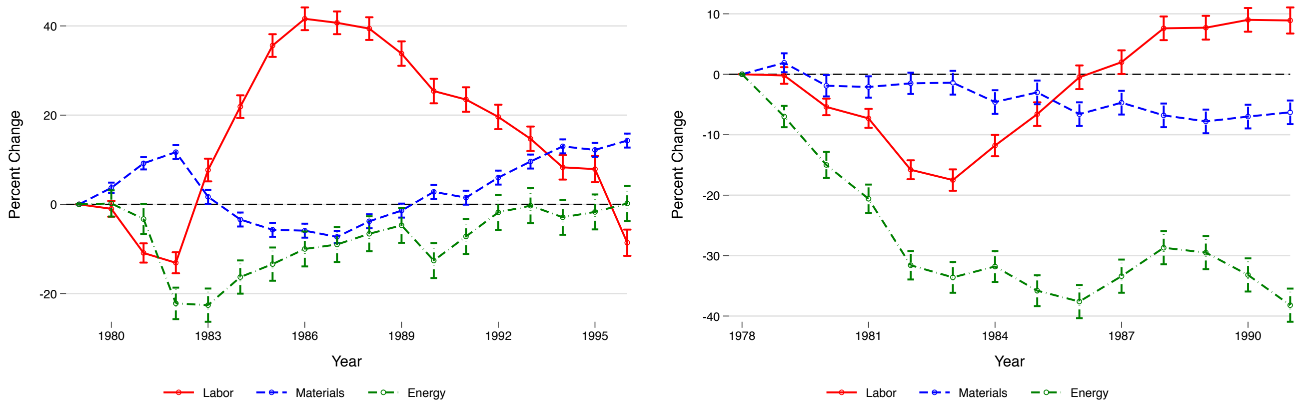
(a) India



(b) Indonesia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 9 Markup Time Trends using Cobb-Douglas Estimates, with Energy: Chile and Colombia

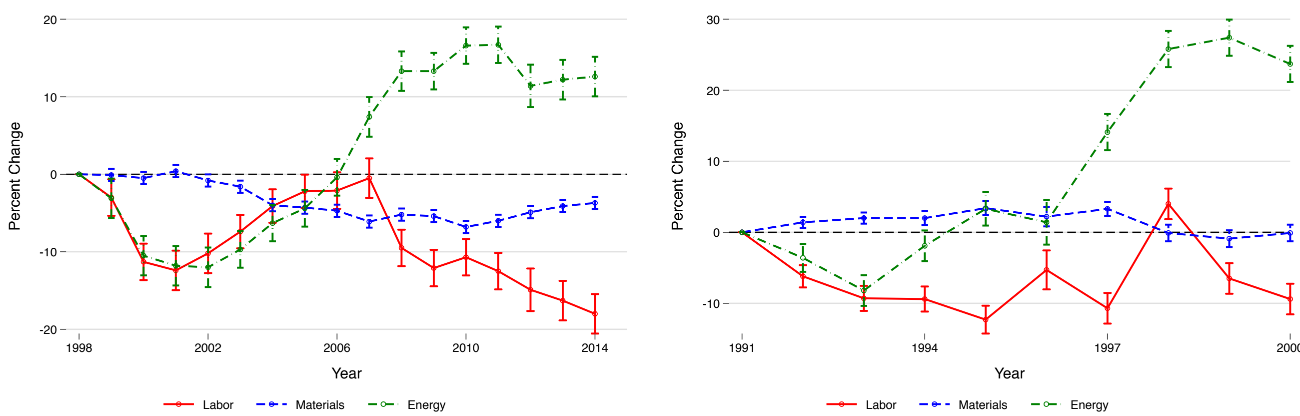


(a) Chile

(b) Colombia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 10 Markup Time Trends using Cobb-Douglas Estimates, with Energy: India and Indonesia



(a) India

(b) Indonesia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

a 2% to 10% decline in the labor markup. These findings are inconsistent with purely labor-specific violations of the cost minimization conditions.

Table XI Relationship between Markup Estimates: Energy and Raw Materials Separated

Dataset	Labor on Raw Materials CD	Labor on Raw Materials TL	Labor on Energy CD	Labor on Energy TL	Raw Materials on Energy CD	Raw Materials on Energy TL
Chile	-0.60	-0.05	0.21	-0.08	-0.13	-0.01
	(0.017)	(0.013)	(0.008)	(0.006)	(0.003)	(0.002)
Colombia	-0.71	-0.05	0.16	-0.05	-0.26	0.00
	(0.014)	(0.011)	(0.006)	(0.005)	(0.006)	(0.003)
India	-1.38	-0.32	0.28	-0.12	-0.11	0.00
	(0.019)	(0.008)	(0.003)	(0.003)	(0.001)	(0.001)
Indonesia	-0.75	-0.18	0.16	-0.10	-0.14	0.01
	(0.023)	(0.019)	(0.005)	(0.006)	(0.002)	(0.002)

Note: Estimates based on (11) for markups from two flexible inputs, so Labor on Raw Materials indicates a regression where the labor markup is the dependent variable and raw materials markup the independent variable. CD is Cobb-Douglas and TL translog. Standard errors are clustered at the establishment level.

A.2 Local Labor Market Controls

One reason why the labor first order condition might be violated is the employer's monopsony power. I examine this explanation using data on the retailer, and controlling for local labor markets through two strategies. First, I proxy for local labor markets through fixed effects for the MSA-year of the retail store. Here, the MSA is either the Metropolitan Statistical Area or Micropolitan Statistical Area of the retail store's location.[25] Second, I use data on the internal structure of the retailer and control for the district that the retail store is located in interacted with year; each district has about 10 to 20 stores.

After controlling for MSA fixed effects, a retail store with a 100% higher materials markup has, on average, a 992% lower labor markup using the translog estimates, compared to a 1008% lower markup without the fixed effects. After controlling for district l;evel fixed effects, a retail store with a 100% higher materials markup has, on average, a 1006% lower labor markup using the translog estimates. Thus, monoposony power in local labor markets is unlikely to explain the patterns that I find.

[25]For retail stores not located in a Metropolitan Statistical Area or Micropolitan Statistical Area, the fixed effect is for all non-MSA locations in the same state.

A.3 Alternative Production Function Estimators

Following De Loecker and Warzynski (2012), I used the control function approach of Ackerberg et al. (2015) to estimate production functions. One explanation for my findings is this estimation approach is misspecified, which could happen for several reasons.

First, the auxiliary assumptions required for the control function approach, such as a Markov assumption on productivity together with timing assumptions on when the firm determines its level of inputs, may not hold. Second, Gandhi et al. (forthcoming) show that the ACF procedure is not identified when applied to gross-output production functions.[26] Third, Flynn et al. (2019), Doraszelski and Jaumandreu (2019), and Bond et al. (2020) show how the ACF procedure can fail to identify production function parameters with non-competitive output markets when the dependent variable is revenue and not quantity produced. Fourth, Rovigatti and Mollisi (2018) find that ACF estimates are quite sensitive to the initial conditions used for optimization. Empirically, Foster et al. (2017) show that estimated output elasticities can vary substantially across different estimation approaches.

To examine whether such issues explain my findings, I examine three additional approaches to production function estimation. First, I use a dynamic panel approach to estimation following Blundell and Bond (2000). Second, Flynn et al. (2019) develop a new method to estimate production functions using a similar set of auxiliary assumptions as Ackerberg et al. (2015) together with constant returns to scale. I use this new method to estimate translog production functions.[27] Finally, I use the cost share approach assuming that productivity differences are neutral using industry-year cost shares, as in De Loecker et al. (2018). The cost share estimates allow the output elasticities of the industry-level production function to change over time, but do not allow non-neutral technological differences through groups as in the previous section.

Using all three methods, the time trends using different inputs estimated using (10) are very different for all cases except for cost shares for Colombia. I depict these in Figure 11 through Figure 18. In addition, after controlling for time trends, I show in Table XII that the labor markup remains negatively correlated with the materials markup, with a decline in the labor markup with a 100% increase in the materials markup ranging from -25% to -100% using the dynamic panel approach, -17% to -705% using the Flynn et al. (2019) approach, and from -24% to -100% for the cost share approach.

Thus, alternative production function estimators assuming neutral productivity differences cannot explain the differing markup estimates across variable inputs that I document.

[26] See Bond and Söderbom (2005) for an early critique in this vein. Ackerberg et al. (2015) state that "we would not suggest applying our procedure to gross output production functions that are not Leontief in the intermediate inputs".

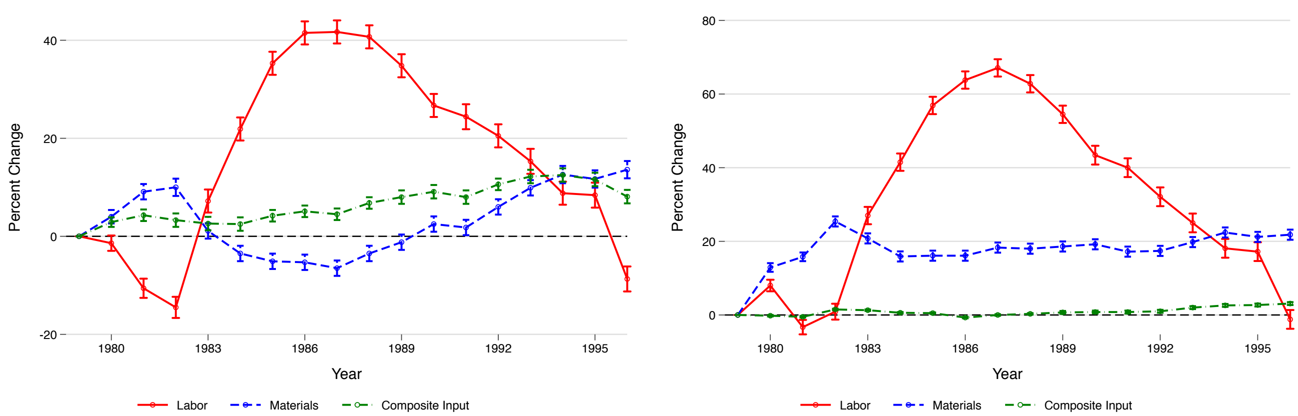
[27] This approach does not converge for one industry for Chile, Colombia, and Indonesia, and two industries for India for the labor and materials specification, as well as one industry for Indonesia and seven industries for India in the composite variable input specification.

