Testing the Production Approach to Markup Estimation*

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Abstract

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

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Measuring the markup, the degree to which firms price above marginal cost, is central to questions across economics. In industrial organization, markup estimates are used to evaluate past mergers, as well as to predict the competitive harm from proposed mergers. For macroeconomists, rising markups provide a potential explanation for the decline in the labor share of income and other aggregate trends. In international trade, measures of markups are required to understand how firms respond to changes in trade barriers.

Despite their importance, it is difficult to measure markups. The power of the *production approach* to markup estimation (De Loecker and Warzynski, 2012) has been to allow economists to easily measure markups across a wide array of industries. Research using this approach has recently suggested a decline in market competitiveness.[1]

For cost minimizing firms facing 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, one can recover the markup given cost data if one knew the production function. The production approach identifies the markup as a variable input's output elasticity divided by the input's share of revenue.

Any flexible input identifies the markup under this approach. With multiple flexible inputs, the markup is thus overidentified. This overidentification provides a natural test: markups estimated using different flexible inputs should have the same distribution. Economists using the production approach have used labor, materials, or cost of goods sold

[1]For example, De Loecker et al. (2018) find that markups have risen substantially over time in the US, while Blonigen and Pierce (2016) find that markups rise after mergers for US manufacturing plants.

(which includes elements of both) as variable inputs, so I compare labor, materials, and a composite variable input of both labor and materials.[2]

I conduct these tests using the manufacturing censuses from Chile, Colombia, India, and Indonesia.[3] In addition, I also use unique data on every retail store of a major nationwide US retailer. Markups should be fairly uniform across stores of the same retailer, as US retailers tend to have near uniform pricing across stores (DellaVigna and Gentzkow, 2017).

I first estimate paired t-tests and Kolmogorov-Smirnov tests to compare the distribution of the markup measured using labor (the "labor markup"), the markup measured using materials (the "materials markup"), and the markup measured using the composite input, across all five datasets. Contrary to what the production approach implies, I strongly reject that the distributions of markups measured with different inputs are the same for all of the 60 tests.

I next examine what features of the markup distribution vary when measuring the markup with different flexible inputs. I first examine trends over time, and find opposing trends in the markup using different flexible inputs in all of the datasets. For example, the average labor markup for Colombia falls by 28% over the sample, while the average materials markup rises by 8%. For Indonesia, the average labor markup and materials markup move in opposite

[2]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).

[3]All of these datasets have been used in the literature estimating production functions. For some examples, see Gandhi et al. (forthcoming), Levinsohn and Petrin (2003), Oberfield (2013), and Pavcnik (2002) for Chile, Fernandes (2007) and Gandhi et al. (forthcoming) for Colombia, Alcott et al. (2015) and Hsieh and Klenow (2009) for India, and Amiti and Konings (2007) for Indonesia.

directions after the 1998 Asian crisis.

I next estimate the cross-sectional correlation of the labor markup with the materials markup. Under the production approach, these correlations should be positive and close to one. Instead, I find *negative* correlations for all the datasets; plants with higher materials markups tend to have substantially lower labor markups.

I then measure the degree of dispersion in markups; under the production approach, markups estimated using different inputs should have similar dispersion. However, across all of the datasets, the dispersion in markups is highest using the labor markup and lowest using the composite variable input, with materials in between. For example, the 90th percentile markup for the retailer is 76% higher than the 10th percentile using labor, compared to only 6% higher using materials and 5% using the composite input.

Finally, I examine the relationship between markups and competition directly for the retailer by exploiting two company-developed classifications of the degree of competition that each retail store faces. For both measures of competition, I find a different sign and magnitude of the relationship between competition and markups when using different inputs.

Several explanations could account for differences in markups estimated using different flexible inputs. First, the production approach assumes static cost minimization for the variable input, which input adjustment costs or non-competitive input markets would violate. Second, the production approach requires a set of auxiliary assumptions on production in order to estimate the output elasticity. Either the form of the production function, or the assumptions required to estimate the production function, could be misspecified. In my baseline results, I estimate Cobb-Douglas or Translog production functions at the industry level using a control function approach (Ackerberg et al., 2015). Finally, the data used on inputs could be measured with error.

I first evaluate explanations due to the violation of the labor first order condition, such as through hiring and firing costs or wage bargaining with unions. After including two alternative flexible inputs through energy and non-energy raw materials, I continue to find differences in markups. I examine two alternative estimation approaches, a new control function method (Flynn et al., 2019) and estimating output elasticities through industry cost shares, and still find widely different markup estimates using different inputs. Finally, measurement error explanations cannot account for similar differences using the internal data of the retailer, which should be of much higher quality than survey responses.

Instead, relaxing the maintained assumption that productivity is Hicks neutral, and so improves all factors equally, can explain these findings. The literature has found that productivities augmenting labor vary across time and establishments (Doraszelski and Jaumandreu, 2018; Oberfield and Raval, 2014; Raval, 2019; Zhang, 2019). In these papers, higher labor augmenting productivity lowers labor's output elasticity relative to materials' output elasticity and lowers labor costs relative to materials costs. If one ignores such productivity differences, markups estimated using different inputs would have opposing time trends and negative correlations.

I then show how to control for differences in labor augmenting productivity by a simple modification of the cost share approach. I group plants into quintiles based on their level of labor costs to materials costs, and estimate output elasticities as input cost shares within each industry quintile. Both in Monte Carlo simulations, and across all five datasets, estimates of markups using this approach result in similar time trends and positive cross-sectional correlations of markups estimated with different inputs.

Taken together, these results provide a cautionary note to those using the production approach to markup estimation. Inferences using markups estimated with the production approach requires good estimates of the firm's production function; in particular, researchers have to account for non-neutral productivity differences.

Within the broad literature on production functions and markups, 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, such as cost of goods sold or selling, general, and administrative expenses, affects the aggregate trend in US markups. De Loecker and Scott (2017) compare markup estimates using the demand approach to those from the production approach using data on US breweries. However, they only examine average markups, which they find to be similar.

In addition, Doraszelski and Jaumandreu (2019) show using Spanish manufacturing data that labor markups and material markups give the opposite estimate of the effect of exporting on markups. They then provide a new method to estimate markups in the presence of labor augmenting productivity differences through a dynamic panel approach.

As in this article, De Loecker et al. (2018) find sharp differences in markups estimated using different variable inputs. They compare labor and materials using manufacturing data from the US Census and find a 60 percentage point increase in the materials markup in the 2000s compared to no change in the labor markup. Their markup for materials is also much higher than for labor, with an average markup of 3 in 1987 using materials compared to 1.65 using labor. Unlike my findings, they report higher dispersion in materials; the 90-50 ratio in the markup is slightly above 3 in 1987 for materials, compared to about 1.7 for labor.[4]

Section 1 lays out the production approach to estimating markups. Section 2 details the various datasets I use, and Section 3 how I estimate production functions. Section 4 tests the approach using markups estimated using different inputs. Section 5 examines potential explanations for my findings, and Section 6 concludes.

1 Production Approach

The key assumptions for the production approach are that the firm cost minimizes in each period with respect to a given variable input, and that it is a price taker in the input market for that input. Below, I derive the estimator for the markup under these assumptions

[4] See Figure 12 compared to Appendix Figures 11.1 and 11.2 in De Loecker et al. (2018). Figure 19 in De Loecker et al. (2018) compares markup estimates using either cost of goods sold or the wage bill using Compustat, and shows opposite time trends for markups using either input between 1970 and 1990.

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} in the output market and faces input prices P_{it}^X for input X in the input market. A cost minimizing firm sets marginal products equal to factor prices. Assuming that the firm is a price taker in the input market, this implies:

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

where X_{it} is one of the inputs in production, P_{it}^X is that input's price, P_{it} is the output price, and λ_{it} is the firm's marginal cost.[5] 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[6], 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:

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

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

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

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

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

This expression for markups holds for *all* inputs that satisfy the static first order condition with a factor market in which they are a price taker. Thus, one can test the production approach by estimating markups using different variable inputs.

2 Data

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

I also use retail store-level data from a major US nationwide retailer, which I will call "Company 1", for three years. This retailer has thousands of stores across the United States.[7]

For each dataset, I have data on capital, labor, materials, and sales at the establishment-

[7]Unfortunately, I am unable to provide further details on the industry or identity of this retailer.

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

year level. An establishment is a manufacturing plant for the Chilean, Colombian, and Indian data, a firm for the Indonesia data, and a retail store for Company 1.

I then obtain 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 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 non-energy 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.[8]

For capital, I construct a perpetual inventory measure of capital for each type of capital.

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

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.[9]

For the manufacturing datasets, I estimate production functions at the industry level. I define industries at a similar level to two digit US SIC.[10] I only include industries with at least 1,000 observations over the entire dataset, and so use between 16 to 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 two major components: 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 typically observed in plant and firm datasets. However, the production function $F_{it}(K_{it}, L_{it}, M_{it})$ has to be specified, and then estimated, in order to recover the output elasticity for input X. In this section, I follow De Loecker and Warzynski (2012) and use the Ackerberg et al. (2015) technique to estimate production functions.

[9] 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.

[10] 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). De Loecker et al. (2018) estimates production functions at the 2 digit NAICS level (so manufacturing is represented by 3 industries), a higher degree of aggregation than in this paper.

3.1 Production Functions

In my baseline estimates, I estimate Cobb-Douglas and Translog production functions. I estimate one specification of the production function with capital, labor, and materials, as well as another specification with 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, 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 with labor and materials, the production function is:

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

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) technique for production function estimation, a control function approach building upon Olley and Pakes (1996) and Levinsohn and Petrin (2003), for my baseline estimates.

The ACF technique 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 after 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:

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

A key assumption of the ACF framework is that materials, or another flexible input, is decided after the firm learns its productivity shock. Thus, materials is a function of the observed inputs and productivity $m_{it} = g(k_{it}, l_{it}, \omega_{it})$. Materials can then be inverted for productivity, so productivity is a function $g^{-1}(k_{it}, l_{it}, m_{it})$.

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

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it} \tag{6}$$

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + g^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} = h(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \tag{7}$$

Since both the production function and productivity are functions of the inputs, we cannot separate the two 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.[11]

The second major assumption of the ACF approach is that productivity follows a first order AR(1) process.[12] Formally,

$$\omega_{it} = \rho\omega_{i,t-1} + \nu_{it} \tag{8}$$

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:

$$\nu_{it}(\beta) = \omega_{it} - \rho\omega_{i,t-1} \tag{9}$$

The innovation in productivity is a function of production coefficients β because ω_{it} =

[11] In practice, I use a third order polynomial in inputs for the function g, and also control for year effects.
[12] This assumption can easily be generalized, such as to a first order Markov assumption on productivity.

