Testing the Production Approach to Markup Estimation*

Devesh Raval

Federal Trade Commission

devesh.raval@gmail.com

December 18, 2019

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.

*First Version: November 2018. I would like to thank Chris Adams, John Asker, Emek Basker, Ben Bridgman, Allan Collard-Wexler, Emin Dinlersoz, Amit Gandhi, Berthold Herrendorf, John Haltiwanger, Dan Hosken, Ethan Kaplan, Rob Kulick, Ryne Marksteiner, Aviv Nevo, Ezra Oberfield, Ariel Pakes, Ted Rosenbaum, Pierre-Daniel Sarte, Dave Schmidt, Marshall Steinbaum, Phillipe Sulger, Nico Trachter, James Traina, Brett Wendling, Kirk White, and Nate Wilson for their comments on this paper, and Jordi Jaumandreu and Paul Scott for discussing this paper at the 2019 IIOC and 2019 NYC IO Day. I also thank Ana Fernandes, Joep Konings, and Benni Moll for providing deflators for various datasets in this paper. Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the Federal Trade Commission, or its Commissioners.

Measuring the markup is central to the evaluation of the effects of mergers, changes in trade barriers, and explanations for aggregate trends such as the decline in the labor share of income. Despite their importance, it is difficult to measure markups. The *production approach* to markup estimation (De Loecker and Warzynski, 2012) has become prominent as it has allowed economists to estimate markups at scale across industries. In contrast, the demand approach (Berry et al., 1995) requires industry studies.[1]

The production approach uses cost minimization for identification. Given competitive input markets, the additional revenue from a marginal increase in a flexible input is equal to the marginal cost of increasing that input multiplied by the firm's markup. Thus, the markup is identified as a variable input's output elasticity divided by the input's share of revenue. If one knew the production function, one can recover the markup given cost data.

Because *any* flexible input identifies the markup, the markup is overidentified with multiple flexible inputs. I test this implication by comparing markups estimated using labor, materials, or a composite of both.[2] I conduct these tests using manufacturing plants or firms from Chile, Colombia, India, and Indonesia, as well as a nationwide US retailer's stores.

Across all five datasets, I strongly reject that different inputs imply the same markup. I then show that non-neutral technological differences can explain these findings, and develop an estimator accounting for them that provides much more consistent estimates across inputs.

[1] Using the demand approach requires one to model demand and competition which vary substantially across industries, and often require detailed, industry specific data including price instruments.

[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).

Across multiple statistical tests, I reject that markups estimated using different inputs are the same in all of the datasets. I then focus on two major features of the markup distribution. First, labor markups are much more disperse than materials markups. For example, the 90th percentile markup for the retailer's stores is 76% higher than the 10th percentile using labor, compared to only 6% higher using materials.

Second, markup measures are *negatively* correlated, both in the cross-section and in time trends. In Colombia, a plant with a 100% larger markup measured using labor (the "labor markup") has, on average, a 28% lower markup measured using materials (the "materials markup"). The average labor markup for Colombia falls by 28% over time, while the average materials markup rises by 8%.

I reconcile these findings by relaxing the maintained assumption that productivity is Hicks neutral. Non-neutral technological improvements affect factors of production asymmetrically. For example, 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. The ratio of labor to materials costs provides a signal of labor augmenting productivity; I estimate output elasticities as input cost shares within bins of this ratio. This flexible cost share estimator does not require data on output quantities, which are typically not observed. Across all five datasets, as well as Monte Carlo simulations, markups estimated with different inputs using this approach are positively correlated and have similar time trends.

I then reexamine several stylized facts for markups. Without controlling for labor augmenting productivity, I find conflicting evidence across datasets and input measures for each stylized fact. Using the flexible cost share estimator estimator, I consistently find that markups are positively correlated with size, exporting, and profit shares. For the retailer, I exploit two company provided classifications of the degree of competition, and find little relationship between the degree of competition and markups.

I then explore several alternative explanations other than non-neutral productivity. Violations of the static labor first order condition, such as through hiring and firing costs, monopsony power, or wage bargaining with unions, cannot explain my findings. For example, I continue to find stark differences in markups after comparing markups estimated using energy and non-energy raw materials instead of labor. Finally, adjustment costs cannot explain long run differences in markup trends across different inputs.

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

My paper 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) compare average markup estimates using the demand approach to those from the production approach using data on US breweries.

My work is also related to the literature estimating labor augmenting productivity differences (Doraszelski and Jaumandreu, 2018; Oberfield and Raval, 2014; Raval, 2019; Zhang, 2019). Within this literature, Doraszelski and Jaumandreu (2019) also 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]

1 Production Approach

The key assumptions for the production approach are that the firm cost minimizes in each period with respect to any variable input for which it is a price taker in the input market. 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

[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.

input prices P_{it}^X for input X. A cost minimizing firm sets marginal products equal to factor prices. This implies, for 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_i^X, is 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:

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

[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}.

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 also use retail store-level data from an anonymous major US nationwide retailer ("Company 1") for three years. This retailer has thousands of stores across the United States. I summarize the characteristics of these datasets in Table I and include further details on data construction in Appendix B.

Table I Datasets

Dataset	Sector	Time Period	No. Establishments	No. Industries Used
Chile	Manufacturing	1979-1996	5,000 / year	16
Colombia	Manufacturing	1978-1991	7,000 / year	21
India	Manufacturing	1998-2014	30,000 / year	23
Indonesia	Manufacturing	1991-2000	14,000 / year	22
Company 1	Retail	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 Company 1. 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 Company 1, 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.

[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 B for more details on capital construction.

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.

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.

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 f_{it} is logged production, k_{it} capital, l_{it} labor,

[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).

and m_{it} materials. For the Cobb Douglas production function with labor and materials, the (logged) production function is:

$$f_{i,t} = \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t}$$

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

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

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 $\beta_m + 2\beta_{mm} m_{i,t} + \beta_{km} k_{i,t} + \beta_{lm} l_{i,t}$.

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.

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 $\omega_{it} = g^{-1}(k_{it}, l_{it}, m_{it})$.

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.[9]

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,

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

[9] In practice, I use a third order polynomial in inputs for the function g, 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:

$$\nu_{it}(\beta) \;=\; \omega_{it} - \rho\omega_{i,t-1} \tag{8}$$

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 $E(\nu_{it}l_{i,t-1})$ or $E(\nu_{it}k_{i,t})$, 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.[10]

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:

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

[10]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.

3.3 Implementation

For each dataset, I estimate industry-level production functions using the ACF 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 Empirical Tests

Under the production approach, any flexible input identifies the markup. I first test the production approach 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 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.[11]

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.[12]

4.2 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

[11] The second highest p-value is 6.1×10^{-17}.

[12] I also examine average markups in Appendix A.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.

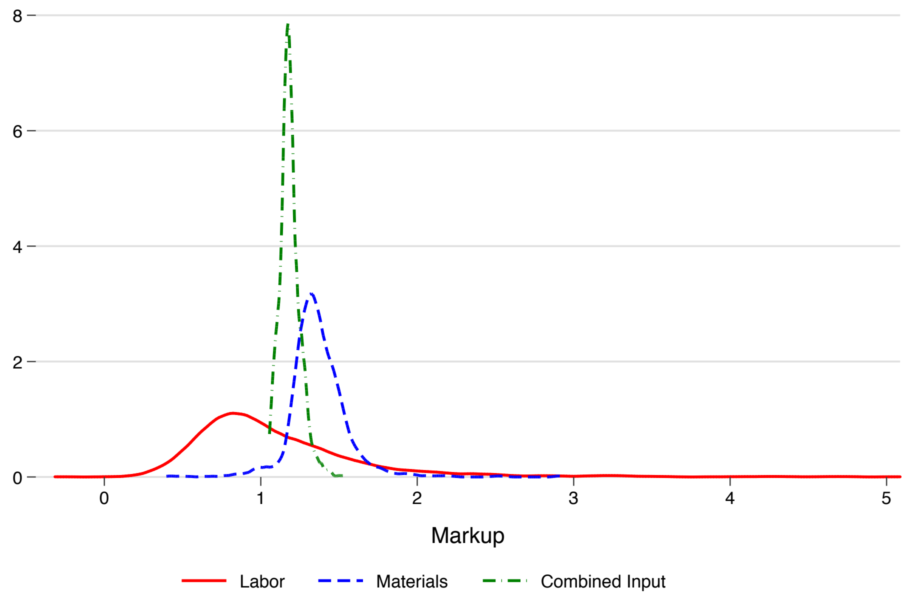


Figure 1 Distribution of Translog Markups for Chilean Food Products, 1996

For all the datasets, I measure dispersion by calculating the 90/50 ratio of the markup estimates, which I report in Table II.[13] 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 estimates, the 90th percentile markup is 103% higher than the median markup for Chile using labor, 39% higher

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

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)
Company 1	1.23	1.30	1.02	1.03	1.02	1.02
	(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.

4.3 Time Trends

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

$$\log(\mu^X_{i,t}) = \alpha + \gamma_t + \delta_n + \epsilon_{i,t} \tag{10}$$

where $\mu^X_{i,t}$ 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.[14]

For Chile, the average labor markup initially declines 25% by 1981, then rises to 29% above its 1979 value by 1987, and then declines again to 22% below its 1979 value by 1996. In contrast, the average materials markup initially rises 14% above its 1979 value in 1981, then declines to 3% below its 1979 value by 1987, and then rises again to 16% above its 1979 value by 1996. The composite input markup is 4% above its 1979 value in 1981 and 1987 and 8% above by 1996.

For Colombia, the average labor markup falls substantially at the beginning of the sample using labor, and remains about 28% lower at the end of the sample compared to the beginning of the sample. The average materials markup rises over time and is about 8% higher at the end of the sample. The composite input markup declines over time, but less then labor, and

[14]I include the Cobb-Douglas trends in Figure 7 and Figure 8 in Appendix A.1. I always find significantly different markup trends using different inputs.

is 3% lower at the end of the sample.