Table XII Relationship between Markup Estimates: Alternative Estimators

Dataset	DP	FGT	CostShare Ind	CostShare SubInd
Chile	-0.25	-0.69	-0.24	-0.20
	(0.015)	(0.018)	(0.015)	(0.014)
Colombia	-0.65	-1.06	-0.65	-0.61
	(0.008)	(0.020)	(0.008)	(0.009)
India	-0.89	-0.17	-0.89	-0.66
	(0.008)	(0.007)	(0.008)	(0.008)
Indonesia	-0.70	-0.82	-0.51	0.02
	(0.011)	(0.020)	(0.010)	(0.016)
Company 1	-1.00	-7.05	-1.00	-1.00
	(0.055)	(0.151)	(0.055)	(0.055)

Note: Estimates based on (11) where the labor markup is the dependent variable and materials markup the independent variable. Columns labeled DP are markups based on Blundell and Bond (2000), and labeled FGT based on Flynn et al. (2019), as described in the text. Columns labeled CostShare Ind are markups based on industry-year level cost shares, and CostShare SubInd are markups based on subindustry-year level cost shares, as described in the text. Standard errors are clustered at the establishment level.

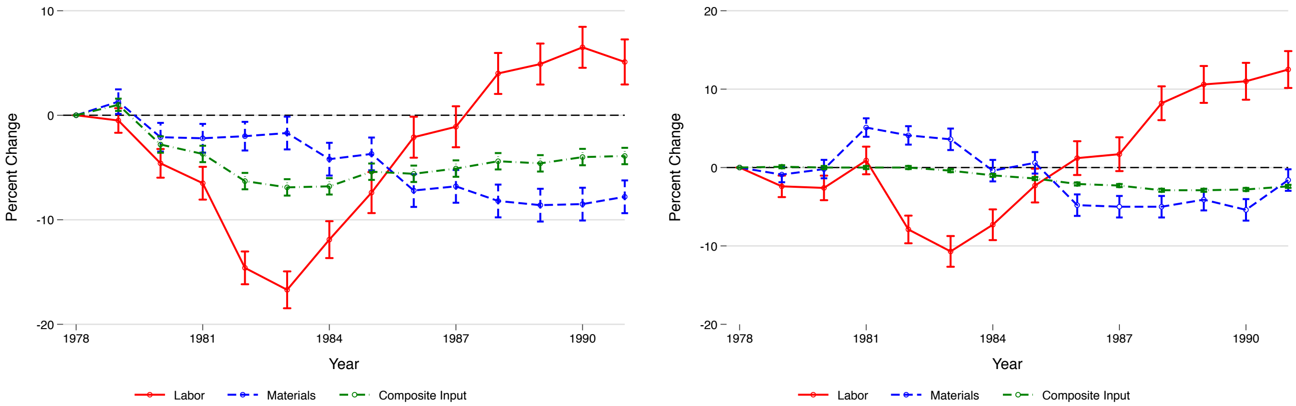
Figure 11 Markup Time Trends, Alternative Estimators: Chile



(a) Dynamic Panel (b) Flynn, Gandhi, Traina

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 12 Markup Time Trends, Alternative Estimators: Colombia

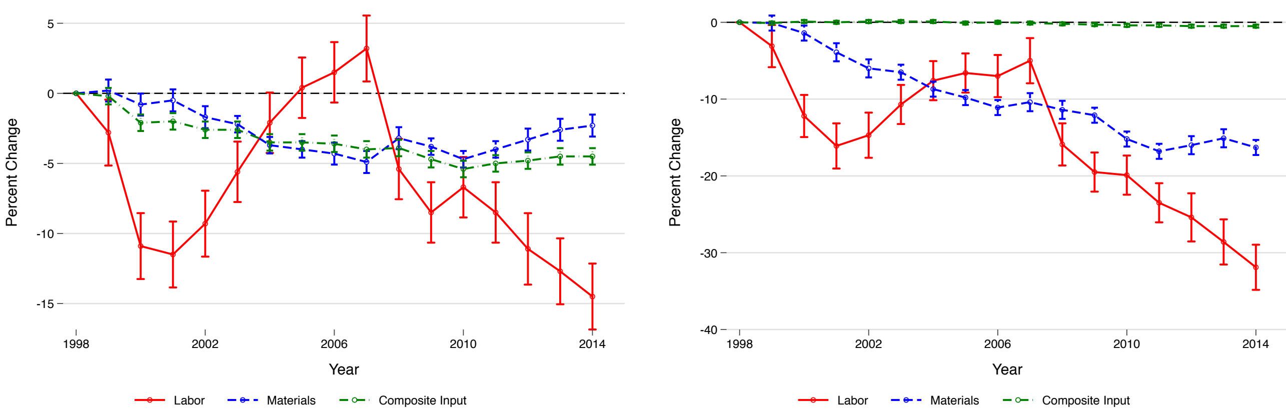


(a) Dynamic Panel

(b) Flynn, Gandhi, Traina

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 13 Markup Time Trends, Alternative Estimators: India

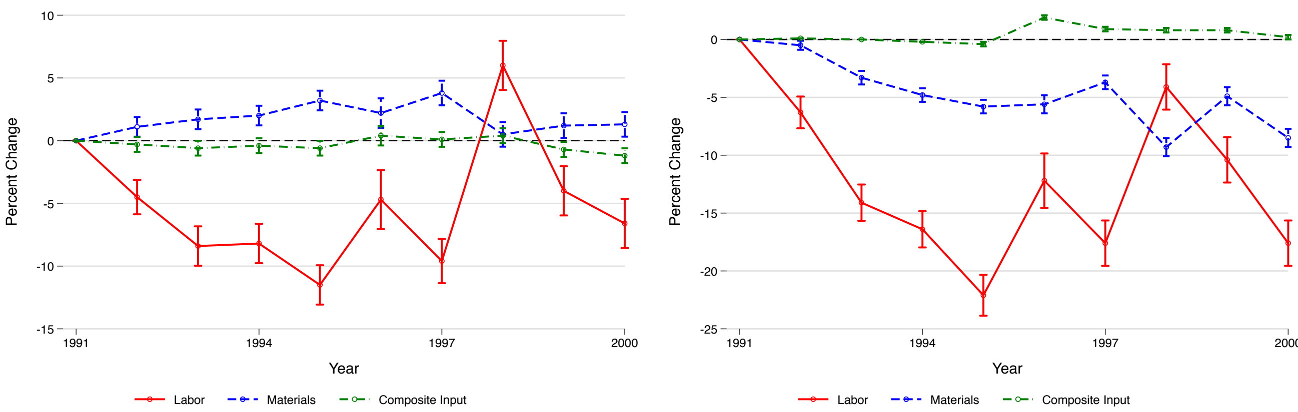


(a) Dynamic Panel

(b) Flynn, Gandhi, Traina

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

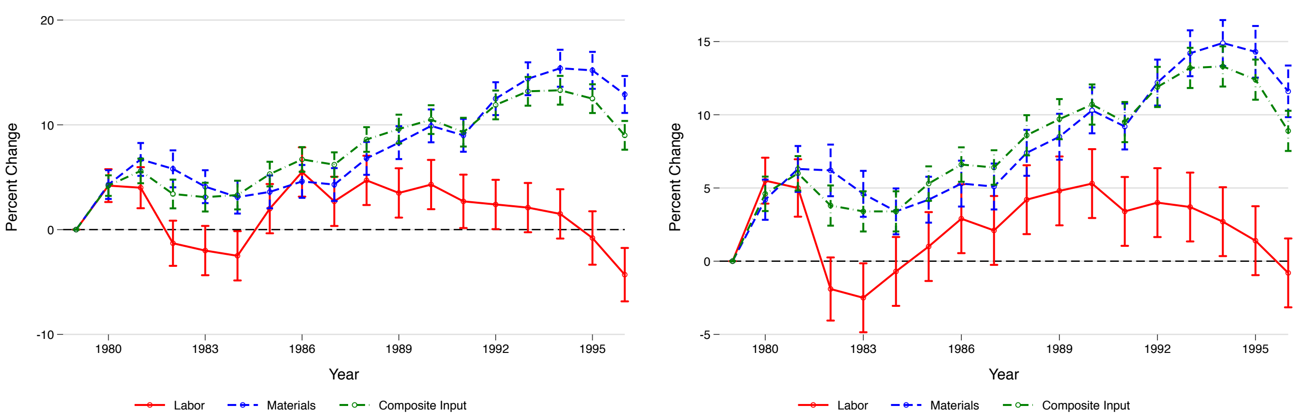
Figure 14 Markup Time Trends, Alternative Estimators: Indonesia



(a) Dynamic Panel (b) Flynn, Gandhi, Traina

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

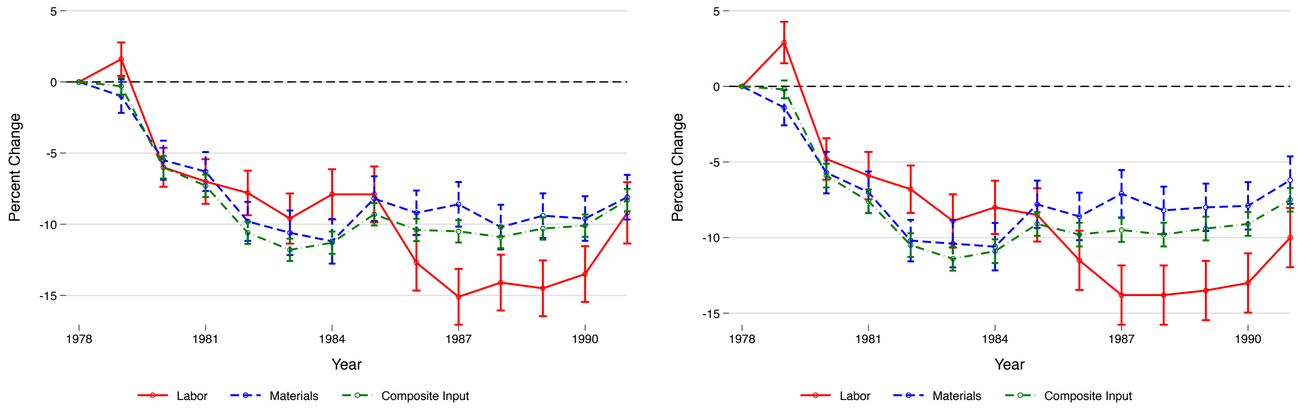
Figure 15 Markup Time Trends, Cost Share Estimators: Chile



(a) Industry Cost Share (b) Subindustry Cost Share

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 16 Markup Time Trends, Cost Share Estimators: Colombia