$y_{it} - \epsilon_{it} - f_{it}(\beta)$, 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.[13]

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 step of the ACF procedure. Thus, for input X, the estimate of the markup is:

$$\hat{\mu_{it}} = \frac{\hat{\beta_i^X}}{s_{it}^X exp(\hat{\epsilon}_{it})}. \tag{10}$$

3.3 Implementation

For each dataset, I estimate industry-level production functions using the ACF control function procedure detailed above. 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 use the resulting output elasticities to estimate markups at the establishment-year level. This process results in six markup estimates for

[13] 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.

each establishment-year, with each markup estimated using either labor, materials, or the composite input as the flexible input and using either a Cobb-Douglas or Translog production function to recover the output elasticity for that input.

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 the implication of the production approach that different inputs estimate the same markup.

4.1 Statistical Tests

I begin by conducting two statistical tests of equality of distribution: the paired t-test and the Kolmogorov-Smirnov test. I conduct these tests for the Cobb-Douglas and Translog production functions comparing labor, materials, and composite variable input markups. I thus conduct 60 tests – 5 datasets, 2 production functions, 3 flexible inputs, and two statistical tests.

I overwhelmingly reject that markups estimated using different flexible inputs have the same distributions. Across the 60 tests, the largest p-value was 1.8×10^{-4}, with all of the other p-values an order of magnitude or more smaller.[14]

Thus, I next turn to examining specific features of the distribution of markups, including dispersion, time series and cross-sectional correlations, and correlation with size and degree of competition.[15]

4.2 Dispersion in Markup Estimates

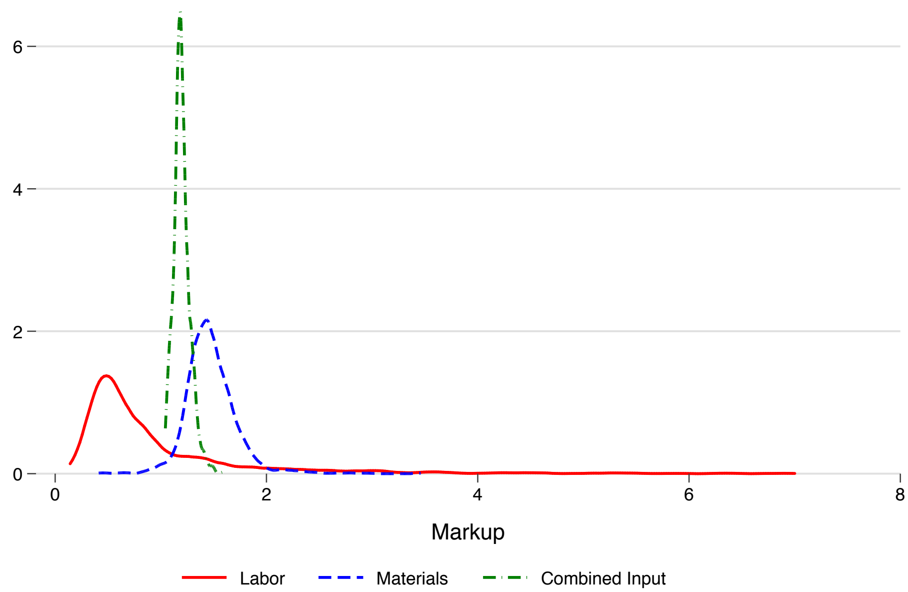
Under the production approach, the degree of markup dispersion should be the same using different flexible inputs. I test this prediction by comparing the degree of dispersion using different inputs. As an example, I plot the distribution of the labor, materials, and composite input markup across manufacturing plants in the Chilean Food Products industry in 1996 in Figure 1; the top figure uses the Cobb-Douglas estimates and the bottom figure Translog estimates. The 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. For both the Cobb-Douglas and Translog estimates, the labor markups are much more disperse than the materials markup, which are in turn more disperse than the composite input markups.[16]

For all the datasets, I measure dispersion by calculating the 90/50 ratio of the markup

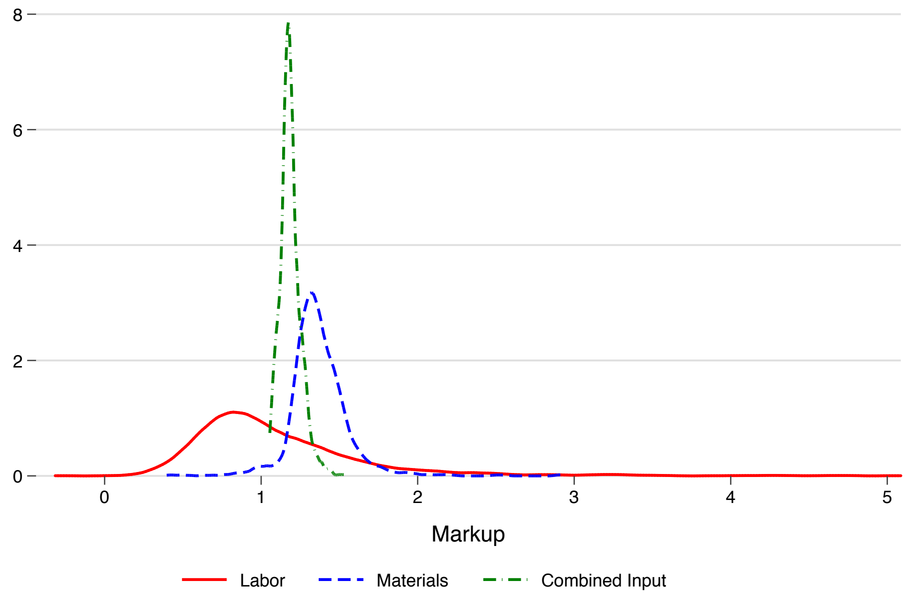
[14]The second highest p-value is 1.6×10^{-18}, and third highest 2×10^{-62}.

[15] I also examine average markups in Appendix A.3.

[16]For the Translog estimates, the 10th percentile markup is 0.5 using labor, 1.2 using materials, and 1.1 using the composite input. The 90th percentile markup is 1.7 using labor, 1.6 using materials, and 1.3 using the composite input.



(a) Cobb-Douglas



(b) Translog

Figure 1 Distribution of Markups for Chilean Food Products, 1996 estimates, which I report in Table II.[17] 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 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
	(0.014)	(0.009)	(0.005)	(0.003)	(0.001)	(0.001)
Colombia	2.88	1.82	1.82	1.43	1.16	1.17
	(0.016)	(0.005)	(0.007)	(0.005)	(0.001)	(0.001)
India	4.73	3.67	1.44	1.38	1.36	1.39
	(0.015)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
Indonesia	4.06	3.12	1.66	1.46	1.15	1.16
	(0.025)	(0.015)	(0.003)	(0.002)	(0.001)	(0.001)
Company 1	1.23	1.30	1.02	1.03	1.02	1.02
	(0.002)	(0.002)	(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.

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

4.3 Changes Over Time

Under the production approach, the time path in markups should be the same using different flexible inputs. I test this prediction by estimating trends in the average markup over time using different inputs. I estimate the following specification:

$$\log(\mu_{i,t}^X) = \alpha + \gamma_t + \delta_n + \epsilon_{i,t} \tag{11}$$

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

For all of the datasets, I find *opposing* patterns over time using labor compared to materials to measure the markup. The composite input markups lie between the two, but much closer to materials, and exhibit less extreme movements.[18]

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

[18] 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.

value by 1996. The composite input markup is 4% above its 1979 value in 1981 and 1987 and 8% above by 1996.

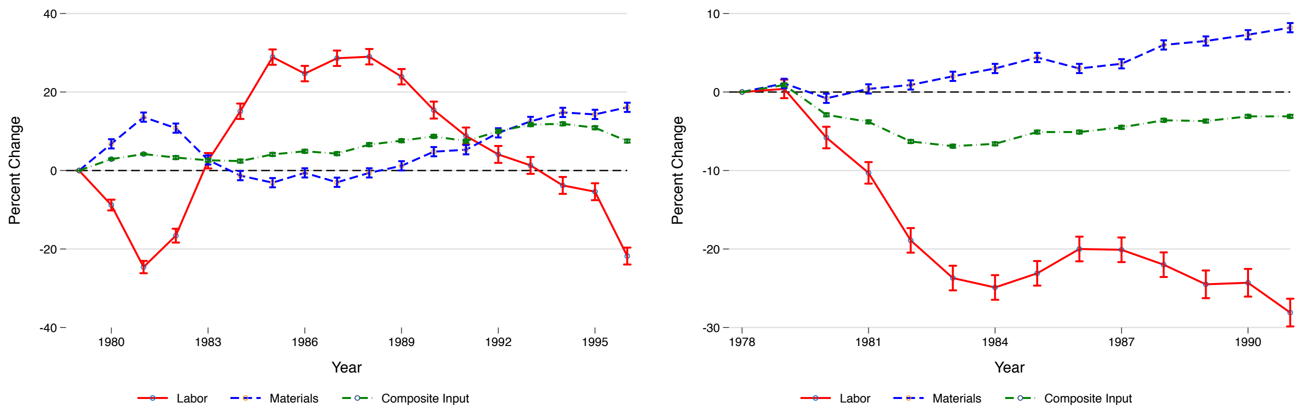
For Colombia, the average labor markup falls substantially at the beginning of the sample using labor, and remains about 28% lower at the end of the sample compared to the beginning of the sample. The average materials markup rises over time and is about 8% higher at the end of the sample. The composite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

For the retailer, the average labor markup rises by 11% over two years, compared to a 3% decline in the average materials markup and composite input markup. For all four countries and the nationwide retailer, the time path of the average markup is very different using alternative inputs for the markup.