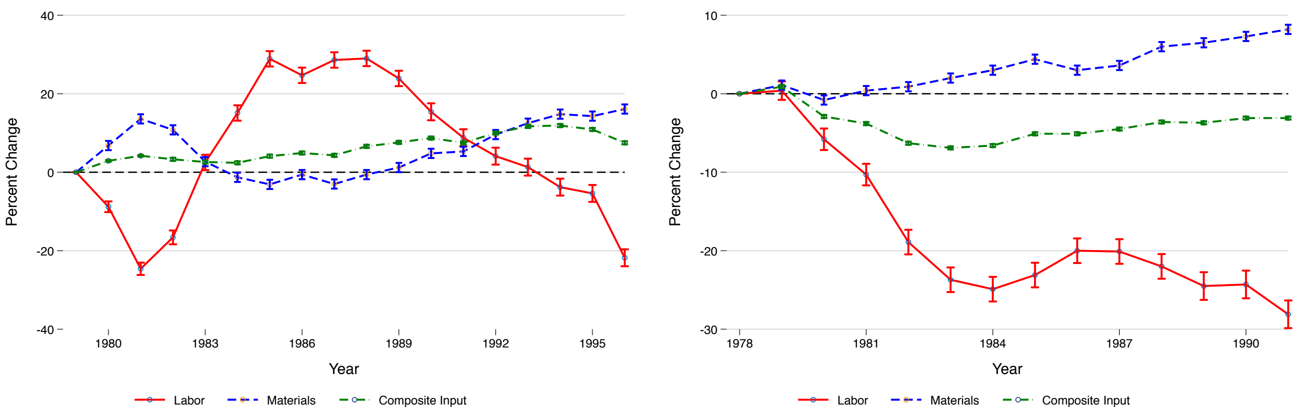
For India, the average labor markup falls substantially over the sample period, and is 46% lower at the end of the sample compared to the beginning of the sample. The decline in the materials markup is an order of magnitude smaller, with a 1% overall decline at the end of the sample. In addition, the materials markup rises post 2008 as the labor markup sharply declines. The composite input markup exhibits a decline of 8%, much smaller than for labor but larger than for materials.

For Indonesia, the average labor markup declines between 1991 and 1997 to about 14% below the 1991 level. With the Asian financial crisis, the average labor markup rises sharply in 1998 to 4% above its 1991 level, but then falls again to 11% below its 1991 level by 2000. The materials markup increases from 1991 to 1997 to 5% above its 1991 level, but falls immediately after the crisis to 1% above its 1991 level in 1998. The composite input markups exhibit very little change over this period.

4.4 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. Each a point is a different manufacturing plant using the translog

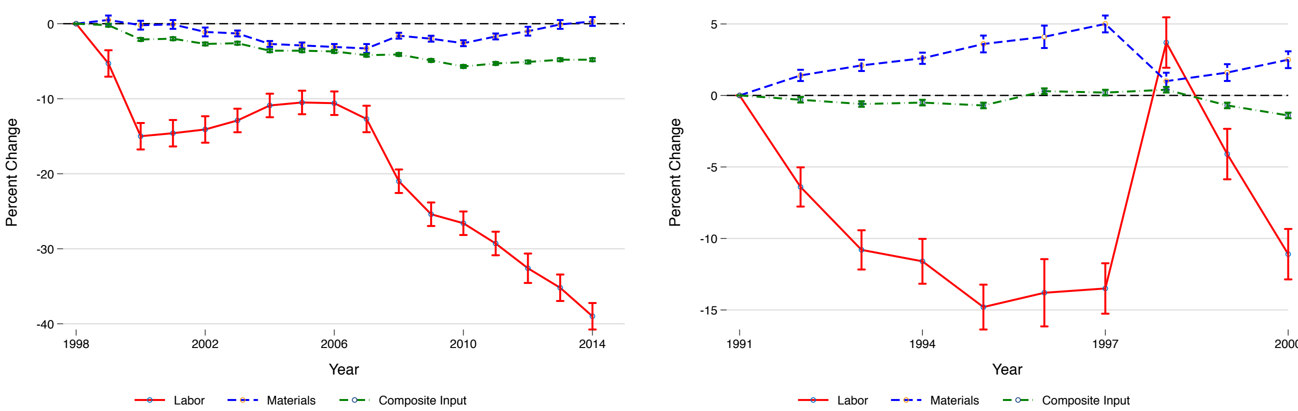
Figure 2 Markup Time Trends using Translog Estimates: Chile and Colombia



(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.

estimates with the best linear fit as a solid black line. There is a slight negative relationship between the labor markup and materials markup.

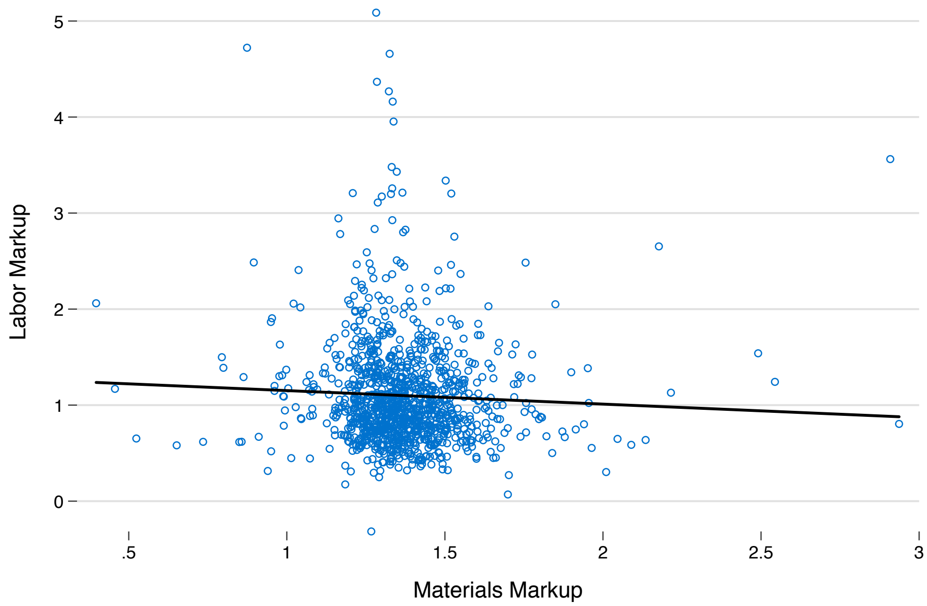


Figure 4 Correlation of Markups for Chilean Food Products, 1996

Note: Each point is a manufacturing plant in Chilean Food Products in 1996. 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:

$$\log(\mu^L_{i,t}) = \alpha + \beta \log(\mu^M_{i,t}) + \gamma_t + \delta_n + \epsilon_{i,t} \tag{11}$$

where $\mu^L_{i,t}$ and $\mu^M_{i,t}$ 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, 17% lower for India, 48% lower for Indonesia, and 1008% lower for Company 1. In general, the magnitude of the negative correlation is even higher using the Cobb-Douglas estimates.[15]

Table III Correlation 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)
Company 1	-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.

[15]The large magnitude of the elasticities for Company 1 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.

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 and time series correlations.

5.1 Theory

I assume a CES production function with elasticity of substitution σ, neutral productivity A, labor augmenting productivity B, and distribution parameters α_l and α_m:

$$Y = A((1-\alpha_l-\alpha_m)K^{\frac{\sigma-1}{\sigma}} + \alpha_l(BL)^{\frac{\sigma-1}{\sigma}} + \alpha_m M^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}. \tag{12}$$

Input shares of revenue are equal to the output elasticity of that input divided by the markup μ:

$$\frac{wL}{PY} = \frac{1}{\mu}(\frac{w}{\lambda})^{1-\sigma}(\alpha_l)^{\sigma}(AB)^{\sigma-1} \tag{13}$$

$$\frac{p_m M}{PY} = \frac{1}{\mu}(\frac{p_m}{\lambda})^{1-\sigma}(\alpha_m)^{\sigma}(A)^{\sigma-1} \tag{14}$$

where λ is the marginal cost, w the wage, and p_m the price of materials.

Changes in labor augmenting productivity B move the output elasticities of labor and materials in different directions. Take the case where the elasticity of substitution σ is less than one, as in Raval (2019). In that case, improvements in B 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 high B would have a low labor share and high materials share, and so a high labor markup and low materials markup. Thus, 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 cost share method has been used in productivity analysis (Foster et al., 2001, 2008), and markup estimation (De Loecker et al., 2018). It estimates the output elasticity of a given input as its share of total industry cost. It assumes constant returns to scale, and requires first order cost minimization conditions to hold for all inputs, including capital, at least on average.

I adapt the cost share estimator by estimating cost shares within groups based on the plant's labor to materials cost ratio. After dividing (13) and (14), the ratio of labor costs to materials costs is a function of labor augmenting productivity B:

$$\frac{wL}{p_m M} = (\frac{w}{p_m})^{1-\sigma}(\frac{\alpha_l}{\alpha_m})^{\sigma}(B)^{\sigma-1}. \tag{15}$$

Thus, plants with a similar labor cost to materials cost ratio should have similar values of B, and so similar output elasticities of labor and materials. For example, by using quintiles, five groups approximate the differences in B across plants. Output elasticities would be the input share of total cost within the industry quintile.

One major advantage of this method is it does not require data on firm quantities; 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). In addition, the econometrician can easily vary the size of the group, as well as estimate production functions at the subindustry or product level at which the number of plants is small.

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.

I simulate an economy in which markups, factor prices, and labor augmenting productivity differences vary across plants. In this economy, 700 locations each contain 100 cost minimizing plants. Wages and materials prices vary by location, with the natural log of each location's wage and materials price a random draw from a uniform distribution between 0 and 1. 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 face is a simple inversion of the demand elasticity; markups range between 1.2 and 2.

Finally, all plants have a common CES production function, as in (12), with substitution elasticity 0.5. I draw neutral productivity A and labor augmenting productivity B from a joint lognormal. I then calibrate the parameters of this lognormal to match data on US manufacturing plants.[16]

I then estimate the correlations of the labor markup with the materials markup using (11). I also examine how the true markup based on the demand elasticity the plant faces is correlated with the labor or materials markup using (16) for input X:

$$\log(\mu_{i,t}^{True}) = \alpha + \beta \log(\mu_{i,t}^{X}) + \gamma_t + \delta_n + \epsilon_{i,t}. \tag{16}$$

[16] I normalize the mean of A to 1, and calibrate the mean of B, the variances and covariance of A and B through moment-matching. I match the following five 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 (2014)) the 90-10 ratio of marginal cost across plants to 2.7 (from Syverson (2004)), and 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). Distribution parameters are 0.1 for capital, 0.3 for labor, and 0.6 for materials.

Here, the (logged) true markup is the dependent variable and the labor or materials markup the independent variable.

In Table IV, I report the averages of this Monte Carlo across 200 simulations, with standard deviations across simulations in parentheses. I simulate an estimator that ignores labor augmenting productivity by estimating output elasticities using industry-wide cost shares, i.e., the traditional cost share approach, in the first row. With industry-wide cost shares, 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 by 127%. In addition, both labor and materials markups are only slightly correlated with the true markup; a 100% increase in the labor markup, or in the materials markup, increases the true markup by only 6% or 27%.