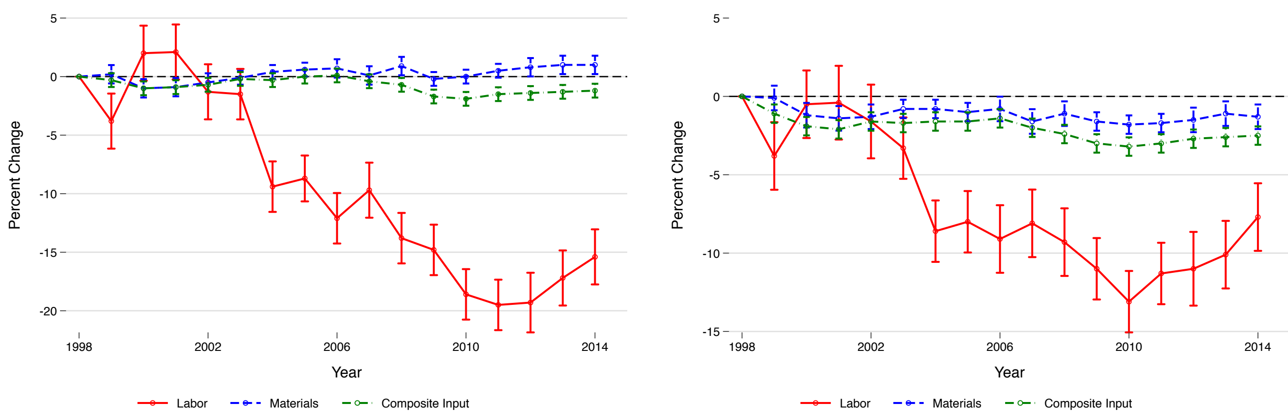


(a) Industry Cost Share

(b) Subindustry Cost Share

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 17 Markup Time Trends, Cost Share Estimators: India

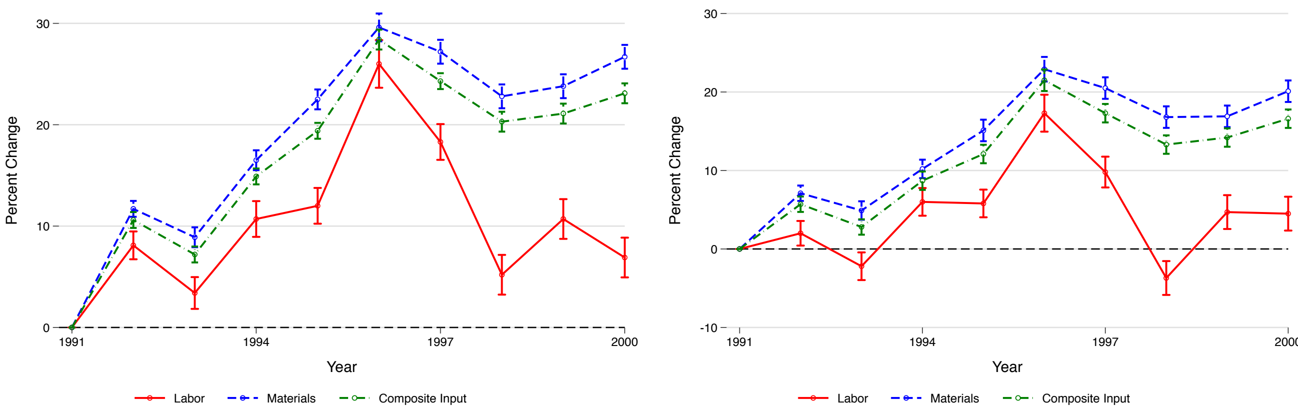


(a) Industry Cost Share

(b) Subindustry Cost Share

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 18 Markup Time Trends, Cost Share Estimators: Indonesia



(a) Industry Cost Share

(b) Subindustry Cost Share

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

A.4 Within Industry Heterogeneity

One potential concern is that production functions vary across subindustries or products within a broader industry. With such variation, production function estimates at the industry level may not identify a plant's production function parameters.

I first examine this concern by estimating production functions at the subindustry level. There are 60 such subindustries for Chile, 82 for Colombia, and 260 for Indonesia. For India, industry definitions vary over time; there are 764 subindustries in the period before 2004, 684 between 2004 and 2007, and 586 in the period after 2007.[28]

I estimate production functions at the subindustry level using subindustry-year cost shares. Time trends, reported in Figure 15 through Figure 18, continue to be very different across inputs. The magnitude of the negative cross-sectional correlation between the labor and materials markup is smaller at the subindustry level; the labor markup is uncorrelated with the materials markup for Indonesia, and is negatively correlated with the materials markup in the other datasets, with a 100% increase in the materials markup decreasing the labor markup by -20% to -100%. See the CostShare SubInd column of Table XII.

For India, I also have access to product-level data and so can estimate product level production functions. I only include manufacturing plants that report only one product within a given year; in 2014, this dataset includes about 25,000 plants and 3,000 products. I then estimate production functions at the product-year level using product-year cost shares. The labor markup is negatively

[28]For Chile and Colombia, the subindustry is defined at the four digit ISIC (Rev.2) level, for Indonesia at the five digit ISIC (Rev.2) level, and for India at the five digit NIC 98 level before 2004, five digit NIC 04 level between 2004 and 2007, and five digit NIC 08 level after 2007.

correlated with the materials markup, with a decline in the labor markup of −45% with a 100% increase in the materials markup using product-year cost shares, compared to −85% estimating production functions using industry-year cost shares on the same data.

Thus, estimating subindustry or product level production functions reduces, but does not eliminate, the negative cross-sectional correlation between markup estimates that I document.

A.5 Revenue Production Functions

Economists typically only have data on revenue, and not output, and so estimate revenue production functions. However, with imperfect competition, the markup is an additional unobservable in the revenue production. With imperfect competition, the control function estimator applied to revenue production functions may fail to identify production function parameters (Flynn et al., 2019; Doraszelski and Jaumandreu, 2019).

I examine this issue by using data on ten Indian homogenous products for which I have the quantity produced and price of the good, in the spirit of Foster et al. (2008).[29] For these products, I estimate product-level quantity production functions using the control function estimator. I only include plants for which at least 75% of their revenue comes from one of these products. The labor markup and materials markup are negatively correlated for these products, with a decline in the labor markup of −42% and −83% with a 100% increase in the materials markup using Cobb-Douglas and translog production functions. Thus, problems with revenue production functions alone cannot explain my findings.

A.6 Measurement Error

Another potential concern is measurement error in data on inputs due to survey collection. For example, manufacturing plants may not respond to all survey questions (White et al., 2016). However, the retailer's data is based on the internal records of the firm, and so should have very little measurement error compared to survey data. I find similar patterns using the retailer's data as I did in the manufacturing datasets.

Measurement error may be more of an issue for smaller, less sophisticated plants compared to large plants. All of my baseline estimates do not weight by size. I examine sales and cost weights, as in De Loecker et al. (2018) and Edmond et al. (2018), below, and find qualitatively similar findings to the unweighted results.

Finally, for the Cobb-Douglas production function, the negative correlation between the labor markup and materials markup is driven by a negative correlation between the labor share of revenue and the materials share of revenue, as the output elasticities are industry-specific constants. For measurement error to account for this correlation, measurement errors in payroll would have to be negatively correlated with measurement errors in materials expenditure. It is unclear why this would be the case.

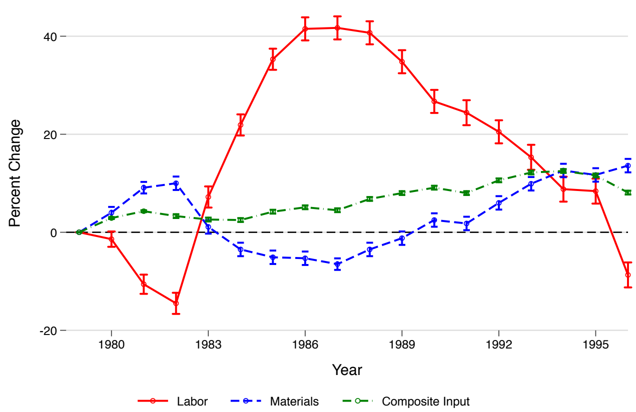
[29] I describe the construction of these products in Appendix D.7; they are Biri Cigarettes, Black Tea, Corrugated Sheet Boxes, Matches, Portland Cement, Processed Milk, Refined Sugar, Parboiled Non-Basmati Rice, Raw Non-Basmati Rice, and Shelled Cashew Nuts.

B Additional Empirical Results

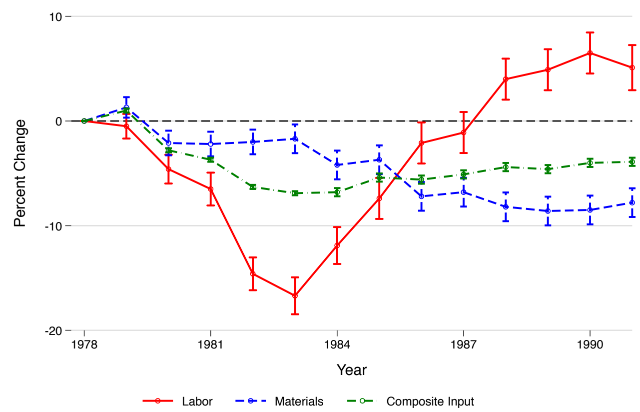
B.1 Trends over Time

In Figure 19 and Figure 20, I depict aggregate markup trends based on labor, materials, or the combined input of both as flexible inputs estimated using Cobb-Douglas production functions.

Figure 19 Markup Time Trends using Cobb-Douglas Estimates: Chile and Colombia



(a) Chile



(b) Colombia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

B.2 Markup Dispersion

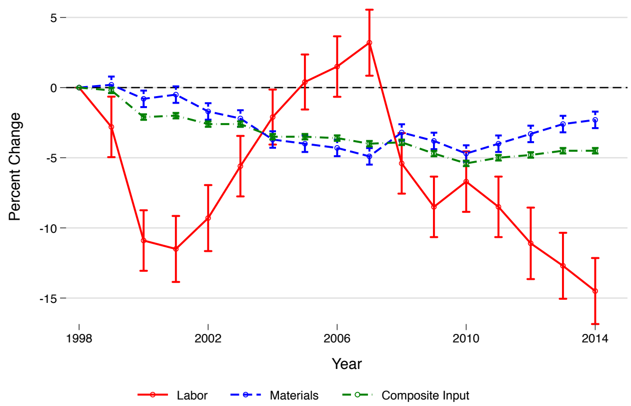
In Table XIII and Table XIV, I report the 75/25 ratio and 90/10 ratio of markup estimates.