Figure 2 Change in Average Markup Over Time using Translog Estimates: Chile and Colombia



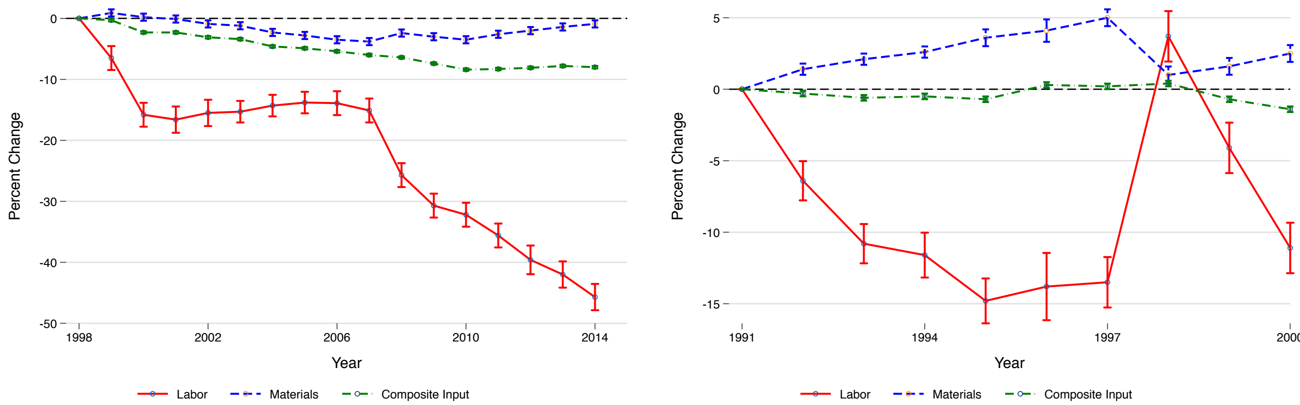
(a) Chile (b) Colombia

Note: Estimates based on (11), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

4.4 Correlations of Markup Estimates

Under the production approach, markup estimates using different inputs should be highly correlated with each other. I test this prediction by measuring how different markup estimates are correlated with each other beyond movements over time. In Figure 4, I plot scatter plots of the materials markup on the x-axis against the labor markup on the y-axis for plants in the Chilean Food Products industry in 1996. Each a point is a different manufacturing plant. The upper plot uses Cobb-Douglas estimates of the production function,

Figure 3 Change in Average Markup Over Time using Translog Estimates: India and Indonesia



(a) India

(b) Indonesia

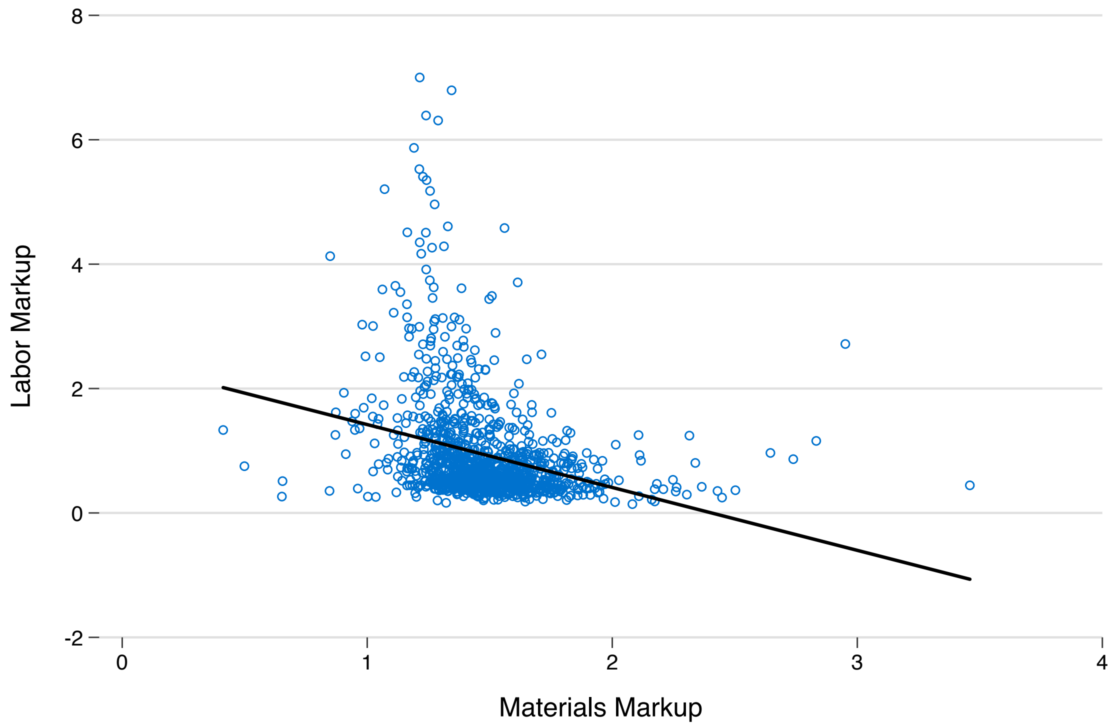
Note: Estimates based on (11), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

and the lower plot Translog estimates. The solid black line is the best linear fit. Using the Cobb-Douglas estimates, the labor markup falls on average as the materials markup rises; using the Translog estimates, there is no discernable relationship between the labor markup and materials markup. Thus, for this industry, I do not find the expected strong positive relationship between markup estimates.

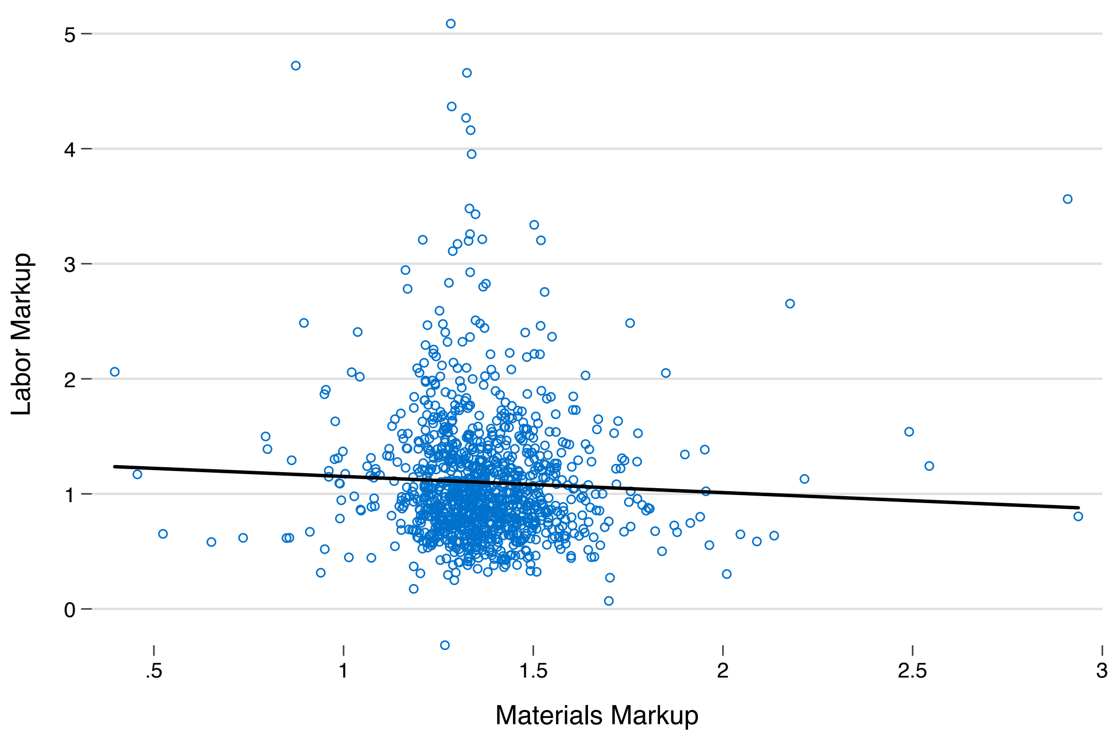
I examine the correlation between markup estimates for all the datasets by estimating the following regression:

$$\log(\mu_{i,t}^{Y}) = \alpha + \beta \log(\mu_{i,t}^{X}) + \gamma_t + \delta_n + \epsilon_{i,t} \tag{12}$$

where $\mu_{i,t}^{Y}$ and $\mu_{i,t}^{X}$ are the markups using input Y and X for establishment i in year t. I also



(a) Cobb-Douglas



(b) Translog

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.

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 input Y with respect to the markup using input X.

I report these correlations between markup measures in Table III; the first two columns are the elasticity of the labor markup with respect to the materials markup. The labor and materials markups are *negatively* correlated with each other, the opposite of the relationship implied by the production approach. An establishment with a 100% higher materials markup has, on average, a 66% lower labor markup for Chile, 99% lower for Colombia, 172% lower for India, 97% lower for Indonesia, and 751% lower for Company 1 under the Cobb-Douglas estimates. The magnitude of the elasticity falls using the Translog, but the correlation is still negative. 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.[19]

In Table III, the third and fourth columns are the elasticity of the labor markup to the composite input markup, and the fifth and sixth columns the elasticity of the materials markup to the composite input markup. Under the Translog estimates, these elasticities are positive, but vary substantially in magnitude across datasets. The elasticity of the labor

[19]The large magnitude of the elasticities for Company 1 is due to the measurement error correction to the input share of revenue as in (10), 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.

markup to the composite input markup varies from 28% to 140% across datasets, while the elasticity of the materials markup to the composite input markup varies from 26% to 157% across datasets.

Table III Correlation between Markup Estimates

	Labor on Materials		Labor on Composite Input		Materials on Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	-0.66	-0.16	-0.34	0.29	1.61	1.31
	(0.017)	(0.014)	(0.065)	(0.059)	(0.023)	(0.018)
Colombia	-0.99	-0.28	-1.08	0.78	2.13	1.10
	(0.015)	(0.021)	(0.060)	(0.049)	(0.032)	(0.015)
India	-1.72	-0.17	0.15	1.40	1.06	0.43
	(0.012)	(0.010)	(0.045)	(0.026)	(0.009)	(0.008)
Indonesia	-0.97	-0.48	0.02	0.28	1.72	1.57
	(0.018)	(0.021)	(0.065)	(0.066)	(0.028)	(0.021)
Company 1	-7.51	-10.08	8.21	1.14	-0.15	0.26
	(0.143)	(0.102)	(0.143)	(0.147)	(0.018)	(0.012)

Note: Estimates based on (12) 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.

4.5 Markups and Size

Theories of variable markups (Atkeson and Burstein, 2008; Melitz and Ottaviano, 2008) often predict markups increasing in firm size. Under the production approach, markups estimated using different flexible inputs should have the same correlations with firm size. I test this prediction by estimating the following regression specification:

$$\log(\mu_{i,t}^X) = \alpha + \beta \log(S_{i,t}) + \gamma_t + \delta_n + \epsilon_{i,t} \qquad (13)$$

where $\mu_{i,t}^{X}$ is the markup estimate for establishment i in year t using input X and $S_{i,t}$ is deflated sales.

I find quite different correlations with sales using different inputs to estimate the markup. I report these in Table IV. Only for the Cobb-Douglas labor estimates do I find a robust increase in the markup with sales, ranging from a 12% to 31% increase in the markup with a 100% increase in sales across datasets. For the Translog labor estimates, I continue to estimate a positive, but smaller increase (between 1 to 9%) for India, Indonesia, and Company 1. I estimate a decline of 1 to 3% in the markup with a 100% increase in sales for Chile and Colombia.

For materials, I estimate a robust *negative* relationship between markups and sales using the Cobb-Douglas estimates, with a 1 to 7% decline in the markup with a 100% increase in sales. Under the Translog estimates, I find no relationship with sales for Chile and Colombia, and a 2 to 3% decline in the materials markup with a 100% increase in sales for India, Indonesia, and Company 1. Thus, the magnitude and sign of the correlation between markups and size depends upon which flexible input is used to measure markups.