Table IV Correlation between Markup Estimates: Monte Carlo Estimates

Cost Share	Labor on Materials	True Markup on Labor	True Markup on Materials
Industry-Wide	-1.27	0.06	0.27
	(0.32)	(0.04)	(0.14)
Quintile	0.19	0.32	0.58
	(0.31)	(0.15)	(0.19)
Decile	0.54	0.52	0.72
	(0.22)	(0.15)	(0.15)

Note: Estimates based on 200 Monte Carlo simulations, using (11) and (16). 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. Markup estimates 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, these correlations are positive once I use the flexible cost share estimator. I estimate output elasticities as cost shares within quintiles (second row) and deciles (third row) of the labor cost to materials cost ratio. A 100% increase in the materials markup increases the labor markup by 19% using quintiles and 54% 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 32% using quintiles and 52% using deciles. A 100% increase in the materials markup increases the true markup by 58% using quintiles and 72% using deciles. Thus, although imperfect, estimates using the flexible cost share estimator are much more correlated with each other and with the true markup.

5.4 Production Datasets

I estimate markups using the flexible cost share estimator on all five datasets. In Table V, I report correlations between markup measures estimating using (11) where output elasticities are the cost share for each industry quintile. Unlike what I previously found, 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 Company 1 under the cost share quintile estimates.

Table V Correlation between Markup Estimates: Cost Share Quintile Estimates

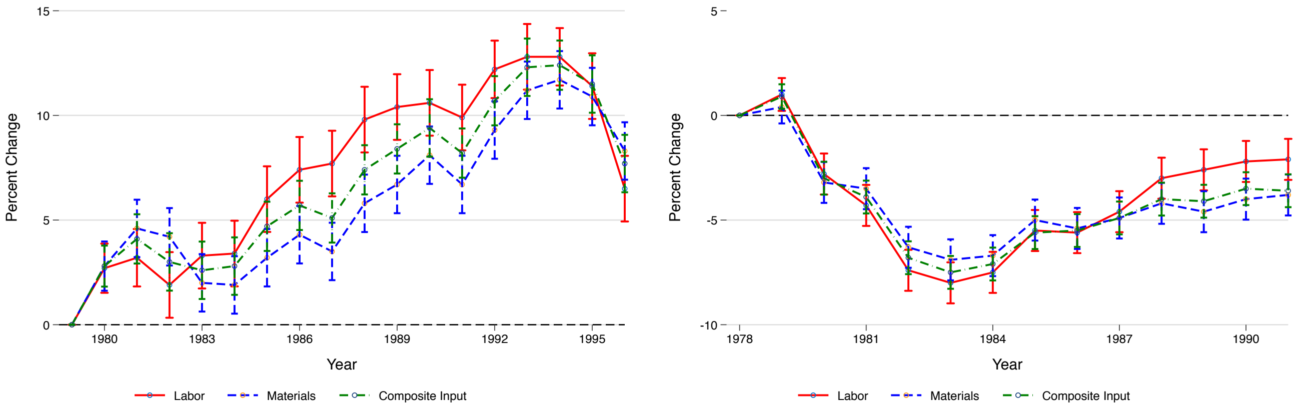
Chile	0.75
	(0.007)
Colombia	0.34
	(0.011)
India	0.68
	(0.004)
Indonesia	0.72
	(0.005)
Company 1	0.89
	(0.012)

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. TL is ACF translog, while Quintile is industry cost share quintiles. Standard errors are clustered at the establishment level.

I next examine time trends estimated using (10) for markups estimated using cost share quintiles in Figure 5 and Figure 6. Across all of the datasets, the time trends in markups are very similar. For example, for Chile, the average labor markup rises 8% by 1987, then rises to 13% above its 1979 value by 1993, and then declines slightly to 7% above its 1979 value by 1996. Similarly, the average materials markup initially rises 4% above its 1979 value in 1987, then rises to 11% below its 1979 value by 1993, and then declines slightly to 8% above its 1979 value by 1996. The magnitudes are also much smaller than in the baseline estimates; for example, the largest markup increase for Chile is between 11 to 13%, compared to 29% 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 cross-sectional and time series correlations.

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

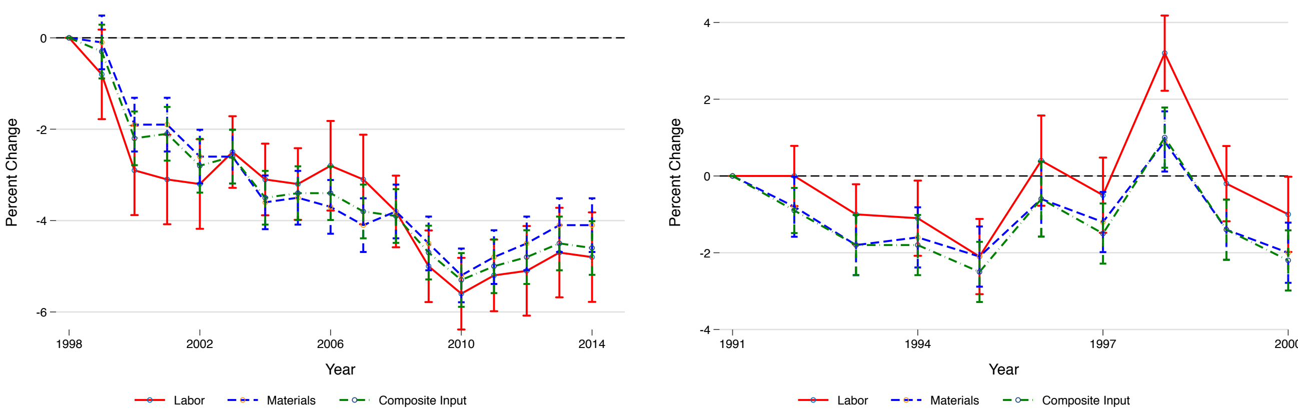


(a) Chile

(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

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

$$\log(\mu_{i,t}^X) = \alpha + \beta Z_{it} + \gamma_t + \delta_n + \epsilon_{i,t} \tag{17}$$

where $\mu_{i,t}^X$ 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 consistent estimates for each stylized fact across both inputs and datasets.[17]

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 (17) regressing markups on the logarithm of deflated sales. I report these estimates in Table VI. 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.

[17] In Appendix A.5, I examine markups estimated without accounting for non-neutral productivity using the ACF estimators. As in Section 4, estimates of all of the stylized facts vary in sign and magnitude across inputs and datasets using the ACF estimators.

Table VI Correlation between Markups and Sales

	Labor	Materials	Composite Input
Chile	0.06	0.04	0.05
	(0.002)	(0.002)	(0.002)
Colombia	0.04	0.02	0.03
	(0.001)	(0.001)	(0.001)
India	0.05	0.02	0.03
	(0.000)	(0.000)	(0.000)
Indonesia	0.07	0.05	0.06
	(0.001)	(0.001)	(0.001)
Company 1	0.09	0.06	0.07
	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (17) where the independent variable is deflated sales. Markups are estimated using industry cost share quintiles. Standard errors are clustered at the establishment level.

6.2 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.[18] Company 1 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 section in Table VII, and a discretized number of competitors in Appendix A.6.

I find a consistent, statistically insignificant increase in the markup of 0.1% using the flexible cost share estimator across all three inputs. Thus, the retailer does not appear to have substantially different markup across stores, consistent with uniform or near-uniform

[18] 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 A.6, and continue to find sharp differences across markup measures using ACF translog estimates and similar correlations using the flexible cost share estimator.

pricing by many large retailers (DellaVigna and Gentzkow, 2017).

Table VII Correlation between Markups and Competition

	Labor	Materials	Composite Input
Medium Competition	-0.003	-0.002	-0.002
	(0.002)	(0.001)	(0.001)
High Competition	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (17) 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 industry cost share quintiles. Standard errors are clustered at the establishment level.

6.3 Exporting

I next examine whether exporters have larger markups, the central question in De Loecker and Warzynski (2012), using an indicator variable for whether the establishment exports.[19] 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.

6.4 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

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

Table VIII Correlation between Markups and Exporting

	Labor	Materials	Combined Input
Chile	0.04	0.05	0.05
	(0.008)	(0.007)	(0.007)
Colombia	0.11	0.08	0.09
	(0.006)	(0.006)	(0.005)
India	0.06	0.05	0.06
	(0.004)	(0.003)	(0.002)
Indonesia	0.09	0.08	0.09
	(0.004)	(0.004)	(0.004)

Note: Estimates are based on (17) where the independent variable is an indicator for whether the establishment exports. Markups are estimated using industry cost share quintiles. Standard errors are clustered at the establishment level.

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.

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 (17). 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

Table IX Correlation between Production Markup Estimates and Profit Based Markup

	Labor	Materials	Composite Input
Chile	0.92	0.96	0.96
	(0.010)	(0.010)	(0.009)
Colombia	0.82	0.84	0.83
	(0.011)	(0.013)	(0.011)
India	0.88	0.84	0.86
	(0.005)	(0.004)	(0.004)
Indonesia	0.44	0.42	0.44
	(0.017)	(0.016)	(0.017)
Company 1	0.80	0.56	0.60
	(0.012)	(0.007)	(0.006)
Company 1 (EBIT)	0.82	0.58	0.62
	(0.012)	(0.007)	(0.007)

Note: Estimates are based on (17) where the independent variable is the profit share based markup. Markups are estimated using industry cost share quintiles. 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.

the profit share based markup.

7 Alternative Mechanisms

In this section, I examine several additional explanations other than non-neutral productivity for the large, substantive differences between markups estimated with different inputs. One explanation is violations of the static cost minimization conditions for the variable input, such as by adjustment costs in labor or wage bargaining. Another concerns production function estimation; perhaps the control function approach or its auxiliary assumptions are misspecified. A third is heterogeneity across different subindustries or products within a broader industry, and a fourth is biases from estimating revenue production functions. A last explanation is measurement error in inputs. I find evidence inconsistent these explanations.

7.1 Static Cost Minimization Conditions

The existence of either adjustment costs for altering input quantities or firms with buyer power in the input market would violate static cost minimization first order conditions. The literature suggests that such violations 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.[20]

I examine this issue 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 estimating using (10), which I depict in Appendix A.1 in Figure 9 to Figure 12. 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 X; for example, "Labor on Energy" indicates that the (logged) labor markup is the dependent variable and

[20] 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).

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 elasticities between -0.13 and -0.26, and has no correlation with the energy markup under the Translog estimates. The labor markup is positively correlated with the energy markup under the Cobb-Douglas estimates, with elasticities between 0.16 and 0.24, but has a negative correlation with the energy markup under the Translog estimates, with elasticities between -0.02 and -0.10. Thus, labor-specific violations of the cost minimization conditions cannot explain the markup differences that I find.

Table X Correlation between Markup Estimates: Energy and Raw Materials Separated

	Labor on Raw Materials		Labor on Energy		Raw Materials on Energy	
Dataset	CD	TL	CD	TL	CD	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.

7.2 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, could be wrong. Second, Gandhi et al. (forthcoming) show that the ACF procedure is not non-parametrically identified when applied to gross-output production functions.[21] Third, Flynn et al. (2019) and Doraszelski and Jaumandreu (2019) 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 output. 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 different 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.

[21] 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".