B.3 Average Markups

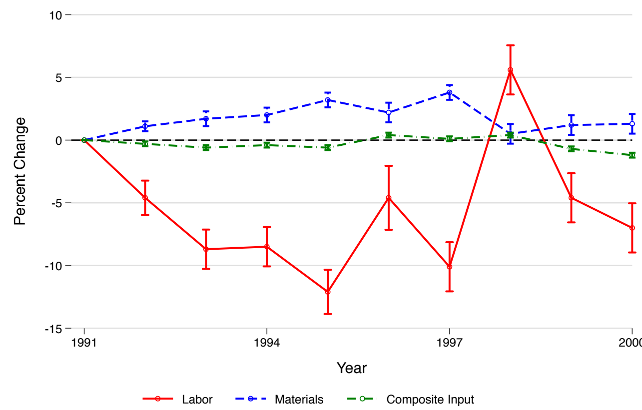
Under the production approach, the average markup should be the same using different flexible inputs. I test this prediction by estimating the average markup across all establishments using different flexible inputs. I find similar average markups in some, but not all, of the datasets.

Using all the datasets, I report the ratio of the average labor markup to the average materials markup in the first two columns of Table XV. The average labor markup is 9% higher than the average materials markup for Chile, 18% higher for Colombia, 98% higher for India, 72% higher for Indonesia, and 106% higher for the retailer under the Cobb-Douglas estimates. Under the translog estimates, the average labor markup is 50% higher than the average materials markup for Chile, 5% lower for Colombia, 46% higher for India, 69% higher for Indonesia, and 5% lower for the retailer.

Figure 20 Markup Time Trends using Cobb-Douglas Estimates: India and Indonesia



(a) India



(b) Indonesia

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Table XIII 75/25 Ratio of Markup Estimates

	Labor		Materials		Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	2.68	2.06	1.41	1.32	1.16	1.15
	(0.009)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
Colombia	2.69	1.87	1.63	1.24	1.14	1.14
	(0.013)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)
India	4.25	3.16	1.32	1.25	1.13	1.12
	(0.011)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)
Indonesia	3.82	2.65	1.55	1.37	1.12	1.13
	(0.022)	(0.010)	(0.002)	(0.002)	(0.000)	(0.000)
Retailer	1.28	1.35	1.03	1.03	1.02	1.03
	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)

Note: CD is Cobb-Douglas and TL translog. Estimates use all establishments and years. Standard errors are based on 20 bootstrap simulations. For India, these estimates ignore the sample weights.

Table XIV 90/10 Ratio of Markup Estimates

Dataset	Labor CD	Labor TL	Materials CD	Materials TL	Composite Input CD	Composite Input TL
Chile	6.25	4.04	2.08	1.81	1.33	1.31
	(0.032)	(0.020)	(0.004)	(0.006)	(0.002)	(0.001)
Colombia	7.87	7.43	2.71	1.68	1.31	1.30
	(0.076)	(0.304)	(0.010)	(0.006)	(0.001)	(0.001)
India	15.81	10.08	1.75	1.58	1.27	1.27
	(0.063)	(0.044)	(0.001)	(0.001)	(0.000)	(0.000)
Indonesia	17.05	8.16	2.34	1.97	1.25	1.28
	(0.142)	(0.061)	(0.005)	(0.004)	(0.001)	(0.001)
Retailer	1.59	1.76	1.05	1.06	1.04	1.05
	(0.004)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)

Note: CD is Cobb-Douglas and TL translog. Estimates use all establishments and years. Standard errors are based on 20 bootstrap simulations. For India, these estimates ignore the sample weights.

Thus, the average markups are close to each other for Colombia and the retailer using the translog estimates, and for Chile and Colombia using the Cobb-Douglas estimates.

Table XV Ratio of Average Markup Estimates

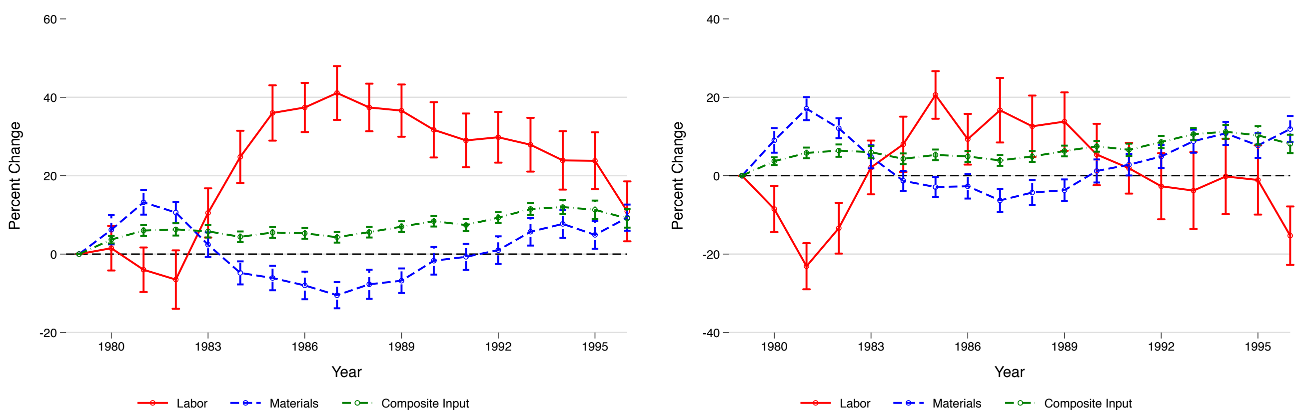
Dataset	Labor/Materials CD	Labor/Materials TL	Labor/Composite Input CD	Labor/Composite Input TL	Materials/Composite Input CD	Materials/Composite Input TL
Chile	1.09	1.50	1.30	1.63	1.19	1.09
	(0.012)	(0.012)	(0.012)	(0.012)	(0.003)	(0.002)
Colombia	1.18	0.95	1.53	1.02	1.30	1.08
	(0.016)	(0.015)	(0.016)	(0.013)	(0.010)	(0.005)
India	1.98	1.46	2.17	1.56	1.10	1.07
	(0.008)	(0.005)	(0.008)	(0.005)	(0.001)	(0.001)
Indonesia	1.72	1.69	2.00	1.89	1.17	1.11
	(0.018)	(0.019)	(0.019)	(0.021)	(0.003)	(0.002)
Retailer	2.06	0.95	1.32	0.95	0.64	1.00
	(0.004)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)

Note: Estimates are the ratio of the average markup between two flexible inputs across all establishments and years, so Labor/Materials indicates the ratio of the average labor markup to average materials markup. CD is Cobb-Douglas and TL translog. Standard errors are clustered at the establishment level.

B.4 Weighted Estimates

De Loecker et al. (2018) weight markups by sales, while Edmond et al. (2018) argue that cost weights are the right benchmark for welfare calculations. In this section, I weight all observations using sales weights (the plant's share of total sales in the year), or cost weights (the plant's share of total costs in the year). I then report the ratio of average markups, trends over time, and correlations between markups, using either labor, materials, or the combined variable input to compute markups. In some of the manufacturing datasets, a few plants have very large sales and cost shares (for example, petroleum refineries in India), so weighted estimates can differ from unweighted estimates substantially. Nevertheless, I continue to find negative correlations between labor markups and materials markups and different trends over time after weighting using sales or cost weights.

Figure 21 Markup Time Trends, Sales Weighted: Chile



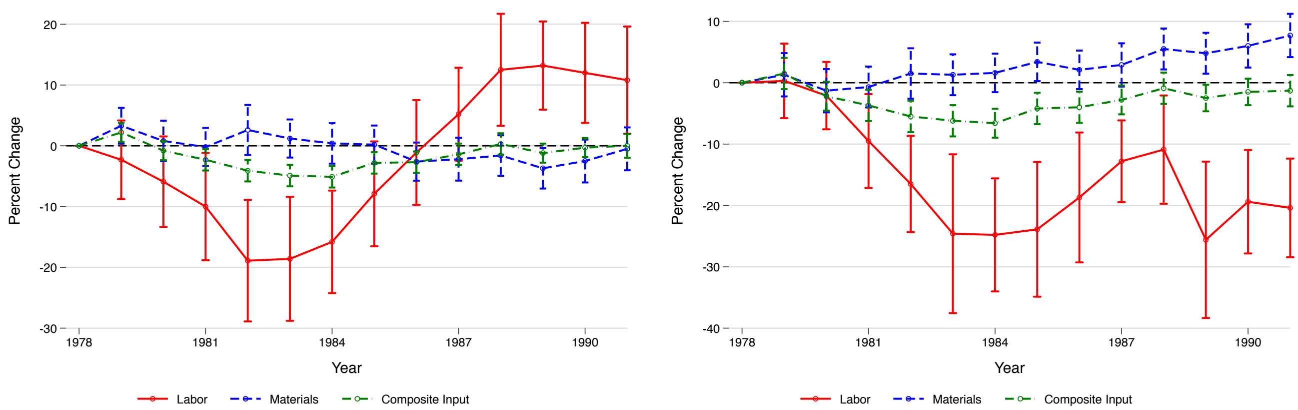
(a) Cobb-Douglas (b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

B.5 Stylized Facts

In this appendix, I examine the same stylized facts as in Section 6, but include the Cobb-Douglas as well as the translog control function estimator to estimate production functions. See Table XVIII to Table XXI. Across all of the stylized facts, estimates vary in sign and magnitude across different datasets and inputs.