4.6 Markups and Competition

One explanation for high markups is less competition. Under the production approach, markups estimated using different flexible inputs should have the same relationship with the degree of competition. I test this prediction using data for Company 1 using two different

Table IV Elasticity between Markup Estimates and Sales

Dataset	Labor CD	Labor TL	Materials CD	Materials TL	Composite Input CD	Composite Input 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	0.22	0.01	-0.02	-0.03	0.01	-0.03
	(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 (13). CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level.

company provided measures of the degree of competition.[20] Company 1 has provided both a band of the degree of competition for each store as either Low, Medium, or High, as well as the number of competitors that the store faces. I examine the competition band in this section, and a discretized number of competitors in Appendix A.6. In order to examine these correlations, I estimate the following regression specification:

$$\log(\mu_{i,t}^X) = \alpha + \beta \log(Comp_i) + \gamma_t + \epsilon_{i,t} \tag{14}$$

where $\mu_{i,t}^X$ is the markup estimate using input X and $Comp_i$ is one of the discretized measures of competition.

[20] 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.

In Table V, I find substantially different relationships between markup estimates and the degree of competition across the different measures of markups. For example, the Cobb-Douglas labor estimates imply no change in markup with competition; moving from Low to High competition lowers the markup by an insignificant 0.3%, while the markup rises by 0.4% using the Cobb-Douglas materials estimates and by 0.6% using the composite input estimates. For the Translog production function, moving from Low to High competition lowers the markup by 8.8% using the labor markup compared to a rise of 0.2% using the materials markup, and a much smaller decline of 1.4% using the composite input markups. I find similar differences using the discretized number of competitors in Appendix A.6. Thus, the relationship between the degree of competition and markup can change dramatically depending upon the measure of markups used.

Table V Percent Change in Markup with Competition for Company 1: Competition Band

	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 (14) and relative to a retail store facing Low Competition. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level.

4.7 Taking Stock

In this section, I have shown that production based markups using different flexible inputs tend to be negatively correlated, both in average time trends and in the cross-section. Moreover, neither the labor markup or materials markup fully matches our intuition on the behavior of markups. For example, the materials markup better matches intuition on dispersion, with much less dispersion, especially for outlets of the same retailer, than the labor markup. On the other hand, it is the labor markup that is negatively correlated with the degree of competition and positively correlated with sales, as we might expect from simple models of variable markups. Clearly, neither the baseline estimates of the labor or materials markups appear to be good measures of the markup.

5 Mechanisms

In this section, I examine a number of potential explanations 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 measurement error in inputs. I find evidence inconsistent with these explanations.

Instead, I show that my findings are consistent with labor augmenting productivity differences. I then develop a simple adaptation of the cost share approach to account for labor augmenting productivity differences and show that, using this technique, markups estimated using different inputs have similar cross-sectional and time series correlations.

5.1 Static Cost Minimization Conditions

Both adjustment costs for adjusting inputs or firms with market power in the input market would violate the static cost minimization first order conditions that the production approach relies on. These violations are likely to be more severe for labor, either due to hiring and firing costs when adjusting labor (Petrin and Sivadasan, 2013), bargaining with unions, or labor monopsony power.[21] As in Dobbelaere and Mairesse (2013), I allow labor to have an additional wedge due to labor market power or adjustment costs.

I do so 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.[22]

I examine time trends separating raw materials and energy estimating using (11), which I depict in Appendix A.1 in Figure 9 to Figure 12. In all four datasets, the raw materials

[21]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).

[22]I exclude the retailer as energy is not a major input into the output of a retail store.

markup has a different time trend than the energy markup.

I estimate the elasticity between markup estimates using (12) and report these elasticities in Table VI. 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, neither the labor or raw materials markup is highly correlated with the energy markup. Thus, labor-specific violations of the cost minimization conditions cannot explain the markup differences that I find.

Table VI 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	-0.96	-0.32	0.24	-0.02	-0.15	-0.01
	(0.008)	(0.010)	(0.003)	(0.004)	(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 (12) 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.

5.2 Measurement Error

Another potential concern is measurement error in the inputs to the production function or the revenue shares of inputs. For example, White et al. (2016) highlight how imputation of missing data affects conclusions in US Census data. However, I find similar patterns using Company 1's data as I did using manufacturing survey datasets. Company 1's data is based on the internal records of the firm, and so should have very little measurement error compared to survey data.

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

Finally, measurement error may be more of an issue for smaller, less sophisticated plants compared to large plants. All of my baseline estimates are unweighted, except using sample probability weights for India. De Loecker et al. (2018) weight markups by sales, while Edmond et al. (2018) argue that, for welfare calculations, markups should be weighted by share of cost. I examine both in Appendix A.4, and find qualitatively similar findings to the unweighted results.

5.3 Alternative Production Function Estimators

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

First, the auxiliary assumptions required for the control function approach, such as a Markov assumption on productivity together with timing assumptions on when the firm determines its level of inputs, could be misspecified. Second, Gandhi et al. (forthcoming) show that the ACF procedure is non-parametrically non-identified when applied to gross-output production functions. 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. 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 substantially different output elasticities using different estimation approaches, with double the average capital elasticity estimated using a control function approach compared to a cost share approach.

I thus examine two different approach to production function estimation that assume constant returns to scale in production.[23] First, Flynn et al. (2019) develop a new method to estimate production functions using a similar set of auxiliary assumptions as Ackerberg et

[23] In addition, in Appendix A.5, I compare my baseline estimates of markups to markups estimated from profit shares.

al. (2015) together with constant returns to scale. I estimate translog production functions using the Flynn et al. (2019) approach.[24]

Second, the cost share method estimates the output elasticity of a given input as its share of total industry cost. The cost share method has been used in productivity analysis (Foster et al., 2001, 2008), and markup estimation (De Loecker et al., 2018), and does not require the Markov assumptions on productivity or timing assumptions on inputs, or in fact, any data on firm quantities. It does assume a Cobb-Douglas production function with constant returns to scale, and requires first order cost minimization conditions to hold for all inputs, at least on average.

I estimate industry cost shares by aggregating inputs to the industry-year level. Thus, the cost share estimates also allow the output elasticities of the industry-level production function to change over time.

Using both methods, the time trends using different inputs estimated using (11) are very different for all cases except for industry cost shares for Colombia. I depict these in Appendix A.1 in Figure 13 through Figure 16. In addition, after controlling for time trends, I show in Table VII that the labor markup remains negatively correlated with the materials markup for both methods, with correlations ranging from -0.24 to -1.00 for the cost share approach, and from -0.17 to -7.05 using the Flynn et al. (2019) approach.

[24]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.

Thus, problems with the ACF approach to production function estimation cannot explain the differing markup estimates across variable inputs that I document.

Table VII Correlation between Markup Estimates: Alternative Estimators

	Labor on Materials		Labor on Composite Input		Materials on Composite Input	
Dataset	Cost Share	FGT	Cost Share	FGT	Cost Share	FGT
Chile	-0.24	-0.69	0.59	-0.56	1.11	1.72
	(0.015)	(0.018)	(0.017)	(0.087)	(0.006)	(0.031)
Colombia	-0.65	-1.06	0.38	-2.03	1.28	2.34
	(0.008)	(0.020)	(0.017)	(0.098)	(0.010)	(0.048)
India	-0.89	-0.17	0.69	0.44	1.01	-0.65
	(0.008)	(0.007)	(0.010)	(0.059)	(0.002)	(0.048)
Indonesia	-0.51	-0.82	0.72	1.25	1.07	1.30
	(0.010)	(0.020)	(0.010)	(0.097)	(0.004)	(0.058)
Company 1	-1.00	-7.05	2.88	6.35	0.70	-0.07
	(0.055)	(0.151)	(0.047)	(0.099)	(0.008)	(0.008)

Note: Estimates based on (12) 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. Columns labeled Cost Share are markups based on industry level cost shares, and labeled FGT based on Flynn et al. (2019), as described in the text. Standard errors are clustered at the establishment level.

5.4 Non-Neutral Productivity

Another potential explanation for differences in markups using different inputs is non-neutral productivity differences across plants. Raval (2019), Doraszelski and Jaumandreu (2018), and Zhang (2019) all find substantial variation in labor augmenting productivity across establishments and over time for US, Spanish, and Chinese manufacturing plants, respectively.

For simplicity, I assume a CES production function with elasticity of substitution σ, neutral productivity A, labor augmenting productivity B, and factor distribution parameters

α_l and α_m:

$$Y = A((1-\alpha_l-\alpha_m)K^{\frac{\sigma-1}{\sigma}} + \alpha_l(BL)^{\frac{\sigma-1}{\sigma}} + \alpha_m M^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}. \tag{15}$$

Assuming competitive factor markets and cost minimization, the input shares of revenue are equal to the output elasticity of that input divided by the markup μ as follows:

$$\frac{wL}{PY} = \frac{1}{\mu}(\frac{w}{\lambda})^{1-\sigma}(AB)^{\sigma-1}(\alpha_l)^{\sigma} \tag{16}$$

$$\frac{p_m M}{PY} = \frac{1}{\mu}(\frac{p_m}{\lambda})^{1-\sigma}(A)^{\sigma-1}(\alpha_m)^{\sigma} \tag{17}$$

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

In this CES framework, changes in labor augmenting productivity B will move the output elasticities of labor and materials in different directions. Take the case where the elasticity of substitution σ is less than one. In that case, improvements in B will decrease labor's output elasticity, but increase materials's output elasticity as the marginal cost of production λ falls. If production function estimates do not account for such labor augmenting productivity differences, markups estimated using different inputs would have quite different patterns, as I have found.

I first demonstrate, through a Monte Carlo exercise, that labor augmenting productivity differences can cause a negative correlation between markups estimated using labor and materials as flexible inputs. I simulate an economy in which both markups and labor augmenting productivity differences vary across plants.

I simulate 700 locations that each contain 100 plants of the same industry. All firms cost minimize given the factor prices they face. 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 (0,1) distribution. The production function is as in (15) with substitution elasticity 0.5; I draw neutral productivity A and labor augmenting productivity B from a joint lognormal calibrated to match data on US manufacturing plants. Plants face an elasticity of demand drawn from a uniform distribution between 2 and 6, so markups range between 1.2 and 2.[25]

In Table VIII, I report the results of this Monte Carlo across 200 simulations, with standard deviations across simulations in parentheses. In the first row, I use industry-wide cost shares to estimate output elasticities, and so estimate markups. Similar to my findings in Section 4.4, 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%.

I next provide a very simple way to allow estimated output elasticities to account for

[25] I normalize the mean of A to 1, and choose the mean of B, the variances of A and B as well as their covariance to 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.