(2015) together with constant returns to scale. I use this new method to estimate translog production functions.[22] Finally, I use the cost share approach assuming that productivity differences are neutral using industry-year cost shares. 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 Appendix A.1 in Figure 13 through Figure 20. In addition, after controlling for time trends, I show in Table XI that the labor markup remains negatively correlated with the materials markup, with correlations ranging from -0.25 to -1.00 using the dynamic panel approach, -0.17 to -7.05 using the Flynn et al. (2019) approach, and from -0.24 to -1.00 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.

7.3 Within Industry Heterogeneity

One potential concern is that production functions vary across subindustries or products within a broader industry. I first examine this concern by estimating production functions

[22] 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 XI Correlation 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.

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.[23]

I estimate production functions at the subindustry level using subindustry-year cost shares. Time trends, reported in Figure 17 through Figure 20, 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 (0.02) with the materials markup for Indonesia, and is negatively correlated with the materials markup in the other datasets, with correlations ranging from -0.20 to -1.00. See

[23]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.

the CostShare SubInd column of Table XI.

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 correlated with the materials markup with a correlation of -0.45 using product-year cost shares, compared to -0.85 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.

7.4 Revenue Production Functions

Economists typically only have data on revenue, and not output, and so estimate revenue production functions. However, with imperfect competition, the ACF 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 using data on the quantity produced of ten Indian homogenous products.[24] I estimate product-level quantity production functions using the ACF estimator

[24] I describe the construction of these products in Appendix B.7; they are Biri Cigarettes, Black Tea, Corrugated Sheet Boxes, Matches, Portland Cement, Processed Milk, Refined Sugar, Parboiled Non-Basmati

for 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 correlation of -0.42 and -0.83 using Cobb-Douglas and Translog production functions. Thus, problems with revenue production functions cannot explain my findings.

7.5 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, I find similar patterns using Company 1's data, based on the internal records of the firm, as I did using manufacturing survey 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), in Appendix A.4, and find qualitatively similar findings to the unweighted results.

8 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. The demand approach to markups cannot do so because models for firm competition and

Rice, Raw Non-Basmati Rice, and Shelled Cashew Nuts.

demand vary substantially across industries.

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.

I then showed that 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.

The development of the 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.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Alcott, Hunt, Allan Collard-Wexler, and Stephen O'Connell, "How Do Electricity Shortages Affect Industry? Evidence from India," *American Economic Review*, 2015.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

_ , _ , and _ , "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market," *Journal of Political Economy*, 2004, *112* (1), 68–105.

Blonigen, Bruce A and Justin R Pierce, "Evidence for the Effects of Mergers on Market Power and Efficiency," Technical Report, National Bureau of Economic Research 2016.

Blundell, Richard and Stephen Bond, "GMM Estimation with Persistent Panel Data: An Application to Production Functions," *Econometric Reviews*, 2000, *19* (3), 321–340.

Bresnahan, Timothy F and Peter C Reiss, "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 1991, *99* (5), 977–1009.

Bridgman, Benjamin, "Markups, Market Power, and Structural Change: Evidence from the National Accounts," *Mimeo*, 2019.

DellaVigna, Stefano and Matthew Gentzkow, "Uniform Pricing in US Retail Chains," Technical Report, National Bureau of Economic Research 2017.

Diewert, W Erwin and Denis A Lawrence, "Progress in Measuring the Price and Quantity of Capital," *Econometrics*, 2000, *2*, 273–326.

Dobbelaere, Sabien and Jacques Mairesse, "Panel Data Estimates of the Production Function and Product and Labor Market Imperfections," *Journal of Applied Econometrics*, 2013, *28* (1), 1–46.

Doraszelski, Ulrich and Jordi Jaumandreu, "Measuring the Bias of Technological Change," *Journal of Political Economy*, 2018, *126* (3), 1027–1084.

_ and _ , "Using Cost Minimization to Estimate Markups," 2019.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "How Costly are Markups?," Technical Report, National Bureau of Economic Research 2018.

Flynn, Zach, Amit Gandhi, and James Traina, "Measuring Markups with Production Data," 2019.

Foster, Lucia, John C Haltiwanger, and Cornell John Krizan, "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in "New Developments in Productivity Analysis," University of Chicago Press, 2001, pp. 303–372.

_ , John Haltiwanger, and Chad Syverson, "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, 2008, *98* (1), 394–425.

Foster, Lucia S, Cheryl A Grim, John Haltiwanger, and Zoltan Wolf, "Macro and Micro Dynamics of Productivity: From Devilish Details to Insights," Working Paper 23666, National Bureau of Economic Research 2017.

Gandhi, Amit, Salvador Navarro, and David Rivers, "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, forthcoming.

Greenstreet, David, "Exploiting Sequential Learning to Estimate Establishment-Level Productivity Dynamics and Decision Rules," 2007. Mimeo.

Gutiérrez, Germán and Thomas Philippon, "Investment-less Growth: An Empirical Investigation," Technical Report, National Bureau of Economic Research 2016.

Harper, Michael J., Ernst R. Berndt, and David O. Wood, "Rates of Return and Capital Aggregation Using Alternative Rental Prices," in D.W. Jorgenson and R. London, eds., *Technology and Capital Formation*, Cambridge, MA: MIT Press, 1989.

Karabarbounis, Loukas and Brent Neiman, "Accounting for Factorless Income," Technical Report, National Bureau of Economic Research 2018.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Loecker, Jan De and Frederic Warzynski, "Markups and Firm-Level Export Status," *American Economic Review*, 2012, *102* (6), 2437–71.

_ and Jan Eeckhout, "Global market power," Technical Report, National Bureau of Economic Research 2018.

— **and Paul T Scott**, "Estimating Market Power: Evidence from the US Brewing Industry," Technical Report, US Census Bureau, Center for Economic Studies 2017.

— **, Jan Eeckhout, and Gabriel Unger**, "The Rise of Market Power and the Macroeconomic Implications," Technical Report, Mimeo 2018.

— **, Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik**, "Prices, Markups, and Trade Reform," *Econometrica*, 2016, *84* (2), 445–510.

Melitz, Marc J and Gianmarco IP Ottaviano, "Market Size, Trade, and Productivity," *The Review of Economic Studies*, 2008, *75* (1), 295–316.

Nickell, Stephen and M Andrews, "Unions, Real Wages, and Employment in Britain 1951-1979," *Oxford Economic Papers*, 1983, *35* (0), 183–206.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," Technical Report, National Bureau of Economic Research 2014.

Petrin, Amil and Jagadeesh Sivadasan, "Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs," *Review of Economics and Statistics*, 2013, *95* (1), 286–301.

Raval, Devesh, "The Micro Elasticity of Substitution and Non-Neutral Technology," *RAND Journal of Economics*, 2019, *50* (1), 147–167.

Rovigatti, Gabriele and Vincenzo Mollisi, "Theory and Practice of Total-Factor Productivity Estimation: The Control Function Approach using Stata," *The Stata Journal*, 2018, *18* (3), 618–662.

Syverson, Chad, "Product Substitutability and Productivity Dispersion," *Review of Economics and Statistics*, 2004, *86* (2), 534–550.

Traina, James, "Is Aggregate Market Power Increasing? Production Trends Using Financial Statements," 2018.

White, T Kirk, Jerome P Reiter, and Amil Petrin, "Imputation in US Manufacturing Data and Its Implications for Productivity Dispersion," *Review of Economics and Statistics*, 2016, (0).

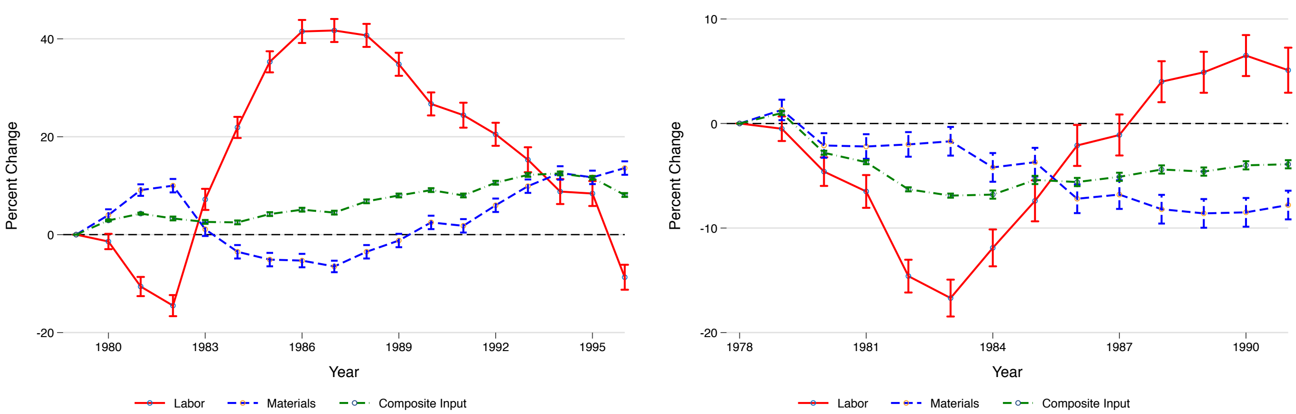
Zhang, Hongsong, "Non-Neutral Technology, Firm Heterogeneity, and Labor Demand," *Journal of Development Economics*, 2019.

A Additional Empirical Results

A.1 Trends over Time

In Figure 7 and Figure 8, I depict aggregate markup trends based on labor, materials, or the combined input of both as flexible inputs estimated using Cobb-Douglas production functions. In Figure 9 to Figure 12, I depict aggregate markup trends based on labor, raw materials, and energy as flexible inputs estimated using either Cobb-Douglas or Translog production functions. In Figure 13 to Figure 20, I depict aggregate markup trends estimated using a dynamic panel approach, Flynn et al. (2019), industry-year cost shares, or subindustry-year cost shares.

Figure 7 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.

A.2 Markup Dispersion

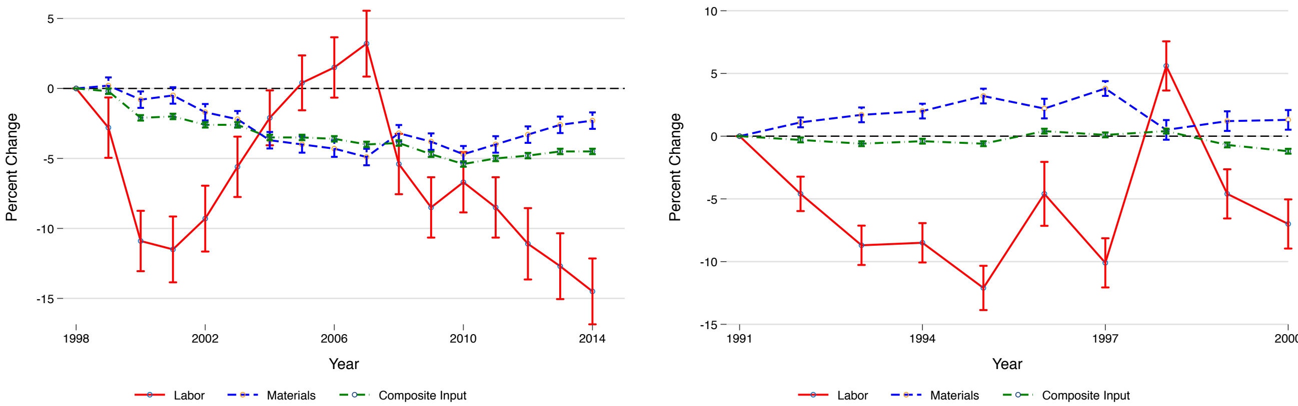
In Table XII and Table XIII, I report the 75/25 ratio and 90/10 ratio of markup estimates.