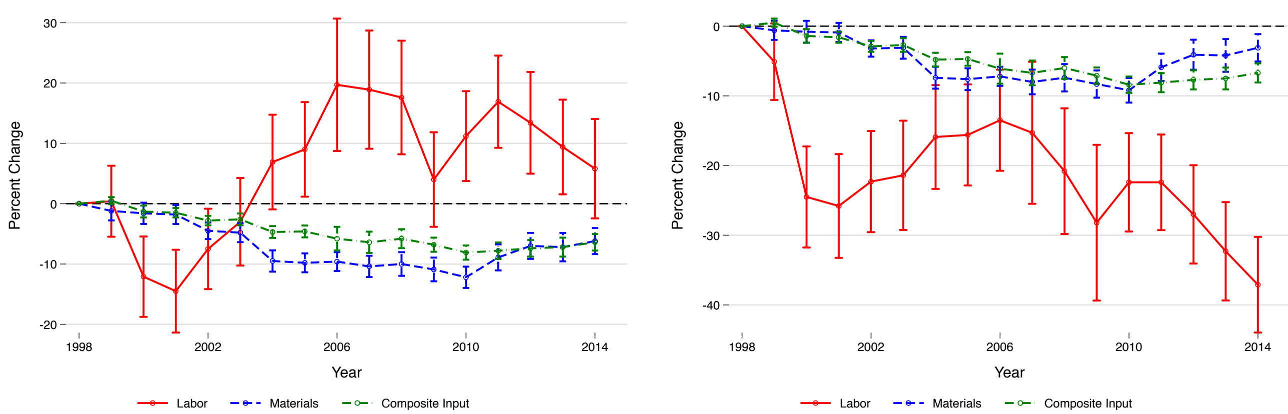
Figure 22 Markup Time Trends, Sales Weighted: Colombia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

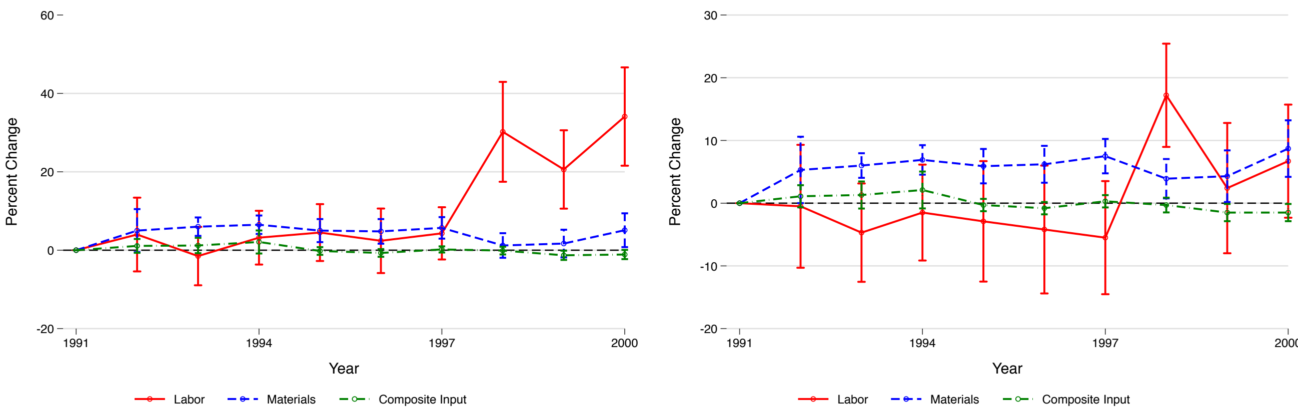
Figure 23 Markup Time Trends, Sales Weighted: India



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

Figure 24 Markup Time Trends, Sales Weighted: Indonesia



(a) Cobb-Douglas

(b) Translog

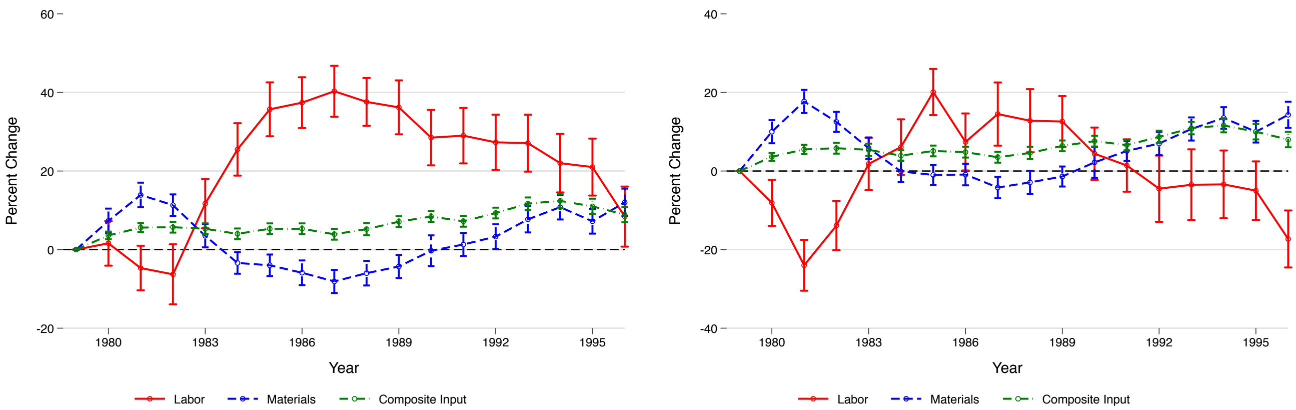
Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

Table XVI Relationship between Markup Estimates: Sales Weighted

Dataset	CD	TL
Chile	-0.83	-0.30
	(0.060)	(0.076)
Colombia	-1.37	-0.09
	(0.087)	(0.199)
India	-1.89	-0.73
	(0.127)	(0.117)
Indonesia	-0.65	-0.30
	(0.094)	(0.111)
Retailer	-7.06	-9.70
	(0.152)	(0.121)

Note: Estimates based on (11) where the labor markup is the dependent variable and materials markup the independent variable. CD is Cobb-Douglas and TL translog. Standard errors are clustered at the establishment level. Estimates weighted with sales weights.

Figure 25 Markup Time Trends, Cost Weighted: Chile

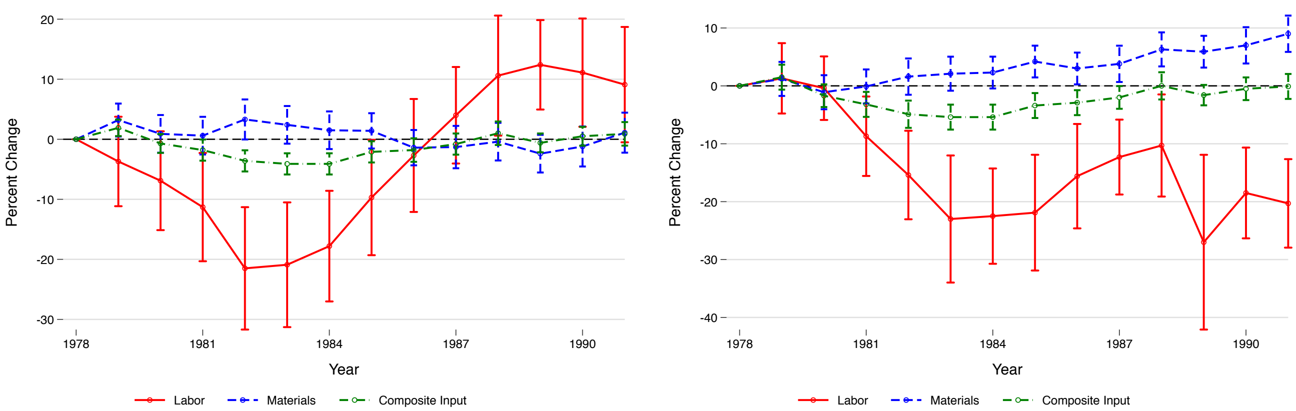


(a) Cobb-Douglas

(b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with cost weights.

Figure 26 Markup Time Trends, Cost Weighted: Colombia

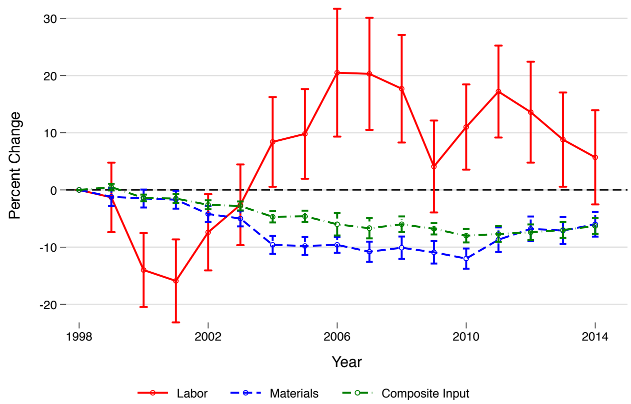


(a) Cobb-Douglas

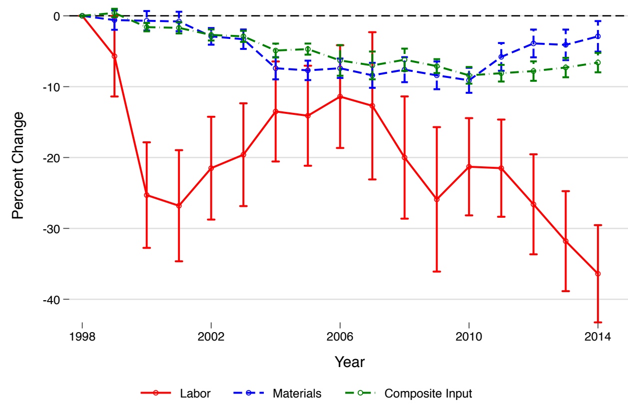
(b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with cost weights.

Figure 27 Markup Time Trends, Cost Weighted: India



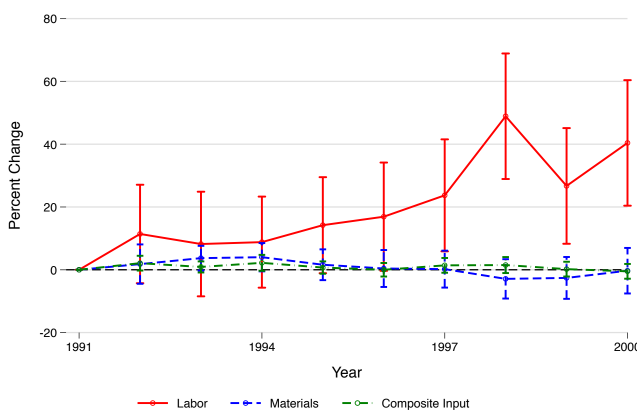
(a) Cobb-Douglas



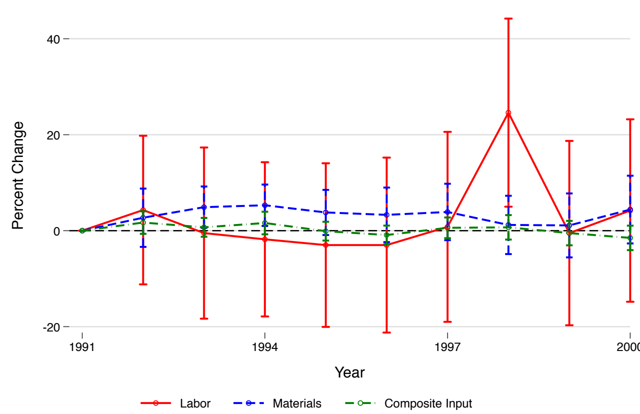
(b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with cost weights.