Table VIII 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 (12) 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. True markup is the actual markup set by the firm in the Monte Carlo simulations. Estimates based on cost share quintiles or deciles as described in the text. Standard deviation across 200 bootstrap estimates in parentheses.

non-neutral productivity differences. In the CES framework above, the ratio of labor costs to materials costs is:

$$\frac{wL}{p_m M} = (\frac{w}{p_m})^{1-\sigma}(B)^{\sigma-1}(\frac{\alpha_l}{\alpha_m})^{\sigma}. \tag{18}$$

Differences in labor augmenting productivity B imply differences in the labor cost to materials cost ratio. Thus, firms with a similar labor cost to materials cost ratio should have similar values of B, and so similar output elasticities of labor and materials.

I thus adapt the cost share method of production function estimation by estimating cost shares within groups based on the plant's labor cost to materials cost ratio in order to approximate for differences in B; plants in each group should have similar levels of labor augmenting productivity B. For example, by using quintiles, output elasticities would be the input share of total cost within the industry quantile. As a cost share method, this approach assumes constant returns to scale.

In Table VIII, I simulate this grouped cost share approach estimating output elasticities as cost shares within quintiles (second row) and deciles (third row) of the labor cost to materials cost ratio. Now, labor markups are *positively* correlated with materials markups; 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.

I then estimate markups using the quintile cost share method on all five datasets; output elasticities are thus the cost share for each industry quintile. In Table IX, I report correlations between markup measures estimating using (12). 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.

I next examine time trends estimated using (11) 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

Table IX Correlation between Markup Estimates: Cost Share Quintile Estimates

Dataset	Labor on Materials	Labor on Composite Input	Materials on Composite Input
Chile	0.75	0.96	1.00
	(0.007)	(0.004)	(0.002)
Colombia	0.34	0.92	1.06
	(0.011)	(0.004)	(0.005)
India	0.68	0.98	0.99
	(0.004)	(0.002)	(0.001)
Indonesia	0.72	0.96	0.98
	(0.005)	(0.002)	(0.002)
Company 1	0.89	1.13	0.97
	(0.012)	(0.013)	(0.003)

Note: Estimates based on (12) 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. Estimates based on industry cost share quintiles. Standard errors are clustered at the establishment level.

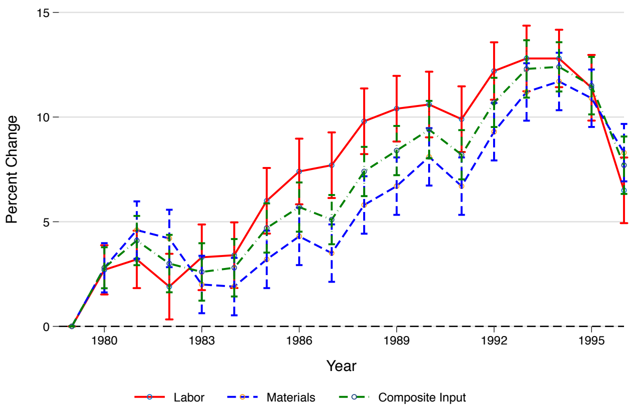
by 1996. Similarly, the average materials markup initially rises 4% above its 1979 value in 1987, then rises to 11% below its 1979 value by 1993, and then declines slightly to 8% above its 1979 value by 1996.

Thus, after accounting for non-neutral productivity differences through an adaptation of the cost share method of estimating production function elasticities, markups estimating using different inputs have similar cross-sectional and time series correlations.

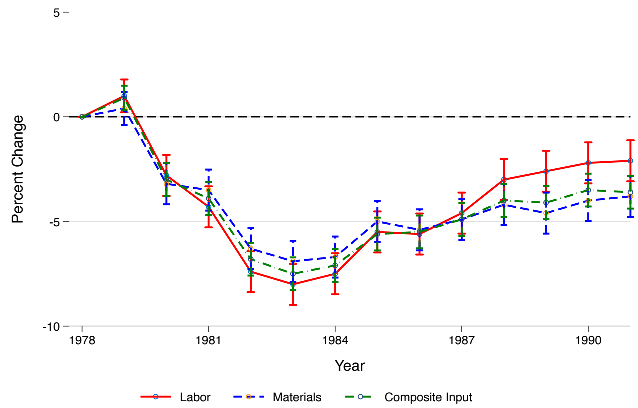
6 Conclusion

A key advantage of the production approach to markups has been that it allows one to estimate markups at scale across widely differing industries, and thus easily estimate the aggregate markup. The demand approach to markups, exemplified by Berry et al. (1995)

Figure 5 Change in Average Markup Over Time using Cost Share Quintile Estimates: Chile and Colombia



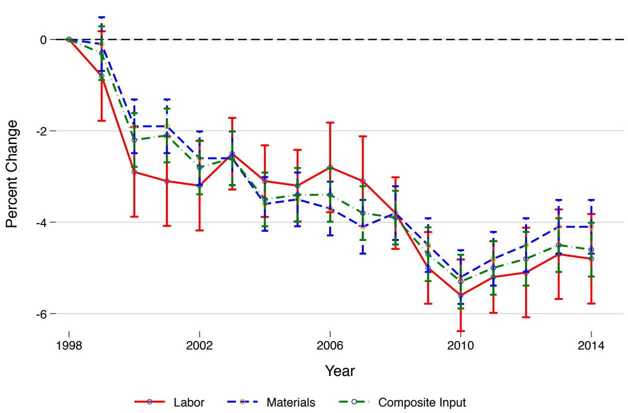
(a) Chile



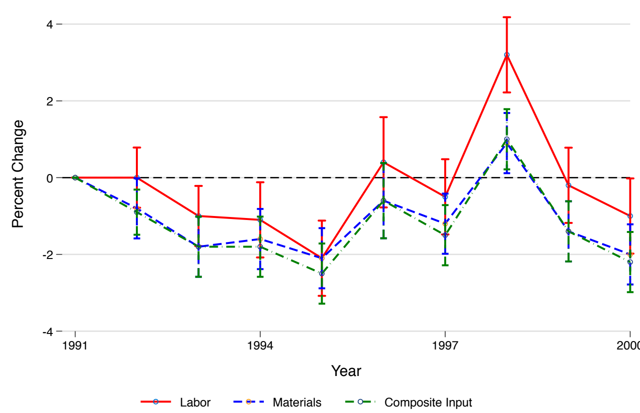
(b) Colombia

Note: Estimates based on (11), 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 Change in Average Markup Over Time using Cost Share Quintile Estimates: India and Indonesia



(a) India



(b) Indonesia

Note: Estimates based on (11), 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.

and Berry et al. (2004), cannot do so because models for firm competition and demand vary substantially across industries.

However, in this article, I have tested the production approach by estimating markups using different alternative flexible inputs, and shown that the production approach delivers very different markup estimates after doing so. Across several datasets, I have found that the implied labor and materials markups are negatively correlated with each other. The labor markup has a much greater degree of dispersion than the materials markup, as well as different trends over time. The magnitude and sign of the correlations of each markup with size and the degree of competition are quite different from each other as well.

The development of the parallel demand approach to markups provides guidance on how to measure markups given these results. The demand approach models the heterogeneity in preferences across consumers and product attributes across producers for each industry. The production approach will have to do the same for differences in production technology.

In this paper, I have shown how to adapt the cost share method to estimating output elasticities in the presence of non-neutral technological differences. After doing so, I have found that markups estimated using different flexible inputs have similar time trends and cross-sectional correlations. In general, allowing more heterogeneity in production technology, as in recent papers (Doraszelski and Jaumandreu, 2018; Gandhi et al., forthcoming; Raval, 2019), may prove fruitful in yielding better measures of markups.

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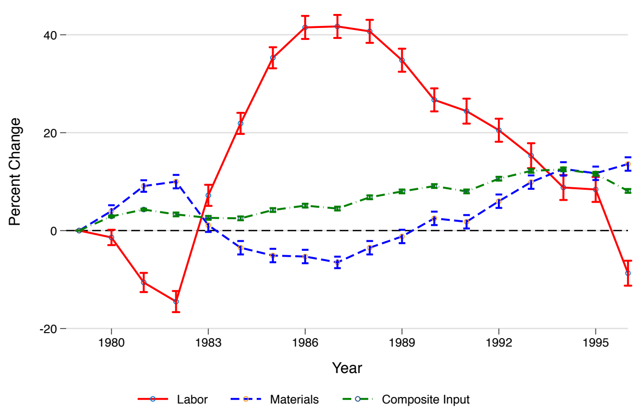
A Additional Empirical Results

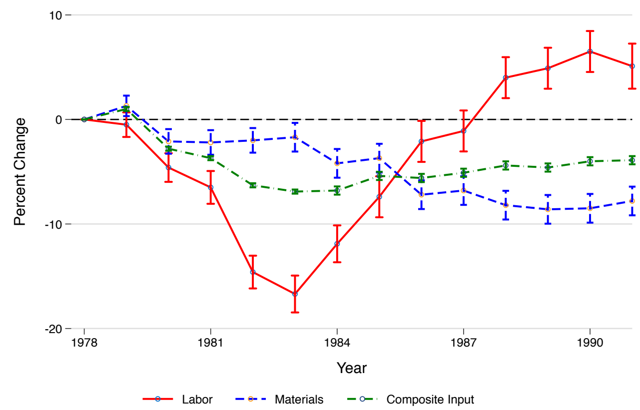
A.1 Trends over Time

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 either 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 16, I depict aggregate markup trends estimated using either an industry-time cost share or Flynn et al. (2019).

Figure 7 Change in Average Markup Over Time using Cobb-Douglas Estimates: Chile and Colombia



(a) Chile



(b) Colombia

Note: Estimates based on (11), 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

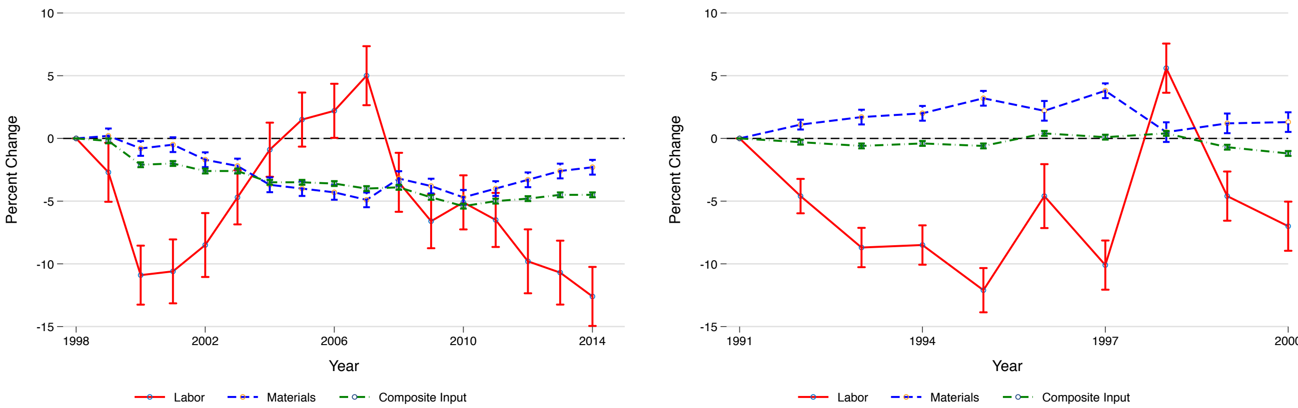
In Table X and Table XI, I report the 75/25 ratio and 90/10 ratio of markup estimates.