A.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 XIV. The average labor markup is 9% higher than the

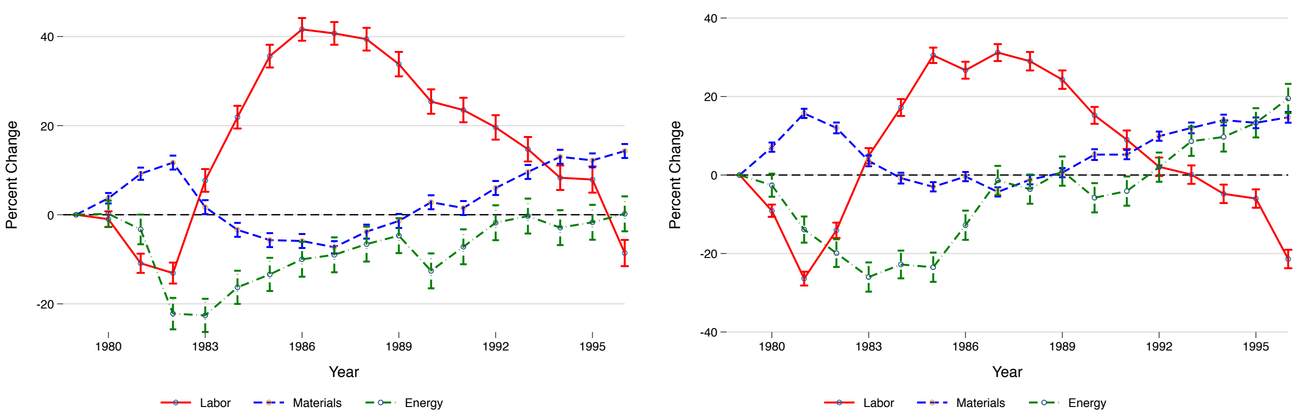
Figure 8 Markup Time Trends using Cobb-Douglas Estimates: India and Indonesia



(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.

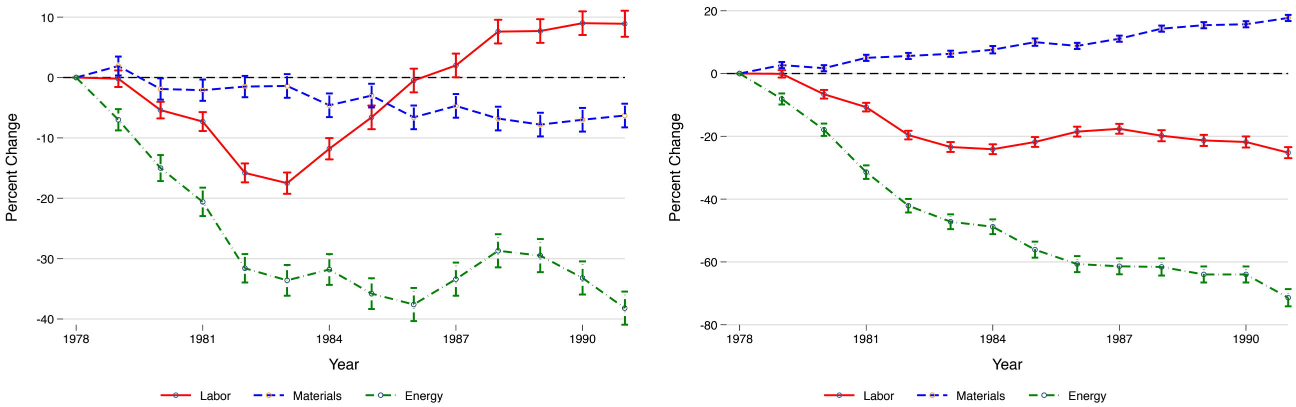
Figure 9 Markup Time Trends, with Energy: Chile



(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.

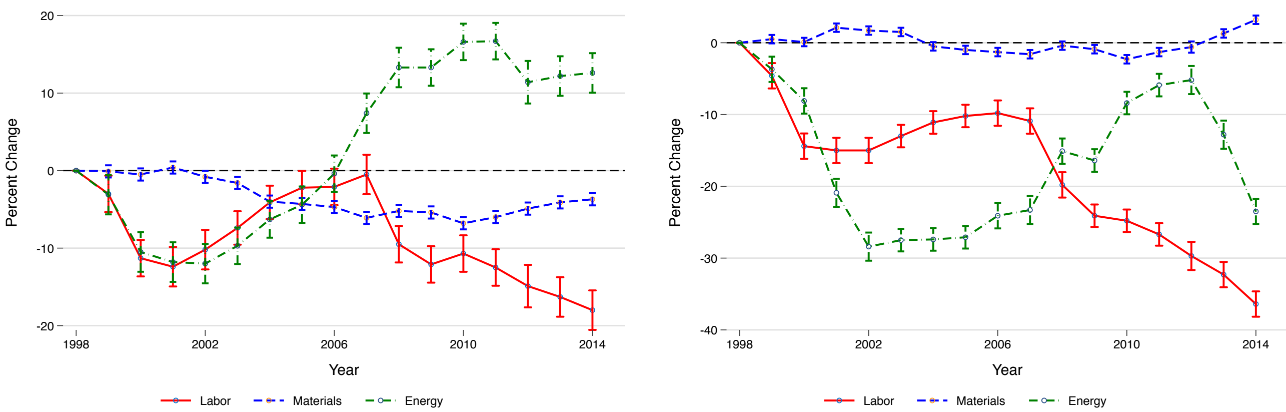
Figure 10 Markup Time Trends, with Energy: Colombia



(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.

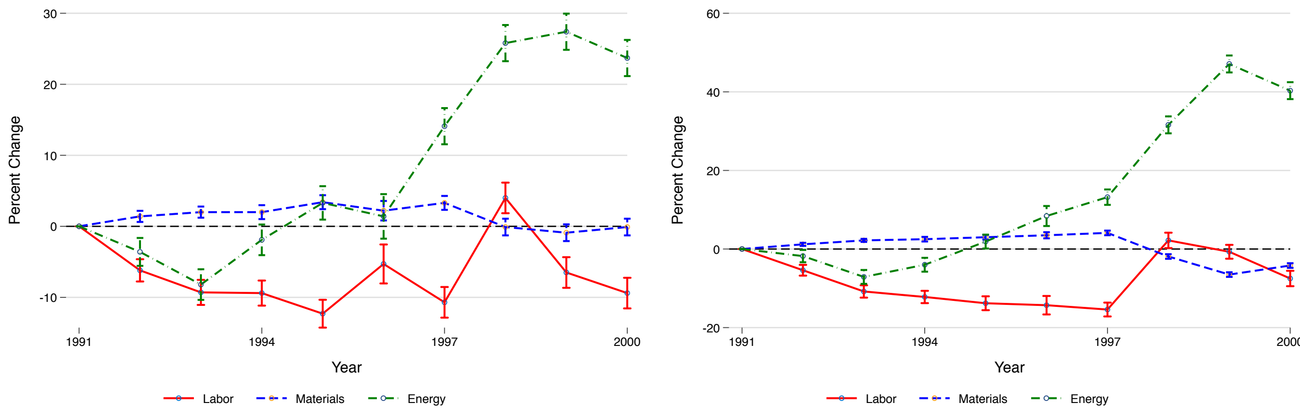
Figure 11 Markup Time Trends, with Energy: India



(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.

Figure 12 Markup Time Trends, with Energy: Indonesia

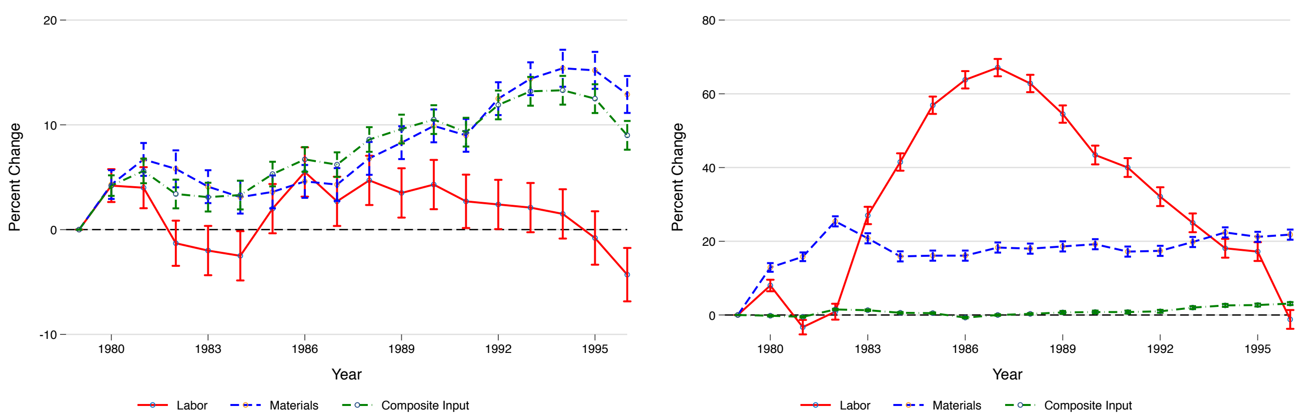


(a) Cobb-Douglas

(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.