Figure 28 Markup Time Trends, Cost Weighted: Indonesia



(a) Cobb-Douglas



(b) Translog

Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with cost weights.

Table XVII Relationship between Markup Estimates: Cost Weighted

Dataset	CD	TL
Chile	-0.83	-0.29
	(0.059)	(0.069)
Colombia	-1.42	-0.08
	(0.068)	(0.161)
India	-1.98	-0.77
	(0.120)	(0.112)
Indonesia	-0.86	-0.46
	(0.116)	(0.126)
Retailer	-7.07	-9.71
	(0.155)	(0.119)

Note: Estimates based on (11) where the labor markup is the dependent variable and materials markup the independent variable. CD is Cobb-Douglas and TL translog. Standard errors are clustered at the establishment level. Estimates weighted with cost weights.

Table XVIII Markups and Sales: Cobb-Douglas and Translog Estimates

	Labor		Materials		Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	0.12	-0.03	-0.02	-0.00	0.01	0.00
	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Colombia	0.16	-0.01	-0.07	-0.00	0.00	0.01
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
India	0.21	0.05	-0.02	-0.00	0.01	0.01
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	0.20	0.04	-0.06	-0.03	0.01	0.01
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Retailer	0.31	0.09	-0.01	-0.02	0.03	-0.04
	(0.004)	(0.008)	(0.000)	(0.001)	(0.000)	(0.001)

Note: Estimates are based on (21) where the independent variable is deflated sales. CD and TL are control function Cobb-Douglas and translog estimators. Standard errors are clustered at the establishment level.

Table XIX Markups and Competition: Cobb-Douglas and Translog Estimates

	Labor		Materials		Composite Input	
Level of Competition	CD	TL	CD	TL	CD	TL
Medium Competition	-0.004	-0.016	0.000	-0.001	0.001	-0.004
	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
High Competition	-0.003	-0.088	0.004	0.002	0.006	-0.014
	(0.006)	(0.009)	(0.001)	(0.001)	(0.000)	(0.001)

Note: Estimates are based on (21) where the independent variable is the company-derived measure of competition; all estimates are relative to a retail store facing Low Competition. CD and TL are control function Cobb-Douglas and translog estimators. Standard errors are clustered at the establishment level.

Table XX Markups and Exporting: Cobb-Douglas and Translog Estimates

	Labor		Materials		Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	0.07	-0.11	0.04	0.03	0.05	0.04
	(0.018)	(0.016)	(0.007)	(0.006)	(0.003)	(0.003)
Colombia	0.17	0.02	-0.04	0.03	0.04	0.04
	(0.016)	(0.014)	(0.009)	(0.004)	(0.003)	(0.003)
India	-0.03	-0.15	0.01	0.02	0.03	0.02
	(0.011)	(0.008)	(0.002)	(0.002)	(0.001)	(0.001)
Indonesia	0.28	0.05	-0.02	0.01	0.03	0.03
	(0.012)	(0.011)	(0.004)	(0.004)	(0.001)	(0.001)

Note: Estimates are based on (21) where the independent variable is an indicator for whether the establishment exports. CD and TL are control function Cobb-Douglas and translog estimators. Standard errors are clustered at the establishment level.

Table XXI Production Markup Estimates and Profit Based Markup: Cobb-Douglas and Translog Estimates

	Labor		Materials		Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	-0.03	-0.06	0.37	0.35	0.09	0.08
	(0.016)	(0.014)	(0.010)	(0.009)	(0.003)	(0.003)
Colombia	-0.15	-0.16	0.01	0.05	-0.00	0.01
	(0.018)	(0.014)	(0.013)	(0.007)	(0.004)	(0.003)
India	0.21	-0.05	0.15	0.18	0.02	-0.01
	(0.010)	(0.008)	(0.003)	(0.004)	(0.001)	(0.001)
Indonesia	0.06	-0.09	-0.12	-0.09	-0.03	-0.04
	(0.011)	(0.011)	(0.006)	(0.005)	(0.002)	(0.002)
Retailer	1.81	-0.09	-0.08	-0.01	0.15	-0.17
	(0.027)	(0.041)	(0.003)	(0.003)	(0.003)	(0.003)
Retailer (EBIT)	2.00	0.85	-0.09	-0.09	0.16	-0.16
	(0.028)	(0.045)	(0.003)	(0.004)	(0.003)	(0.003)

Note: Estimates are based on (21) where the independent variable is the profit share based markup. CD and TL are control function Cobb-Douglas and translog estimators. Standard errors are clustered at the establishment level. All profit based markups are through a factor cost based profit measure, except for the last row which is an accounting profit (EBIT) based measure.

B.6 Correlations with Competition

In Section 6.4, I examined the relationship between markups and competition for the retailer using a company developed competition band of Low, Medium, or High, and found similar effects for markups estimated using different inputs.

I find very similar patterns using the number of competitors instead of the company's competition band in Table XXII. I discretize the number of competitors provided by the company into bins of 0-1, 2, 3, 4, 5-9, or 10 or more competitors. Stores with more competitors have similar markups to those with less competitors.

One potential driver of both the number of competitors and markups is market size, as in Bresnahan and Reiss (1991). I thus examine the relationship between the number of competitors and markups after controlling for market size through fixed effects for the MSA-year of the retail store. Here, the MSA is either the Metropolitan Statistical Area or Micropolitan Statistical Area of the retail store's location.[30]

I thus re-estimate (21) replacing the year fixed effects with MSA year fixed effects. Table XXIII and Table XXIV contain these estimates; I find slightly higher markups for stores with higher competition in these estimates.

[30] For retail stores not located in a Metropolitan Statistical Area or Micropolitan Statistical Area, the fixed effect is for all non-MSA locations in the same state.

Table XXII Markup and Number of Competitors

Number of Competitors	Labor	Materials	Combined Input
2	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)
3	-0.004	-0.001	-0.002
	(0.002)	(0.002)	(0.002)
4	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
5-9	-0.002	-0.002	-0.002
	(0.002)	(0.001)	(0.001)
10+	-0.000	0.000	0.000
	(0.003)	(0.002)	(0.002)

Note: Estimates are based on (21) and are relative to a retail store with 0-1 competitors. Markups are estimated using industry cost share quintiles. Standard errors are clustered at the establishment level.

Table XXIII Markup and Competition Band, MSA-Year Controls

Level of Competition	Labor	Materials	Combined Input
Medium Competition	0.003	0.002	0.002
	(0.001)	(0.001)	(0.001)
High Competition	0.009	0.005	0.006
	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (21), including MSA-year fixed effects where MSAs are the Metropolitan or Micropolitan Statistical Area of the retail store. Estimates relative to a retail store facing Low Competition. Markups are estimated using industry cost share quintiles. Standard errors are clustered at the establishment level.

Table XXIV Markup and Number of Competitors, MSA-Year Controls

Number of Competitors	Labor	Materials	Combined Input
2	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
3	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)
4	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)
5-9	0.007	0.003	0.003
	(0.002)	(0.001)	(0.001)
10+	0.010	0.006	0.007
	(0.003)	(0.002)	(0.002)

Note: Estimates are based on (21), including MSA-year fixed effects where MSAs are the Metropolitan or Micropolitan Statistical Area of the retail store. Estimates are relative to a retail store with 0-1 competitors. Markups are estimated using industry cost share quintiles. Standard errors are clustered at the establishment level.

C Additional Monte Carlo Simulations

C.1 Factor Price Differences

In this section, I add differences in wages and materials prices across plants to the Monte Carlo exercise described in Section 5.3. I find that the flexible cost share estimator performs similarly to the Monte Carlo without factor price differences across plants.

I simulate an economy in which markups and labor augmenting productivity differences vary across plants. In this economy, 1000 cost minimizing plants produce for 10 years. All plants have a common CES production function, as in (12), with substitution elasticity 0.5. The logarithm of neutral productivity A and labor augmenting productivity B evolve over time through an autoregressive process with a productivity persistence parameter of 0.9 and jointly normal shocks. Productivity is thus distributed as a joint lognormal. I then calibrate the parameters of this lognormal to match moments from data on factor shares and productivity from US manufacturing plants.[31]

[31] I initialize productivities in their first year to the stationary distribution given the persistence process. I normalize the mean of the stationary distribution of $\log A$ to 1, and calibrate the mean of the stationary distribution of $\log B$ and the variances and covariance of $\log A$ and $\log B$ through moment-matching. I match the following six moments: an aggregate capital share of capital and labor cost of 0.3, a value of the weighted variance of capital shares of capital and labor of 0.1, and the aggregate materials share of total cost of 0.55 (all from Oberfield and Raval (2020)) the 90-10 ratio of marginal cost across plants to 2.7 (from Syverson (2004)), the coefficient of a regression of the capital cost to labor cost ratio on the log of the plant's total cost of capital and labor (weighting by the plant's total cost of capital and labor) of 0.08 from Raval (2019), and

Plants face CES demand with an elasticity of demand drawn from a uniform distribution between 2 and 6. Because demand is CES, the markup plants choose is a simple inversion of the demand elasticity; markups range between 1.2 and 2. Plants then set all inputs flexibly given the factor prices they face and their productivity draws.

The main difference from Section 5.3 is that plants differ in their wages and materials prices. The log wage and log materials price are both distributed via a uniform distribution, with different draws for each plant that are persistent over time.

I estimate the relationship between markup estimates using (19) and (20). First, I compare the labor markup to the materials markup using (19). Second, I examine how the true markup based on the demand elasticity the plant faces is correlated with different production based markups for input X using (20). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table XXV, I report the average of β across 200 Monte Carlo simulations, with standard deviations across simulations in parentheses. I first examine three estimators that ignore labor augmenting productivity: the Cobb Douglas and translog control function estimators, as well as industry-wide cost shares, i.e., the traditional cost share approach, in the first three rows.[32] With all three of these estimators, B is assumed not to vary across plants.

Labor markups are negatively correlated with materials markups for the Cobb-Douglas control function and industry-wide cost share estimators. A 100% increase in the materials markup decreases the labor markup on average by 161% using the Cobb-Douglas control function estimator and 39% using the industry wide cost share estimator. For the translog estimator, a 100% increase in the materials markup increases the labor markup by 3%.

In addition, both labor and materials markups are only slightly correlated with the true markup using the control function estimators; on average, the true markup is only 0.4% higher using the Cobb-Douglas estimator, or 2% lower using the translog estimator, after a 100% increase in the labor markup. The true markup is 2% higher using the Cobb-Douglas estimator, or 1% lower using the translog estimator, after a 100% increase in the materials markup. For the industry wide cost share estimator, the true markup is 24% higher on average with a 100% increase in the labor markup, and 53% higher with a 100% increase in the materials markup.