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 XII. The average labor markup is 9% higher than the

Figure 8 Change in Average Markup Over Time using Cobb-Douglas Estimates: India and Indonesia

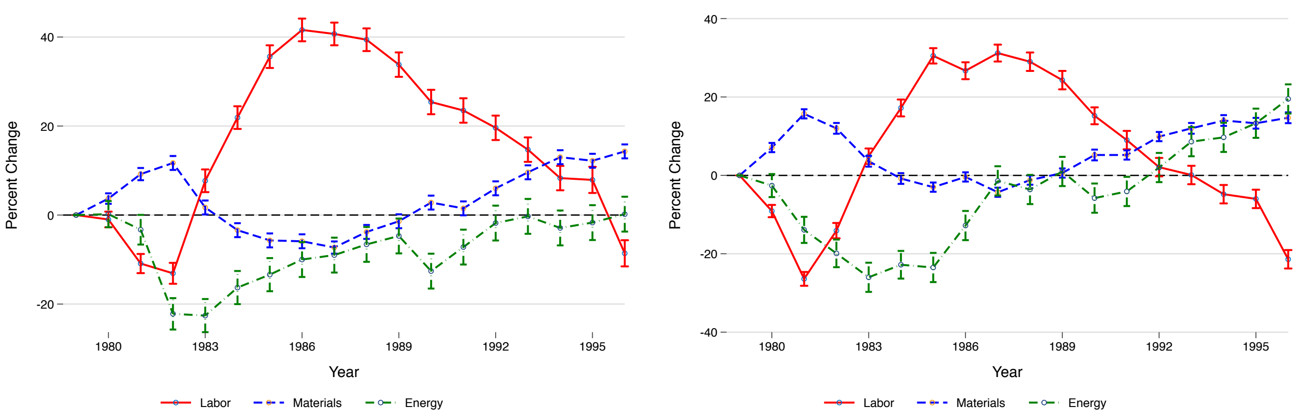


(a) India

(b) Indonesia

Note: Estimates based on (11), 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 Change in Average Markup Over Time, with Energy: Chile

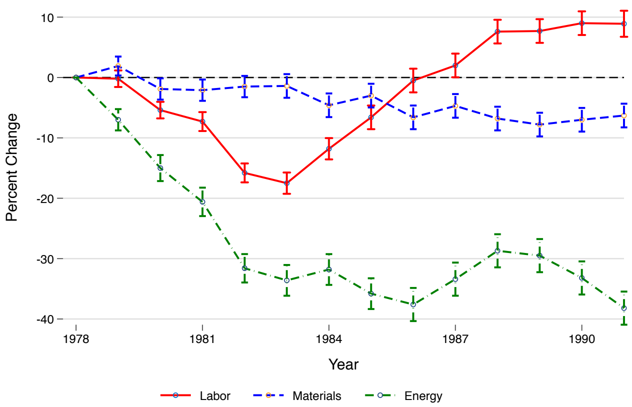


(a) Cobb-Douglas

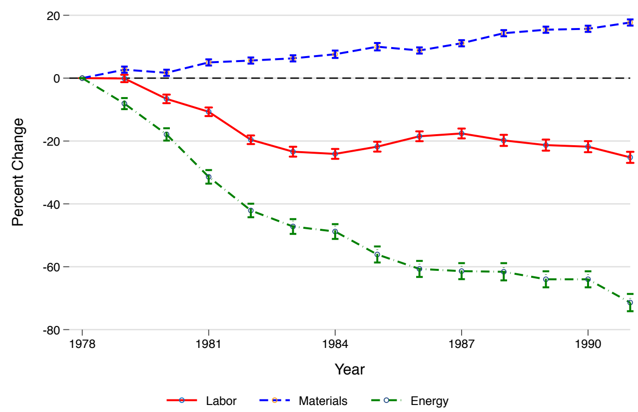
(b) Translog

Note: Estimates based on (11), 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 Change in Average Markup Over Time, with Energy: Colombia



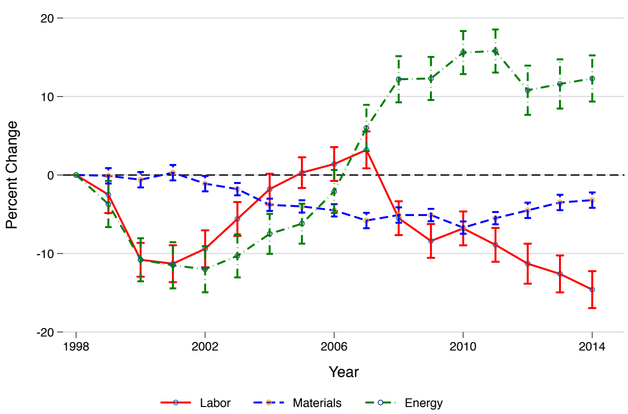
(a) Cobb-Douglas



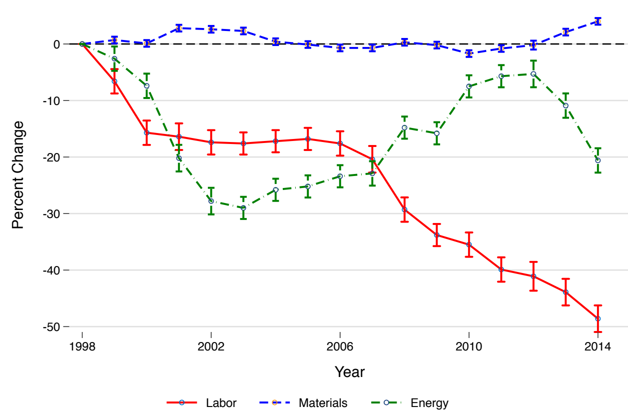
(b) Translog

Note: Estimates based on (11), 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 Change in Average Markup Over Time, with Energy: India



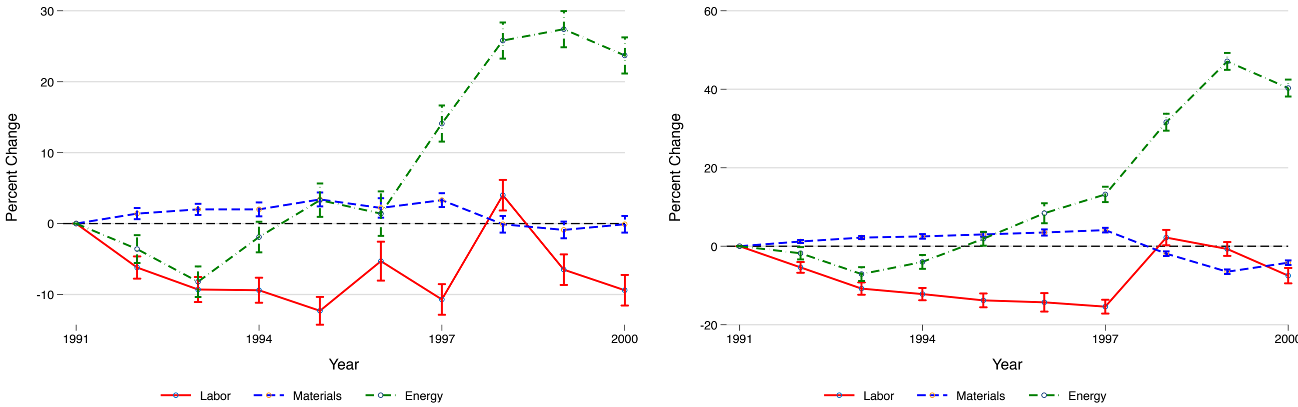
(a) Cobb-Douglas



(b) Translog

Note: Estimates based on (11), 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 Change in Average Markup Over Time, with Energy: Indonesia

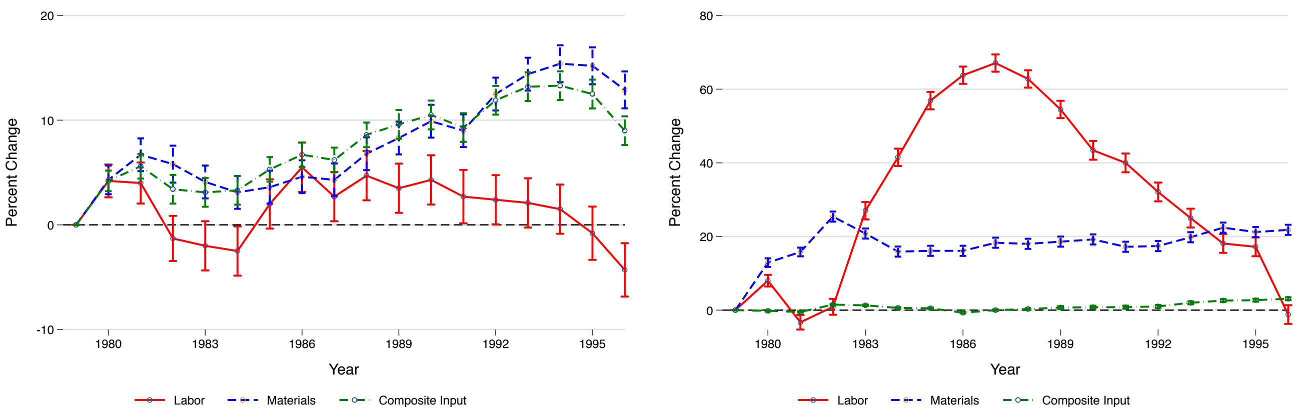


(a) Cobb-Douglas

(b) Translog

Note: Estimates based on (11), 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 Change in Average Markup Over Time, Alternative Estimators: Chile