Figure 13 Markup Time Trends, Alternative Estimators: Chile

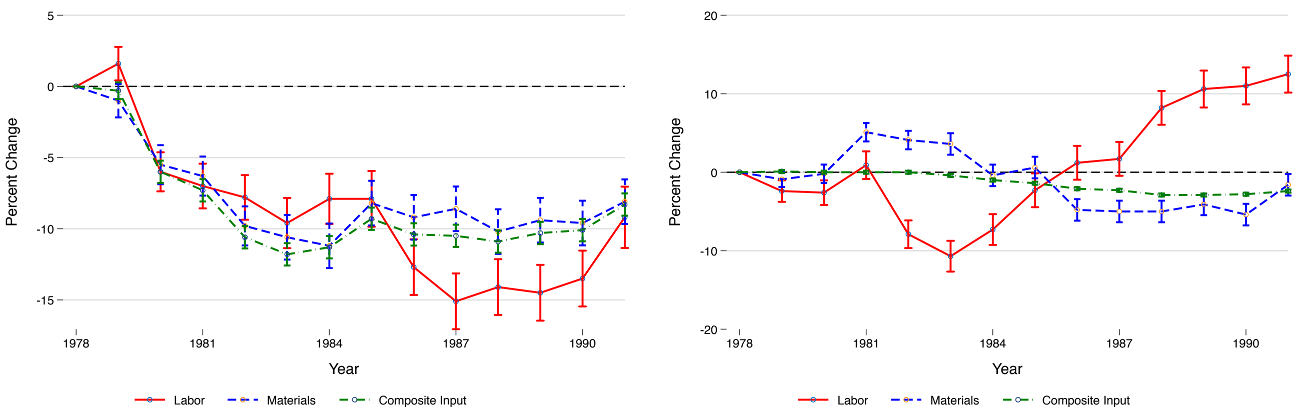


(a) Dynamic Panel

(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 14 Markup Time Trends, Alternative Estimators: Colombia

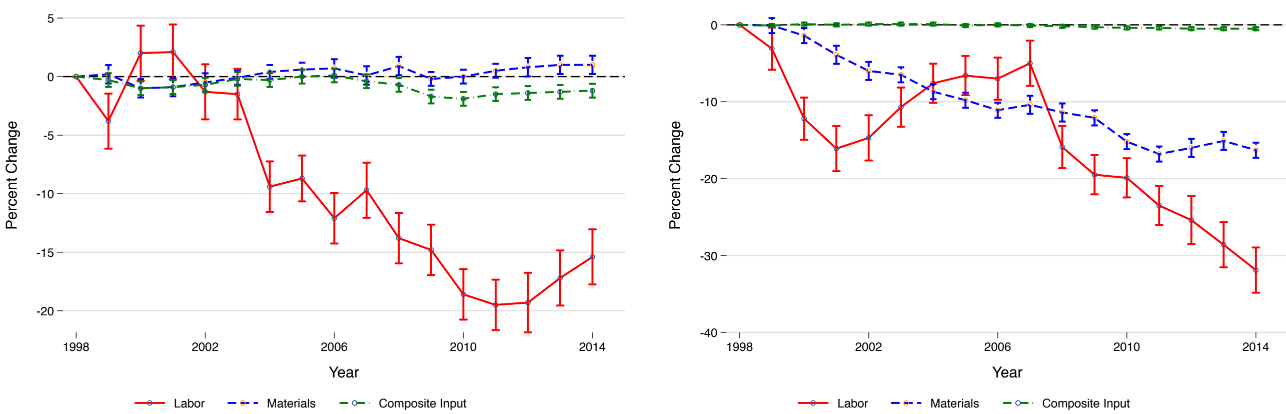


(a) Dynamic Panel

(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 15 Markup Time Trends, Alternative Estimators: India

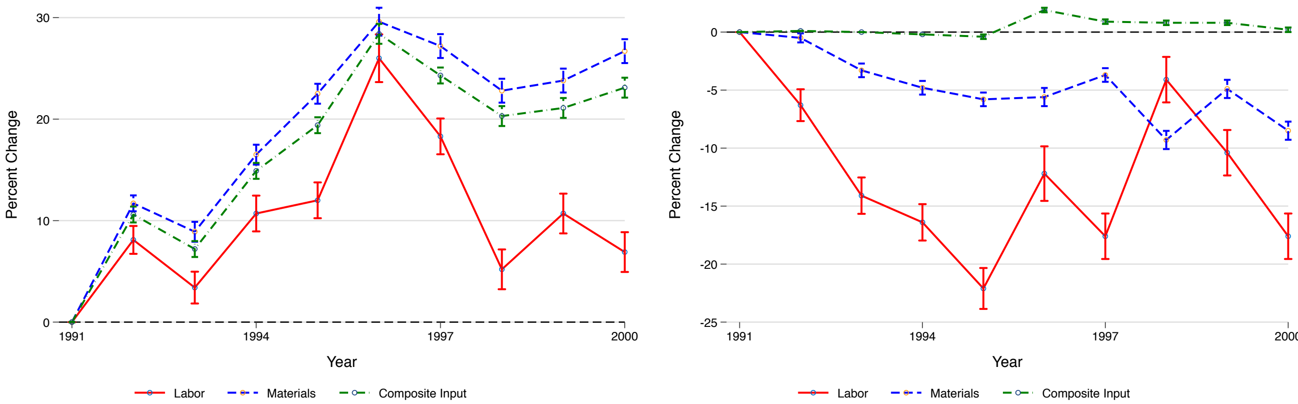


(a) Dynamic Panel

(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 16 Markup Time Trends, Alternative Estimators: Indonesia

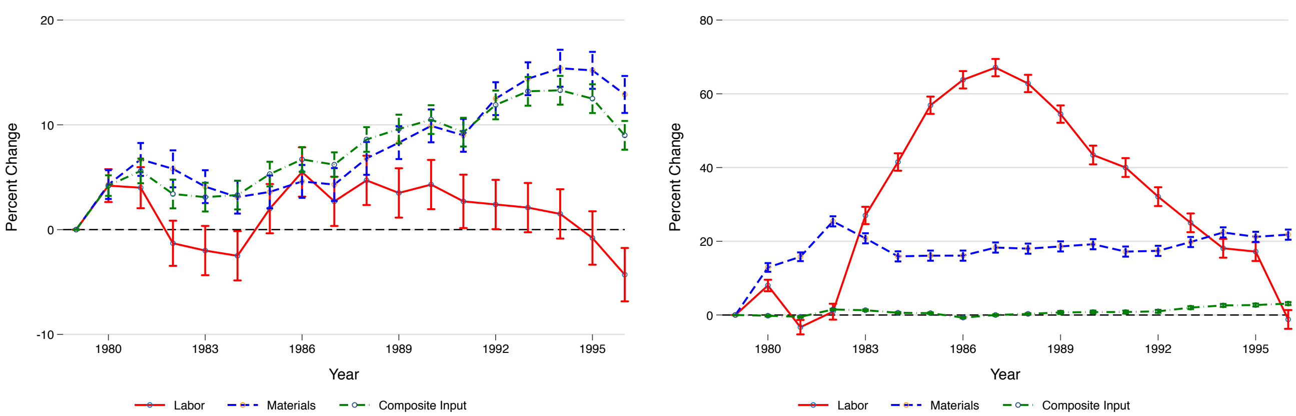


(a) Dynamic Panel

(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 17 Markup Time Trends, Cost Share Estimators: Chile

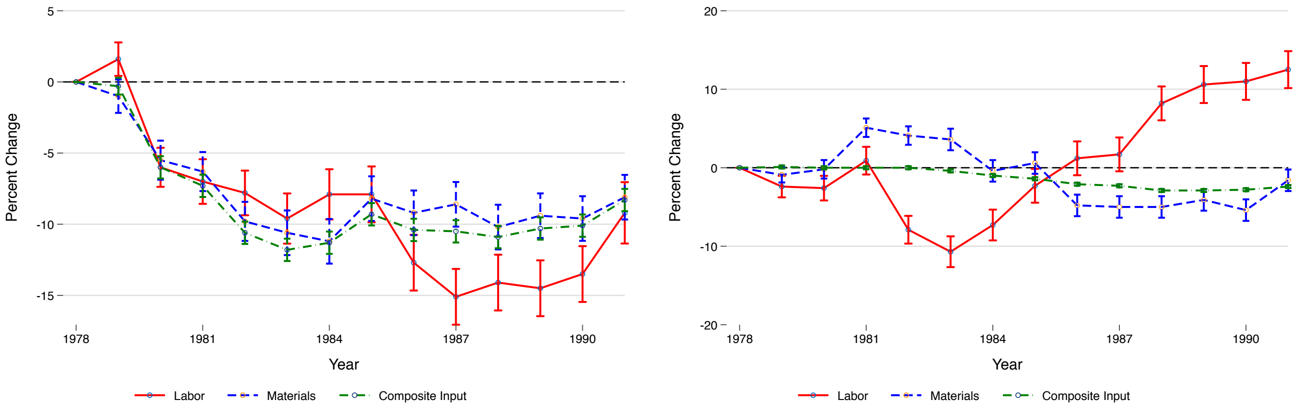


(a) Industry Cost Share

(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 18 Markup Time Trends, Cost Share Estimators: Colombia

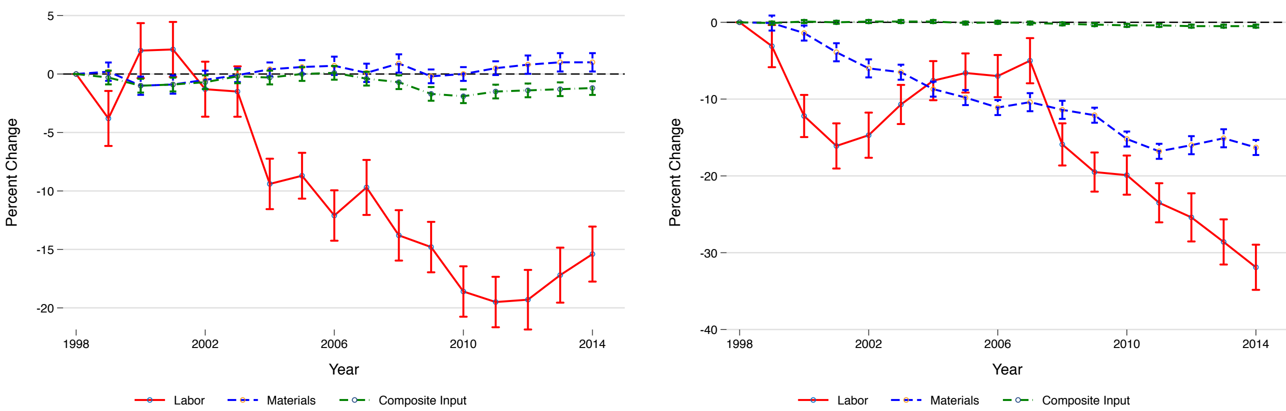


(a) Industry Cost Share

(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 19 Markup Time Trends, Cost Share Estimators: India

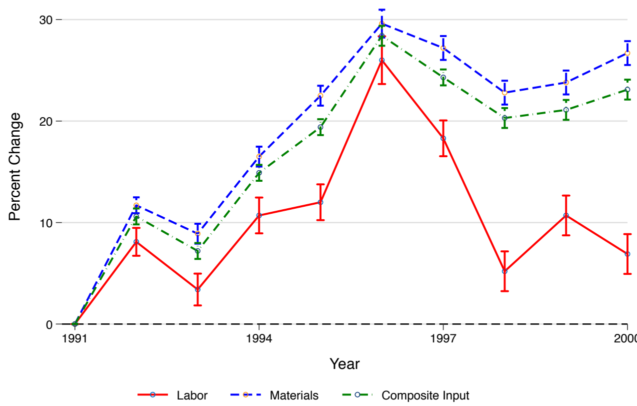


(a) Industry Cost Share

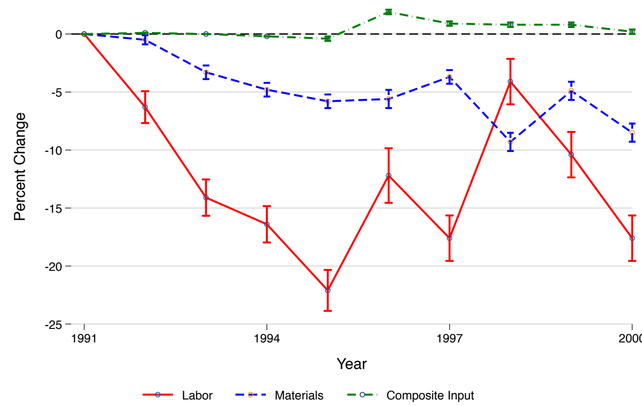
(b) Flynn, Gandhi, Traina

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 20 Markup Time Trends, Cost Share Estimators: Indonesia



(a) Industry Cost Share



(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.