However, the correlation between the labor and materials markup is positive once I use the flexible cost share estimator. I estimate output elasticities as cost shares within quintiles (fourth row) and deciles (fifth row) of the labor cost to materials cost ratio. A 100% increase in the materials markup increases the labor markup by 59% using quintiles and 76% using deciles.

In addition, both labor and materials markups have much higher correlations with the true markup. A 100% increase in the labor markup increases the true markup by 61% using quintiles and 73% using deciles. A 100% increase in the materials markup increases the true markup by 78% using quintiles and 83% using deciles. Thus, although imperfect, estimates using the flexible cost

a log of total industry cost of $\log(10,000)$ (to keep the same size industry across simulations). Distribution parameters are 0.1 for capital, 0.3 for labor, and 0.6 for materials.

[32] The Cobb Douglas estimates are based on 25 of 200 simulations for labor and materials, and 81 of 200 simulations for the composite input, as in some simulations the output elasticity on labor or materials was negative for all plants.

share estimator are much more correlated with each other and with the true markup.[33]

In all specifications, the composite input markup is more highly correlated with the true markup than labor or materials, as might be expected as the composite input combines two negatively correlated inputs. A 100% increase in the composite input markup increases the true markup by 96% using quintiles and 97% using deciles.

Table XXV Relationship between Markup Estimates: Monte Carlo Estimates With Plant Specific Input Prices

Estimator	Labor on Materials	True Markup on Labor	True Markup on Materials	True Markup on Composite Input
Cobb-Douglas CF	-1.61	0.004	0.02	0.78
	(0.15)	(0.002)	(0.01)	(0.16)
Translog CF	0.03	-0.02	-0.01	0.33
	(0.10)	(0.01)	(0.03)	(0.23)
Industry-Wide CS	-0.39	0.24	0.53	0.94
	(0.69)	(0.16)	(0.24)	(0.05)
Quintile CS	0.59	0.61	0.78	0.96
	(0.40)	(0.28)	(0.24)	(0.01)
Decile CS	0.76	0.73	0.83	0.97
	(0.29)	(0.24)	(0.21)	(0.007)

Note: Estimates based on 200 Monte Carlo simulations, using (19) and (20). For example, True Markup on Materials indicates a regression where the true markup is the dependent variable and materials markup the independent variable. True markup is the actual markup set by the firm based on its demand elasticity in the Monte Carlo simulations. For the first two rows, markups estimates are based on ACF control function estimators. For the last three rows, markup estimates are based on the flexible cost share approach, using either one group (industry wide), five groups (quintiles), or ten groups (deciles). Standard deviation across 200 bootstrap estimates in parentheses.

C.2 Time to Build Adjustment Frictions

In Section 5.3, I examined Monte Carlo simulations where labor augmenting technology B varies across plants. In this section, I examine another Monte Carlo simulation in which production functions are Cobb-Douglas but Cobb-Douglas production parameters vary across plants. In addition, while labor and materials are flexible inputs, capital takes one year to build and so capital stock at time $t+1$ is decided at time t. Finally, wages and materials prices vary across plants over time. I then show that the flexible cost share estimator continues to perform well in this environment.

[33] While I have not focused on the average markup in this paper, the flexible cost share estimator also delivers similar average markups. On average across plants, the true markup is 1.4. Using the flexible cost share estimator, the average markup is 1.42 using labor and 1.41 using materials with quintiles, and 1.40 using labor and 1.40 using materials with deciles.

In this economy, 1,000 plants produce for 100 years. Plants face CES demand with an elasticity of demand drawn from a uniform distribution between 2 and 6. Wages and materials prices are both i.i.d. normally distributed with a mean of 1 and a standard deviation of 0.1. The rental price of capital is fixed at 0.1.

Plants face Hicks neutral productivity shocks and demand shocks. Each shock follows an AR(1) process with persistence parameter set at 0.7 and a normally distributed error shock with standard deviation 0.1.

The 1,000 plants are equally divided into five groups, each of which has Cobb-Douglas output elasticities of capital, labor, and materials of either (0.1, 0.5, 0.4), (0.1, 0.4, 0.5), (0.1, 0.3, 0.6), (0.2, 0.2, 0.6), or (0.2, 0.1, 0.7).

Because demand is CES, the markup plants choose is a simple inversion of the demand elasticity; markups range between 1.2 and 2. Plants set labor and materials flexibly given the factor prices they face, their draw of the productivity and demand shocks, and the level of capital. Since capital faces time to build adjustment frictions, capital for next period is decided this period given expectations of demand and productivity shocks.

I initialize capital in the first period at the capital chosen if it was perfectly flexible. I then simulate demand and productivity shocks, and optimal choices of capital, labor, and materials, for 100 periods.

I estimate the relationship between markup estimates using (19) and (20). First, I compare the labor markup to the materials markup using (19). Second, I examine how the true markup based on the demand elasticity the plant faces is correlated with different production based markups for input X using (20). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table XXVI, I report the averages of this Monte Carlo across 200 simulations, with standard deviations across simulations in parentheses. Because of the initialization of capital, I exclude the first 20 time periods from the analysis.

I first examine three estimators that ignore labor augmenting productivity: the Cobb Douglas and translog control function estimators, as well as industry-wide cost shares, i.e., the traditional cost share approach, in the first three rows.

With the Cobb-Douglas control function and industry-wide cost share estimators, labor markups are negatively correlated with materials markups. A 100% increase in the materials markup decreases the labor markup by 157% using the Cobb-Douglas estimator and 151% using industry-wide cost shares. In contrast to the results in Section 5.3, labor and materials markups are positively correlated using the translog estimator, with a 74% increase in the labor markup with a 100% increase in the materials markup.

In addition, both labor and materials markups are only slightly correlated with the true markup using all three of these estimators; a 100% increase in the labor markup, or in the materials markup, increases the true markup between 3% and 36% across specifications.

The correlation between the labor and materials markup is positive once I use the flexible cost share estimator. I estimate output elasticities as cost shares within quintiles (fourth row) and deciles (fifth row) of the labor cost to materials cost ratio. A 100% increase in the materials markup increases the labor markup by 62% using quintiles and 66% using deciles.

Table XXVI Correlation between Markup Estimates: Monte Carlo Estimates with Time to Build Frictions

Cost Share	Labor on Materials	True Markup on Labor	True Markup on Materials	True Markup on Composite Input
Cobb-Douglas CF	-1.57	0.03	0.17	0.83
	(0.04)	(0.01)	(0.01)	(0.01)
Translog CF	0.74	0.27	0.36	0.51
	(0.05)	(0.03)	(0.01)	(0.01)
Industry-Wide CS	-1.51	0.05	0.32	0.84
	(0.05)	(0.007)	(0.01)	(0.009)
Quintile CS	0.62	0.60	0.77	0.91
	(0.06)	(0.04)	(0.02)	(0.009)
Decile CS	0.66	0.72	0.78	0.92
	(0.11)	(0.07)	(0.04)	(0.009)

Note: Estimates based on 200 Monte Carlo simulations, using (19) and (20). For example, True Markup on Materials indicates a regression where the true markup is the dependent variable and materials markup the independent variable. True markup is the actual markup set by the firm based on its demand elasticity in the Monte Carlo simulations. For the first two rows, markups estimates are based on ACF control function estimators. For the last three rows, markup estimates are based on the flexible cost share approach, using either one group (industry wide), five groups (quintiles), or ten groups (deciles). Standard deviation across 200 bootstrap estimates in parentheses.

In addition, compared to the control function estimators, both labor and materials markups have much higher correlations with the true markup. A 100% increase in the labor markup increases the true markup by 60% using quintiles and 72% using deciles. A 100% increase in the materials markup increases the true markup by 77% using quintiles and 78% using deciles. Thus, although imperfect, estimates using the flexible cost share estimator are much more correlated with each other and with the true markup.[34]

D Data Notes

In this section, I describe how I construct the main data variables for each dataset.

D.1 Country Datasets

The first dataset is the Chilean annual census of the manufacturing sector, Encuesta Nacional Industrial Anual (ENIA), spanning the years 1979 to 1996. This data covers all Chilean manufacturing plants with at least 10 employees, and so contains about 5,000 plants per year.

The second dataset is the annual Colombian Manufacturing census provided by the Departamento Administrativo Nacional de Estadistica between 1981 and 1991. This data contains about 7,000 plants per year. Plants with less than 10 employees are excluded in 1983 and 1984.

The third dataset is India's Annual Survey of Industries (ASI) from 1998 to 2014. Manufacturing establishments with over 100 workers are always sampled, while a rotating sample of one-third of all plants with at least ten workers (twenty if without power) are also sampled. I thus weight by the provided sample weights in samples using the Indian data. This data contains about 30,000 plants per year.

The fourth dataset is the Manufacturing Survey of Large and Medium-Sized Firms (Survei Industri, SI) from 1991 to 2000. This dataset is an annual census of all manufacturing firms in Indonesia with 20 or more employees, and contains about 14,000 firms per year.

D.2 Capital

Capital costs are the most involved variable to construct. For each country, a capital stock is constructed for each type of capital. Capital services is the sum of the stock of each type multiplied by its rental rate plus rental payments. This provides an approximation to a Divisia index for capital given different types of capital. See Diewert and Lawrence (2000) and Harper et al. (1989) for details on capital rental rates and aggregation.

The capital rental rate is the sum of the real interest rate R and depreciation rate δ for that type of capital. I base the real interest rate on private sector lending rates reported in the World Bank

[34] While I have not focused on the average markup in this paper, the flexible cost share estimator also delivers similar average markups. However, estimated average markups are higher than the true markup. On average across plants, the true markup is 1.4. Using the flexible cost share estimator, the average markup is 1.59 using labor and 1.58 using materials with quintiles or deciles.

World Development Indicators, which come from the IMF Financial Statistics, for each country. This real interest rate is constructed as the private sector lending rate adjusted for inflation using the change in the GDP deflator. Thus, real interest rate R is defined as $R = \frac{i_t - \pi_t}{1+\pi_t}$ for lending rate i_t and inflation rate π_t.

I average this real interest rate over the sample period, so that, since capital rental rates are constant over time, no variation in the capital stock over time is due to changing rental rates.[35]

For depreciation rates, I match the depreciation rates calculated for US industries to the equivalent industries in each country for structures and equipment. For transportation, I set the depreciation rate to 0.19.[36]

Across datasets, there are some differences in the construction of capital stocks. For Chile, I use end of year capital stocks constructed by Greenstreet (2007). Greenstreet (2007) constructed capital stocks for three types of capital – structures, equipment, and transportation – using a permanent inventory type procedure using data on capital depreciation.