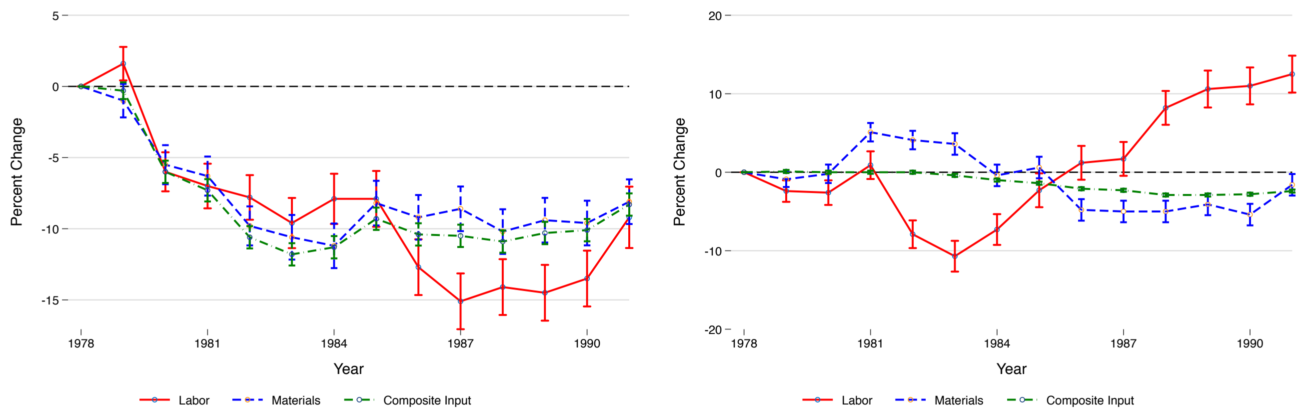


(a) Industry Cost Share

(b) Flynn, Gandhi, Traina

Note: Estimates based on (11), 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 Change in Average Markup Over Time, Alternative Estimators: Colombia

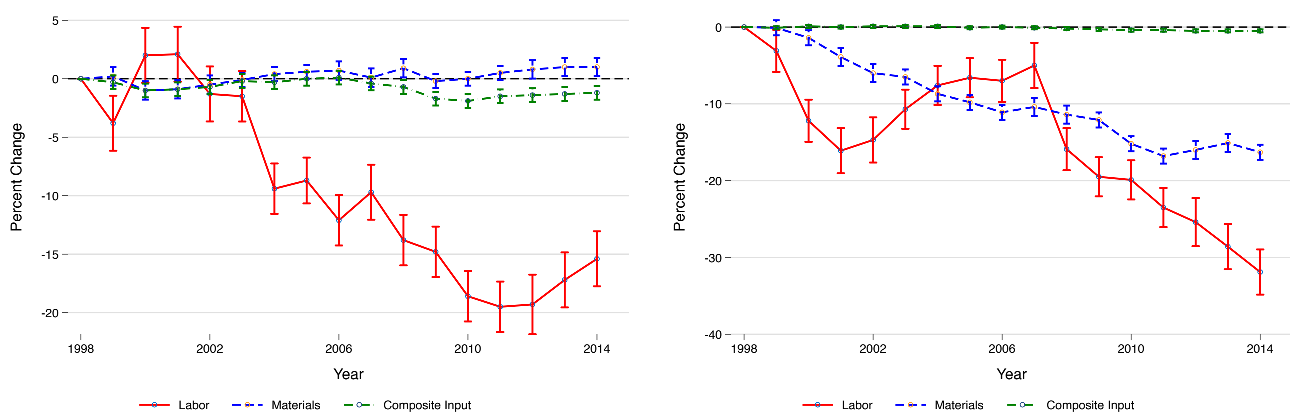


(a) Industry Cost Share

(b) Flynn, Gandhi, Traina

Note: Estimates based on (11), 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 Change in Average Markup Over Time, Alternative Estimators: India

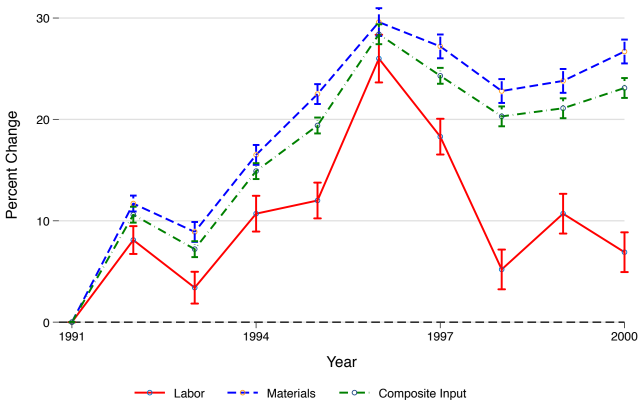


(a) Industry Cost Share

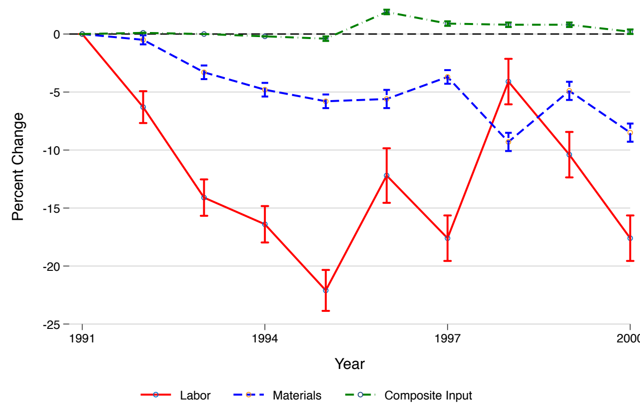
(b) Flynn, Gandhi, Traina

Note: Estimates based on (11), 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 Change in Average Markup Over Time, Alternative Estimators: Indonesia



(a) Industry Cost Share



(b) Flynn, Gandhi, Traina

Note: Estimates based on (11), 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 X 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
	(0.012)	(0.006)	(0.002)	(0.002)	(0.001)	(0.001)
Colombia	2.69	1.87	1.63	1.24	1.14	1.14
	(0.011)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)
India	5.65	8.88	1.40	1.37	1.24	1.27
	(0.020)	(0.132)	(0.000)	(0.001)	(0.001)	(0.001)
Indonesia	3.82	2.65	1.55	1.37	1.12	1.13
	(0.015)	(0.006)	(0.002)	(0.002)	(0.001)	(0.000)
Company 1	1.28	1.35	1.03	1.03	1.02	1.03
	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)

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

Table XI 90/10 Ratio of Markup Estimates

Dataset	Labor CD	Labor TL	Materials CD	Materials TL	Combined Input CD	Combined Input TL
Chile	6.25	4.04	2.08	1.81	1.33	1.31
	(0.036)	(0.022)	(0.006)	(0.005)	(0.002)	(0.001)
Colombia	7.87	7.43	2.71	1.68	1.31	1.30
	(0.068)	(0.332)	(0.014)	(0.006)	(0.001)	(0.001)
India	-84.70	-3.77	1.99	2.01	1.79	1.95
	(1.450)	(0.021)	(0.003)	(0.002)	(0.002)	(0.004)
Indonesia	17.05	8.16	2.34	1.97	1.25	1.28
	(0.145)	(0.047)	(0.006)	(0.005)	(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, 11% higher for Colombia, 127% 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, 3% higher for Colombia, 1% lower for India, 69% higher for Indonesia, and 5% lower for Company 1. Thus, the average markups are close to each other for three of the five datasets – Colombia, India, and Company 1 – using the Translog estimates, and for Chile and Colombia using the Cobb-Douglas estimates.

The third and fourth columns of Table XII examine the ratio of the average labor markup to the average combined input markup, and the fifth and sixth columns the ratio of the average materials markup to the average combined input markup. Across datasets, the combined input markup tends to be lower than both the average labor and materials markups. However, under the Translog estimates, the average combined input markups are close to the average materials markup, with the average materials markup only 0 to 11% higher than the average combined input markup across datasets.

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

Table XII Ratio of Average Markup Estimates

	Labor/Materials		Labor/Combined Input		Materials/Combined Input	
Dataset	CD	TL	CD	TL	CD	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	2.27	0.96	2.36	1.02	1.04	1.07
	(0.011)	(0.009)	(0.011)	(0.010)	(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.

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.

A.5 Markups and the Profit Share

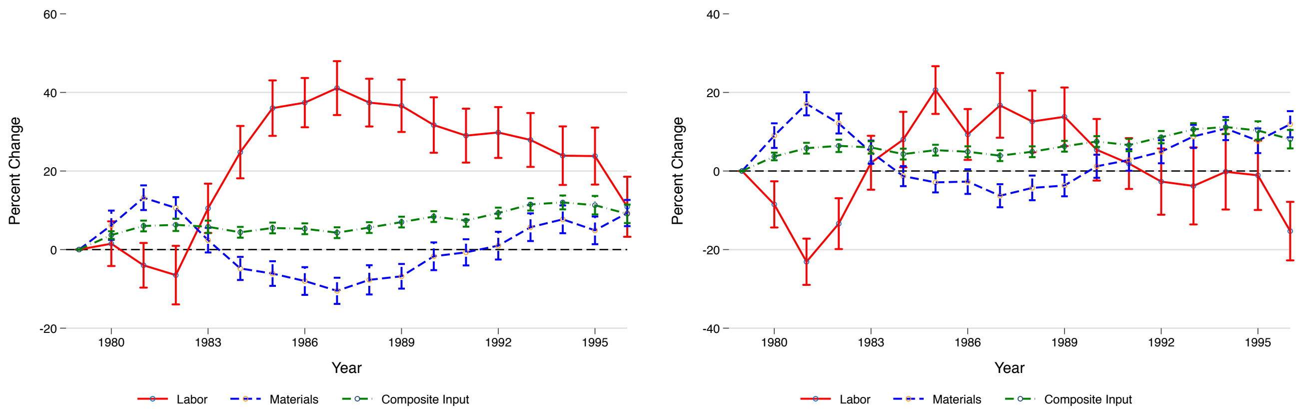
Instead of estimating markups using production function estimates, researchers have often used data on profits to measure of markup. Formally, returns to scale (RTS) are equal to the markup multiplied by one minus the share of profits s_π:

$$RTS = \mu(1 - s_\pi). \tag{19}$$

Thus, if one is willing to assume constant returns to scale, one can invert the profit share to estimate the markup.

I examine two ways of estimating the profit share to recover the markup. 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, or EBIT) and so can calculate a profit based markup as sales divided by sales minus profits. I examine whether profit based measures of the markup line up with markups

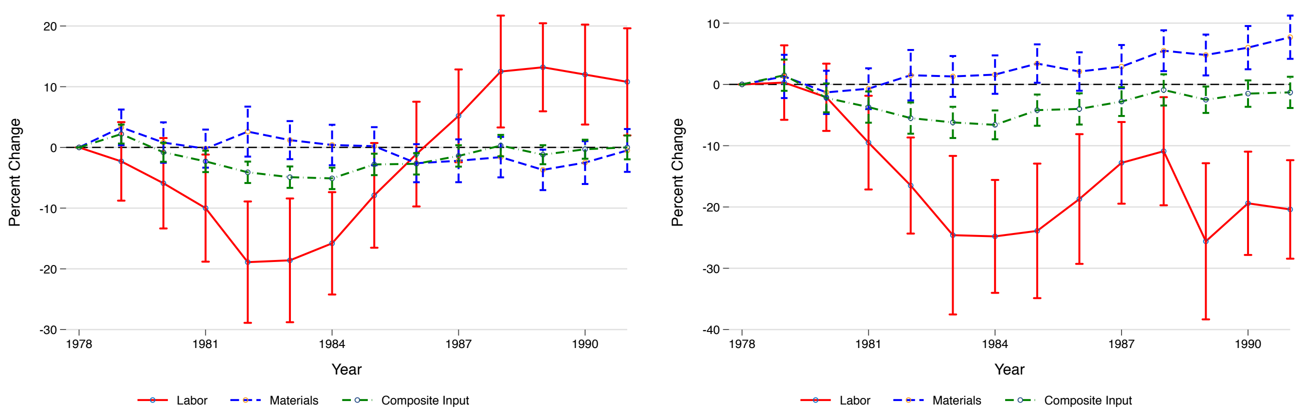
Figure 17 Change in Average Markup Over Time, Sales Weighted: Chile



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (11), 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.