Table XII 75/25 Ratio of Markup Estimates

	Labor		Materials		Combined 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)
Company 1	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 XIII 90/10 Ratio of Markup Estimates

	Labor		Materials		Combined Input	
Dataset	CD	TL	CD	TL	CD	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)
Company 1	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.

average materials markup for Chile, 18% higher for Colombia, 198% higher for India, 72% higher for Indonesia, and 106% higher for Company 1 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 Company 1. Thus, the average markups are close to each other for Colombia and Company 1 – using the Translog estimates, and for Chile and Colombia using the Cobb-Douglas estimates.

A.4 Weighted Estimates

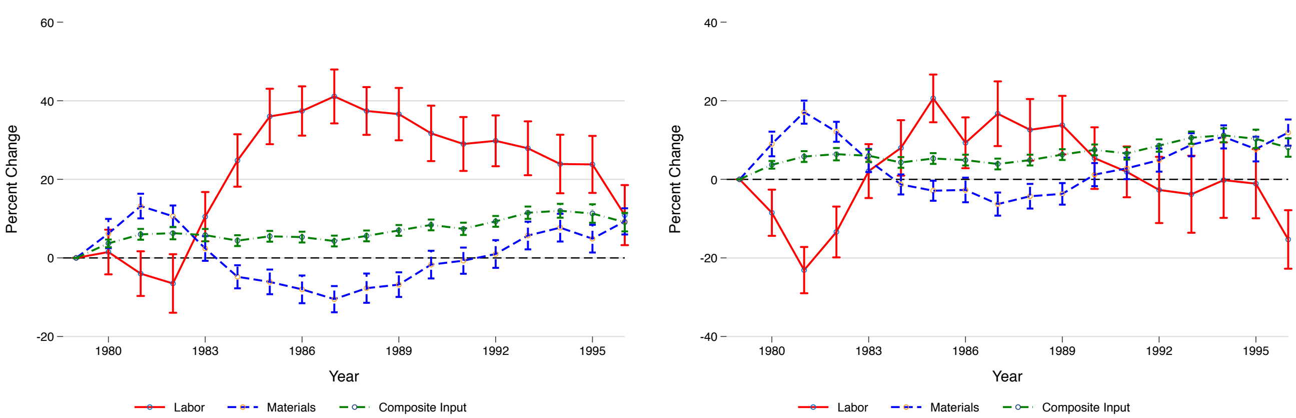
De Loecker et al. (2018) weight markups by sales, while Edmond et al. (2018) argue that cost weights are the right benchmark for welfare calculations. In this section, I weight all observations using sales weights (the plant's share of total sales in the year), or cost weights (the plant's share of total 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.

Table XIV Ratio of Average Markup Estimates

Dataset	Labor/Materials CD	Labor/Materials TL	Labor/Combined Input CD	Labor/Combined Input TL	Materials/Combined Input CD	Materials/Combined 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)
Company 1	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.

Figure 21 Markup Time Trends, Sales Weighted: Chile

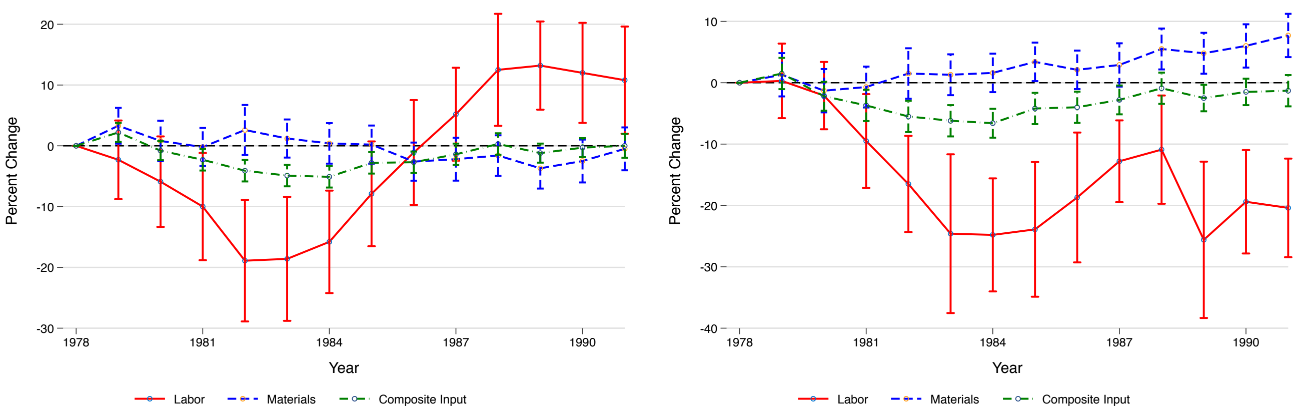


(a) Cobb-Douglas

(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.

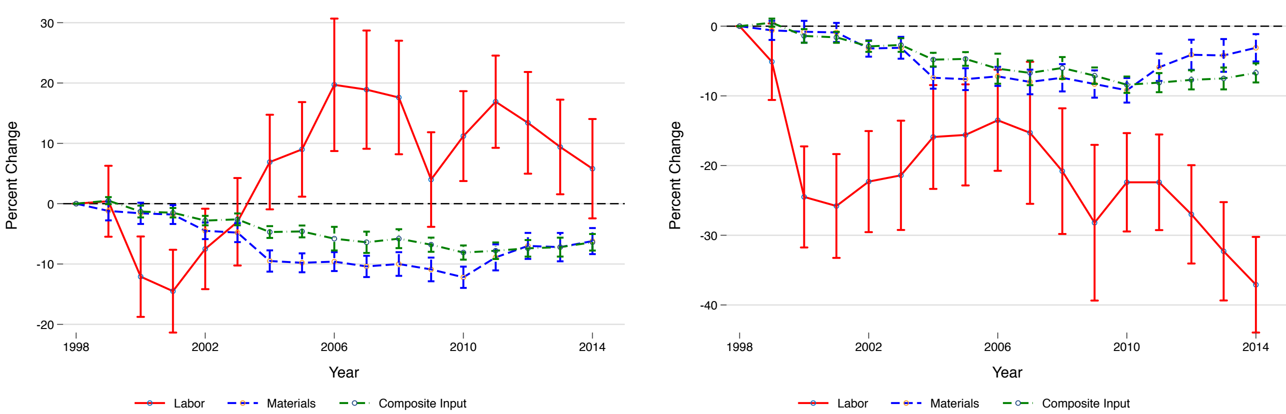
Figure 22 Markup Time Trends, Sales Weighted: Colombia



(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.

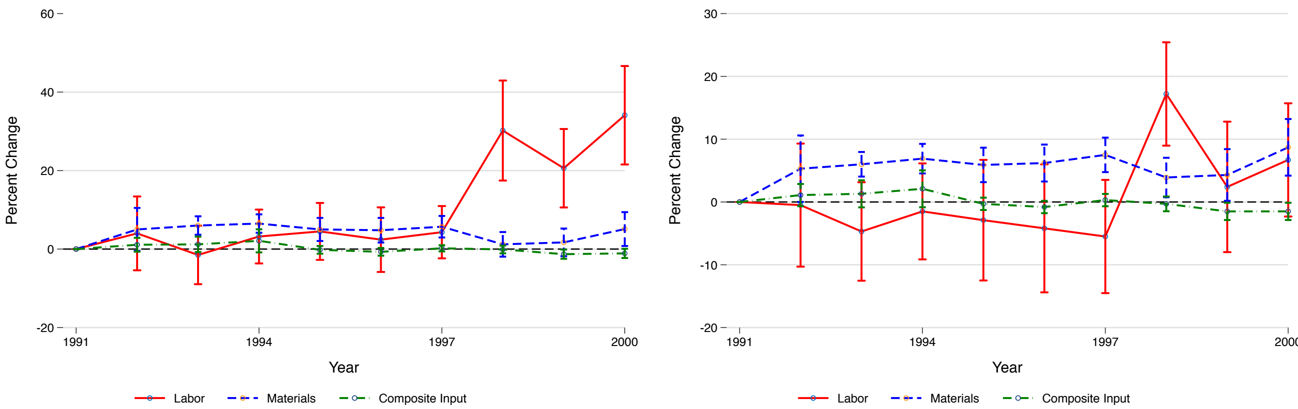
Figure 23 Markup Time Trends, Sales Weighted: India



(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

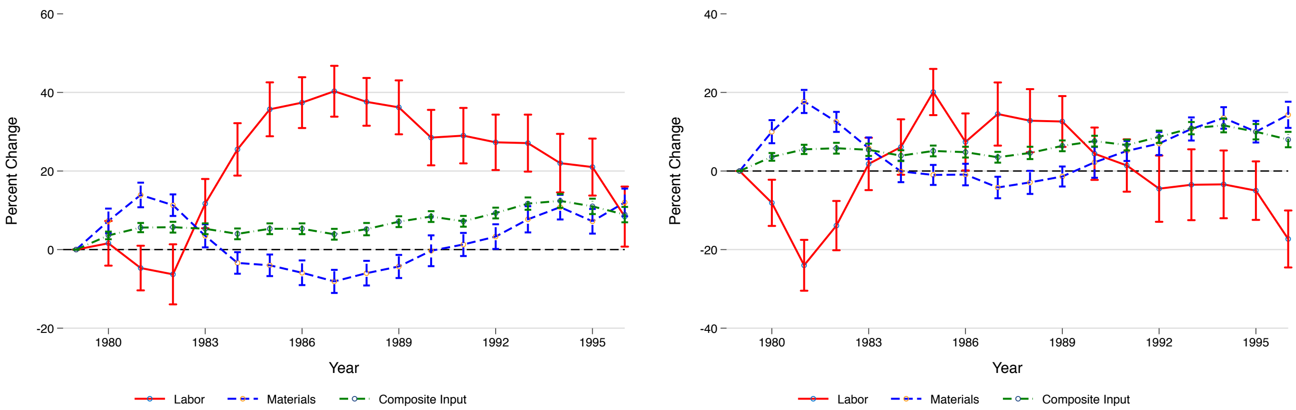
Note: Estimates based on (10), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

Table XV Correlation between Markup Estimates: Sales Weighted

	Labor on Materials		Labor on Combined Input		Materials on Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	-0.83	-0.30	-0.40	0.45	1.24	0.98
	(0.060)	(0.076)	(0.167)	(0.192)	(0.062)	(0.053)
Colombia	-1.37	-0.09	-1.45	1.50	1.56	0.96
	(0.087)	(0.199)	(0.211)	(0.221)	(0.056)	(0.069)
India	-1.89	-0.73	-0.89	0.31	1.04	0.94
	(0.127)	(0.117)	(0.342)	(0.233)	(0.047)	(0.045)
Indonesia	-0.65	-0.30	-1.10	0.33	1.54	1.21
	(0.094)	(0.111)	(0.537)	(0.345)	(0.150)	(0.113)
Company 1	-7.06	-9.70	7.22	1.75	-0.03	0.24
	(0.152)	(0.121)	(0.240)	(0.144)	(0.030)	(0.011)

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. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level. Estimates weighted with sales weights.