For the other datasets, I construct asset-specific capital stocks using a perpetual inventory method for each type of capital. For Colombia, there are four types of capital: land, structures, equipment (combining office equipment and machinery), and transportation. For India, there are six types of capital: land, structures, equipment, transportation, computers, and other (including pollution equipment). For Indonesia, there are five types of capital: land, structures, equipment, other capital (for which I use the equipment deflator), and transportation.[37] For each asset type, I construct a perpetual inventory measure of capital starting with the first year reporting a positive value of the book value of capital. I also construct a backwards perpetual inventory measure of capital to create capital stocks for plants missing capital stocks using the forward perpetual inventory calculation.[38] I drop observations with zero or negative capital services for equipment or for total capital.

Capital deflators for Chile and Colombia are at the 3 digit ISIC level, and I have separate deflators for structures, equipment, and transportation. For India and Indonesia I use a general capital deflator, at the 4 digit ISIC level for Indonesia and at the yearly level for India.

For the retailer, I have better data on capital than in the manufacturing datasets – the history of all investments by store going back to the early 1980s separately for land, structures, and equipment. I use this data to construct a perpetual inventory measure of capital for each type of capital. I obtain capital deflators and rental prices for each type of capital from the BLS Multifactor Productivity program, constructed for the retail trade industry.

Nominal capital services are then the sum of the real capital stock of each asset type multiplied by the appropriate deflator and capital rental rate, plus rent. Real capital services are the sum

[35] For Chile and Colombia, the real interest rate series starts in 1985 and 1986, respectively, so I use interest rates starting from these dates.

[36] The US depreciation rates are based on NIPA data on depreciation rates of assets; I then use asset-industry capital tables to construct depreciation rates for structures and equipment for each industry. Industries for the US are at the 2 digit SIC level. The US light truck depreciation rate is 19%.

[37] For other capital, I use the depreciation rate and deflator for equipment. For computers, I use a depreciation rate of 31.19%, the US depreciation rate for computer equipment.

[38] For Indonesia, only total capital and total investment are available in 1996. I thus restart the perpetual inventory capital measure in 1997, and the backwards PI measure in 1995.

of the real capital stock of each asset type multiplied by the appropriate capital rental rate, plus deflated rent.[39]

D.3 Labor

For Chile, Colombia, and Indonesia, I use the total number of workers as my measure of labor. For India, I use the total number of days worked by all workers, while for the retailer, I use the total number of hours worked by all workers.

For labor costs, I use the sum of total salaries and benefits for all of the datasets.

D.4 Energy and Materials

Total energy costs are expenses on all energy inputs, subtracting out any electricity sold to other parties.

Real energy input requires energy deflators. For Chile, I have data on both value and quantity of energy inputs for 10 different inputs (plus other fuel). I follow Greenstreet (2007)'s construction of deflators for each energy input as the ratio of total value over total quantity for each 3 digit industry-year. Other fuel is deflated using a value weighted average of the other fuels. Electricity is deflated calculating an electricity price as the average total value of electricity over total quantity for the year.

For Colombia, I calculate the average electricity price as the median ratio of value to quantity across all plants for a given year and province and deflate electricity using this electricity price. For fuels, I only have aggregate fuel value, which I deflate using the output deflator for the 3 digit petroleum and coal industry.

For India, I deflate fuels and electricity using yearly deflators for each input.

For Indonesia, I calculate the average electricity price as the median ratio of value to quantity across all plants for a given year and deflate electricity using this electricity price. For fuels, I have data on both value and quantity of energy inputs for 7 different inputs (plus other fuel). I thus create deflators for each energy input based on the median value to amount ratio by year. I use the diesel oil deflator for other fuel inputs.

For Chile, Colombia, and India, I calculate total raw materials as total spending on raw materials, with an adjustment for inventories of raw materials by adding the difference between the end year and beginning year value of inventories of raw materials. For Indonesia, total amount of raw materials used are reported, which I use for total raw materials.

For Chile and Colombia, materials deflators are at the 3 digit ISIC level. For Indonesia, they are at the 5 digit ISIC level and for India at the 4 digit NIC 2008 level. For Chile, I also deflate lubricants, water, and grease using value to quantity ratios as for the energy inputs described above, following Greenstreet (2007). For Indonesia, I also do the same for lubricants.

[39] For Chile, rent is not differentiated by capital type, so I deflate using the structures deflator. Colombia differentiates between structures rent and machinery rent, India between land rent, building rent, and machinery rent (I use net rents for all three), and Indonesia between land rent and structures/machinery rent. For the retailer I deflate rent using the structures deflator, as most capital is structures.

For the retailer, materials are the total cost of goods sold at the store. Real materials are constructed by deflating goods using the appropriate deflators from the PPI.

D.5 Sales

For all of the manufacturing datasets, I calculate total sales as total production value (both domestic sales and exports, and sales to other establishments of the same company), plus the difference between the end year and beginning year value of inventories of finished goods. Real sales are nominal sales deflated by the output deflator. The output deflator is measured at the 3 digit ISIC level in Chile and Colombia, at the 4 digit NIC 08 level in India, and the 5 digit ISIC level in Indonesia. For the retailer, I deflate total sales using PPI deflators for the relevant goods.

D.6 Industry Sectors and Data Cleaning

For Indonesia, I drop all duplicated observations. The industry definition also changes in 1998 from ISIC rev.2 to ISIC rev. 3 (with both reported in 1998). I assign plants in 1999 and 2000 the reported ISIC rev. 2 industry in 1998 if they exist in 1998; if not, I use the modal 5 digit ISIC rev.2 given the reported value of ISIC rev. 3 using data from 1998.

For India, the industry definition repeatedly changes over the sample period. I use the panel structure of the data to create a consistent industry definition at the NIC 08 level. For plants with a NIC 98 or NIC 04 industry, I set the plant's industry to either the modal industry at the NIC 08 level across years for the plant, or, if this fails, the modal industry at the NIC 08 level for the given NIC 04 or NIC 98 industry.

For both India and Indonesia, I follow Alcott et al. (2015) and drop plants with an electricity share of sales above one and a labor, materials, or energy share of sales above two, or sales below 3 currency units.

D.7 Products

I construct ten homogeneous products in the Indian data. When doing so, I have to account for the fact that the product coding changes several times over the sample period. I describe each product below.

Biri cigarettes are recorded in thousands of cigarettes. In the 1998 to 2007 data, I use ASICC code 15323. In the 2008 to 2009 data, I use ASICC code 15325. In the 2010 to 2014 data, I use ASICC code 2509001.

Black Tea is recorded in kilograms. I include several product codes that correspond to black tea, but exclude non-black tea, tea bags, and instant tea. In the 1998 to 2009 data, I use the following ASICC codes: ASICC code 12211 [tea (black) leaf (blended)], ASICC code 12212 [tea (black) leaf (unblended)], ASICC code 12213 [tea (black) dust (blended)], ASICC code 12214 [tea (black) dust (unblended)], and ASICC code 12215 [tea (black) leaf (darjeeling)]. In the 2010 to 2014 data, I use the following ASICC codes: ASICC code 2391301 [Black Tea (CTC) "crush, tear, curl"], ASICC code 2391302 [darjeeling tea black leaf], ASICC code 2391303 [non-darjeeling black leaf], and ASICC code 2391308 [tea dust].

Boxes, Corrugated Sheet are recorded in number of boxes. In the 1998 to 2009 data, I use ASICC code 57104. In the 2010 to 2014 data, I use ASICC code 3215301.

Matches are recorded in kilograms. In the 1998 to 2009 data, I use ASICC code 37304. In the 2010 to 2014 data, I use ASICC codes 3899801 [Matches safety (match box)] and 3899899 [Matches n.e.c.].

Portland Cement is recorded in tonnes. In the 1998 to 2007 data, I use ASICC code 94415. In the 2008 to 2009 data, I use ASICC code 94414. In the 2010 to 2014 data, I use ASICC code 3744008.

Processed Milk is recorded in fluid liters. In the 1998 to 2009 data, I use the following ASICC codes: ASICC code 11401 [fresh milk], ASICC code 11402 [flavored milk], ASICC code 11403 [chilled/frozen milk], and ASICC code 11404 [skimmed/pasteurized milk]. In the 2010 to 2012 data, I use ASICC code 2211000 [processed liquid milk]. In the 2013 to 2014 data, I use the following ASICC codes: ASICC code 2211001 [full cream milk], ASICC code 2211002 [toned milk], ASICC code 2211003 [skimmed milk], and ASICC code 2211099 [other processed milk (nec)].

Refined Sugar is recorded in tonnes. In the 1998 to 2009 data, I use ASICC code 13103. After 2009, refined sugar is initially split into multiple codes with different units (kilograms vs. tonnes), so I do not include refined sugar after 2009.

Rice, Parboiled Non-Basmati is recorded in tonnes. In the 1998 to 2009 data, I use ASICC code 12311. In the 2010 to 2014 data, I use ASICC codes 2316107 [Rice (other than basmati), par-boiled milled] and 2316202 [Rice (other than basmati), par-boiled brown/ husked].

Rice, Raw Non-Basmati is recorded in tonnes. In the 1998 to 2009 data, I use ASICC code 12312. In the 2010 to 2014 data, I use ASICC codes 2316108 [Rice (other than basmati), non-boiled (atap) milled] and 2316203 [Rice (other than basmati), non-boiled (atap) brown/ husked].

Shelled Cashew Nuts is recorded in tonnes. In the 1998 to 2007 data, I use ASICC code 12111. In the 2008 to 2009 data, I use ASICC code 12131. In the 2010 to 2014 data, I use ASICC code 2142400.

I only keep manufacturing plants with a 75% of greater revenue share of a given product. I define the price of a product as the gross value of the product minus any reported expenses (excise duty, sales tax, and other expenses) divided by the quantity sold. I then drop all plants whose price is greater than five times, or less than 20%, of the median price for a given product in a given year.

Table XXVII below contains the total number of observations, and number of distinct manufacturing plants, for each product.

Table XXVII Homogeneous Products

Product	Number of Observations	Number of Distinct Plants
Biri Cigarettes	3234	1053
Black Tea	7263	1316
Boxes, Corrugated Sheet	4234	2299
Matches	2725	676
Portland Cement	2262	598
Processed Milk	2143	784
Refined Sugar	3612	600
Rice, Parboiled Non-Basmati	6433	4481
Rice, Raw Non-Basmati	5535	4061
Shelled Cashew Nuts	3118	979