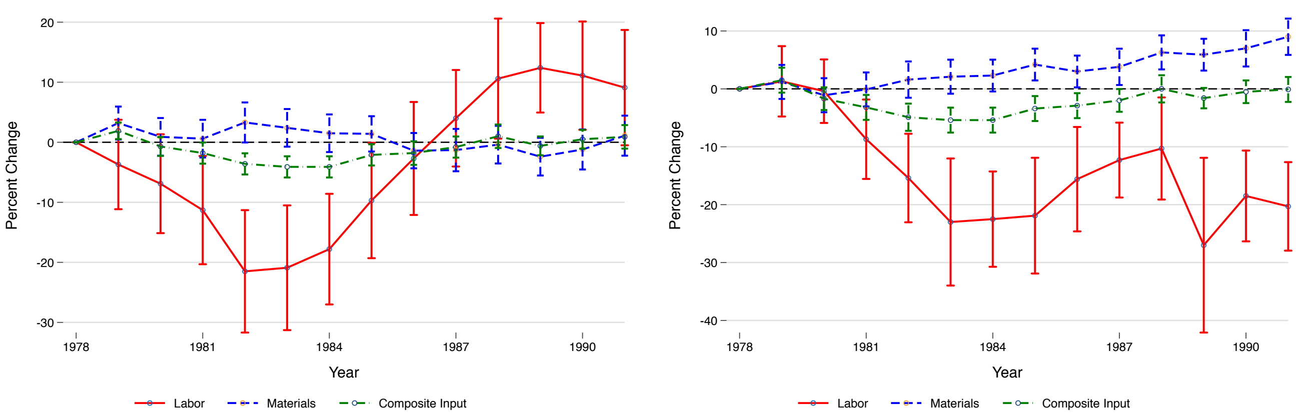
Figure 25 Markup Time Trends, Cost Weighted: Chile



(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.

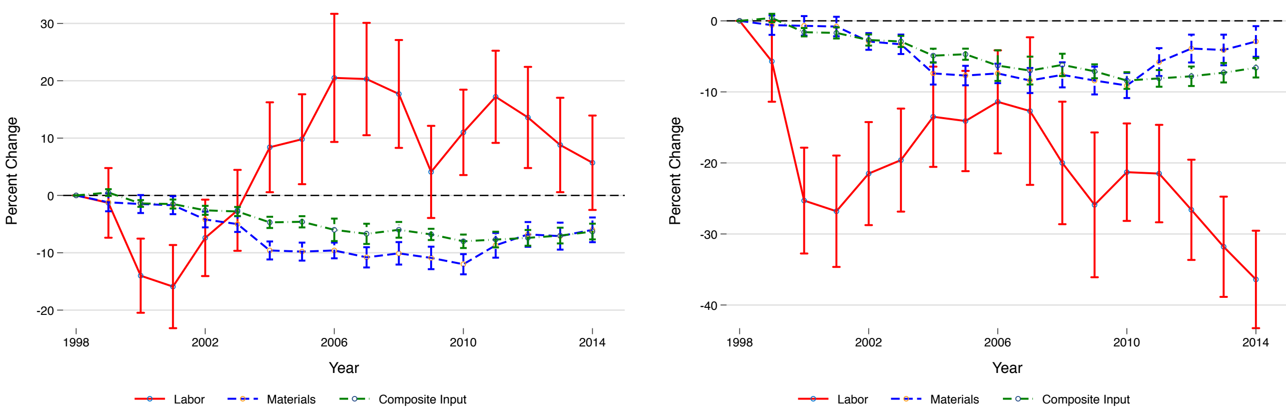
Figure 26 Markup Time Trends, Cost Weighted: Colombia



(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.

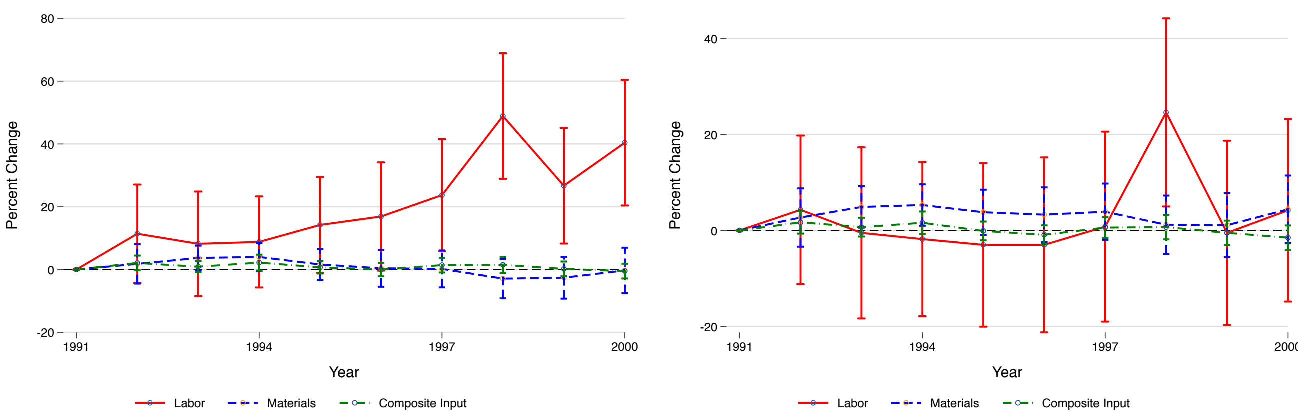
Figure 27 Markup Time Trends, Cost Weighted: India



(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 XVI Correlation between Markup Estimates: Cost Weighted

Dataset	Labor on Materials CD	Labor on Materials TL	Labor on Combined Input CD	Labor on Combined Input TL	Materials on Combined Input CD	Materials on Combined Input TL
Chile	-0.83	-0.29	-0.45	0.44	1.26	0.99
	(0.059)	(0.069)	(0.178)	(0.196)	(0.058)	(0.047)
Colombia	-1.42	-0.08	-1.54	1.54	1.52	0.89
	(0.068)	(0.161)	(0.199)	(0.229)	(0.057)	(0.063)
India	-1.98	-0.77	-1.24	0.30	1.06	0.93
	(0.120)	(0.112)	(0.369)	(0.264)	(0.055)	(0.053)
Indonesia	-0.86	-0.46	-1.18	0.03	1.45	1.24
	(0.116)	(0.126)	(0.314)	(0.292)	(0.095)	(0.082)
Company 1	-7.07	-9.71	7.27	1.72	-0.03	0.24
	(0.155)	(0.119)	(0.241)	(0.144)	(0.030)	(0.011)

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. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level. Estimates weighted with cost weights.

A.5 Stylized Facts

In this appendix, I examine the same stylized facts as in Section 6, but use the Cobb-Douglas and Translog ACF estimator to estimate production functions. See Table XVII to Table XX. Across all of the stylized facts, estimates vary in sign and magnitude across different datasets and inputs.

A.6 Correlations with Competition

REDO SECTION

In Section 6.2, I examined the relationship between markups and competition for Company 1 using a company developed competition band of Low, Medium, or High, and found sharp differences between markups estimated using different inputs.

I find very similar patterns using the number of competitors instead of the company's competition band in Table XXI. 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.[25]

[25] For retail stores not located in a Metropolitan Statistical Area or Micropolitan Statistical Area, the fixed

Table XVII Correlation between Markups and Sales

	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)
Company 1	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 (17) where the independent variable is deflated sales. CD and TL are ACF Cobb-Douglas and Translog estimators. Standard errors are clustered at the establishment level.

Table XVIII Correlation between Markups and Competition

	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 (17) 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 ACF Cobb-Douglas and Translog estimators. Standard errors are clustered at the establishment level.

Table XIX Correlation between Markups and Exporting

Dataset	Labor CD	Labor TL	Materials CD	Materials TL	Combined Input CD	Combined Input 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 (17) where the independent variable is an indicator for whether the establishment exports. CD and TL are ACF Cobb-Douglas and Translog estimators. Standard errors are clustered at the establishment level.

Table XX Correlation between Production Markup Estimates and Profit Based Markup

Dataset	Labor CD	Labor TL	Materials CD	Materials TL	Composite Input CD	Composite Input 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)
Company 1	1.81	-0.09	-0.08	-0.01	0.15	-0.17
	(0.027)	(0.041)	(0.003)	(0.003)	(0.003)	(0.003)
Company 1 (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 (17) where the independent variable is the profit share based markup. CD and TL are ACF 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.

I thus re-estimate (17) replacing the year fixed effects with MSA year fixed effects. Table XXII and Table XXIII contain these estimates; I find slightly higher markups for stores with higher competition in these estimates.

Table XXI Correlation between 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 (17) 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 XXII Correlation between 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 (17), 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.

B Data Notes (Online Appendix)

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

effect is for all non-MSA locations in the same state.

Table XXIII Correlation between 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 (17), 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.

B.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.

B.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 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.[26]

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.[27]

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.[28] 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.[29] 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 (Company 1), 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

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

[27] 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%.

[28] 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.

[29] 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.

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 of the real capital stock of each asset type multiplied by the appropriate capital rental rate, plus deflated rent.[30]

B.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 Company 1, 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.

B.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.

[30] 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 Company 1 I deflate rent using the structures deflator, as most capital is structures.

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.

For Retailer 1, 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.

B.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.

B.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.

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

Table XXIV 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