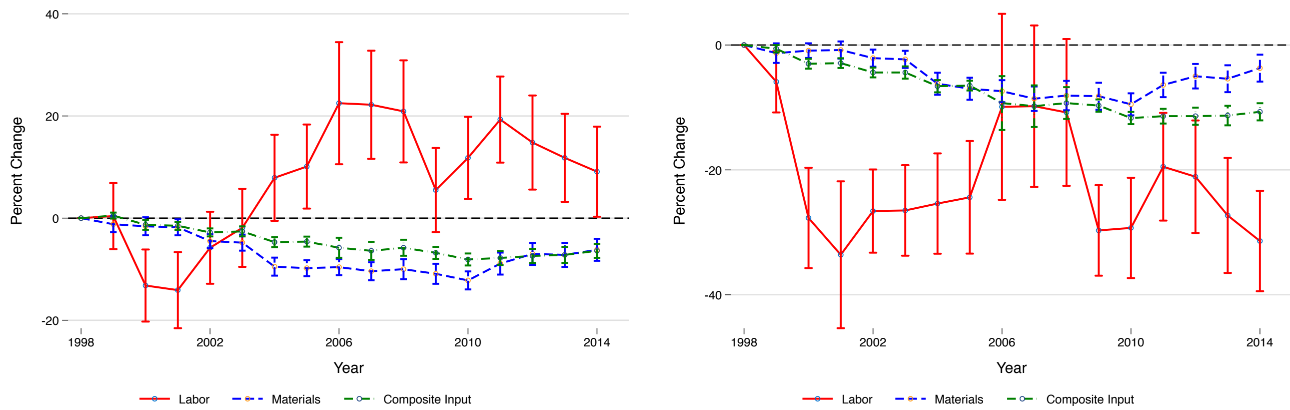
Figure 18 Change in Average Markup Over Time, Sales Weighted: Colombia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (11), 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 19 Change in Average Markup Over Time, Sales Weighted: India

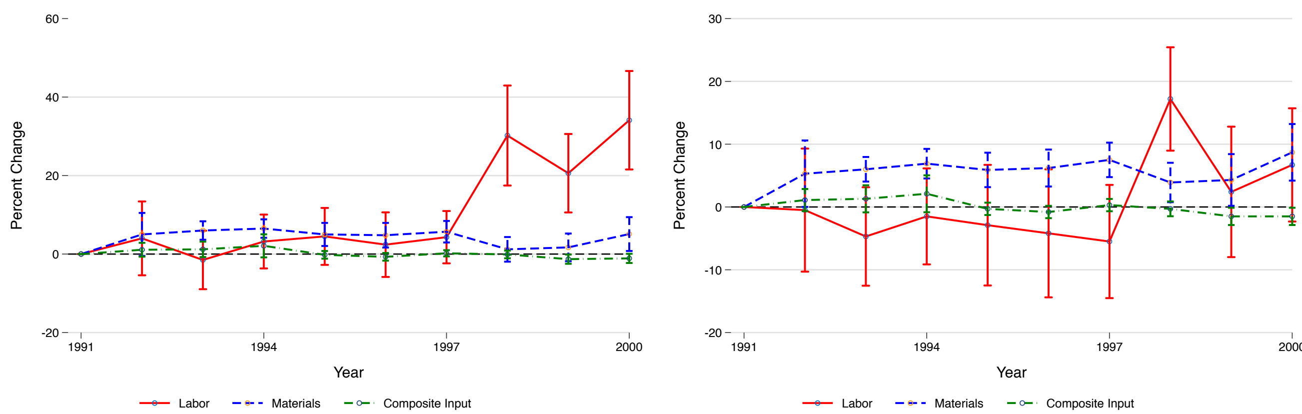


(a) Cobb-Douglas

(b) Translog

Note: Estimates based on (11), 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 20 Change in Average Markup Over Time, Sales Weighted: Indonesia



(a) Cobb-Douglas

(b) Translog

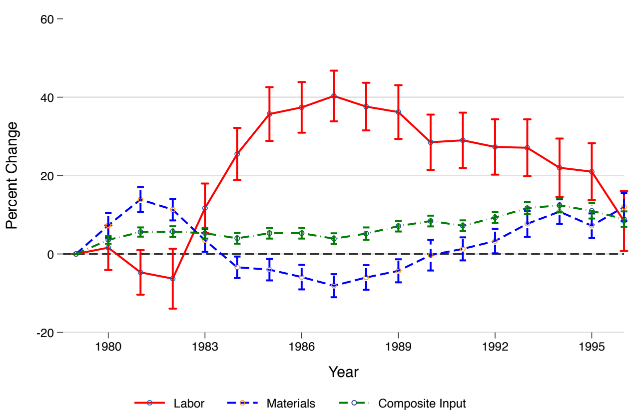
Note: Estimates based on (11), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero. Estimates weighted with sales weights.

Table XIII Correlation between Markup Estimates: Sales Weighted

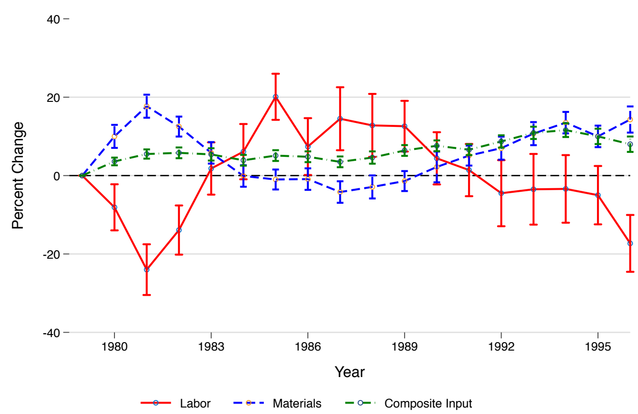
	Labor on Materials		Labor on Combined Input		Materials on Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	-0.83	-0.30	-0.40	0.45	1.24	0.98
	(0.060)	(0.076)	(0.167)	(0.192)	(0.062)	(0.053)
Colombia	-1.37	-0.09	-1.45	1.50	1.56	0.96
	(0.087)	(0.199)	(0.211)	(0.221)	(0.056)	(0.069)
India	-1.98	-0.28	-1.51	0.43	1.04	0.47
	(0.137)	(0.091)	(0.451)	(0.517)	(0.047)	(0.046)
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 (12) 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 21 Change in Average Markup Over Time, Cost Weighted: Chile



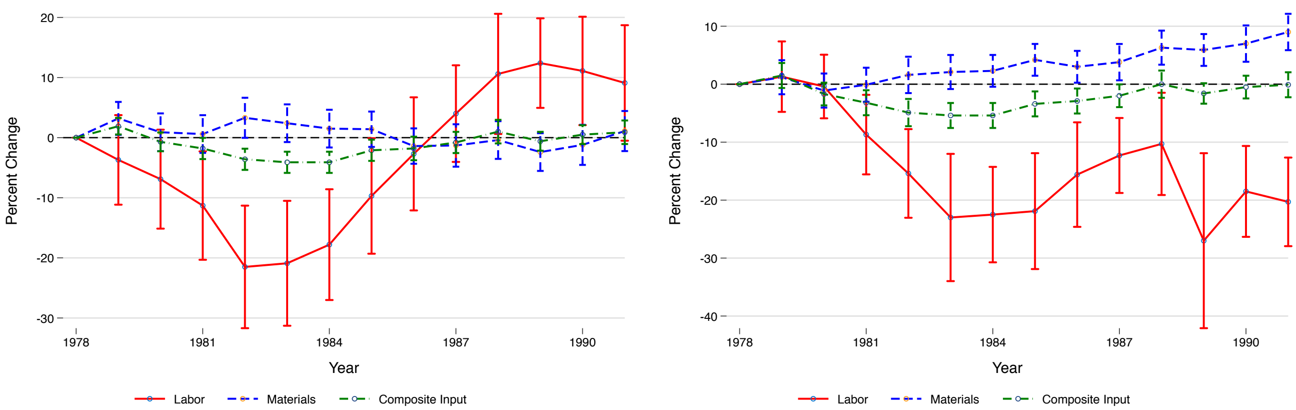
(a) Cobb-Douglas



(b) Translog

Note: Estimates based on (11), 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.

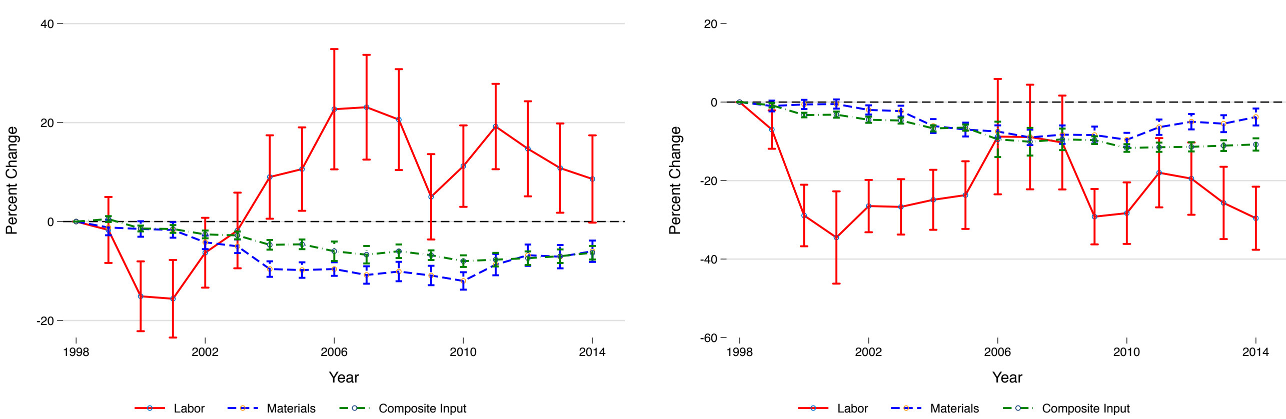
Figure 22 Change in Average Markup Over Time, Cost Weighted: Colombia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (11), 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.

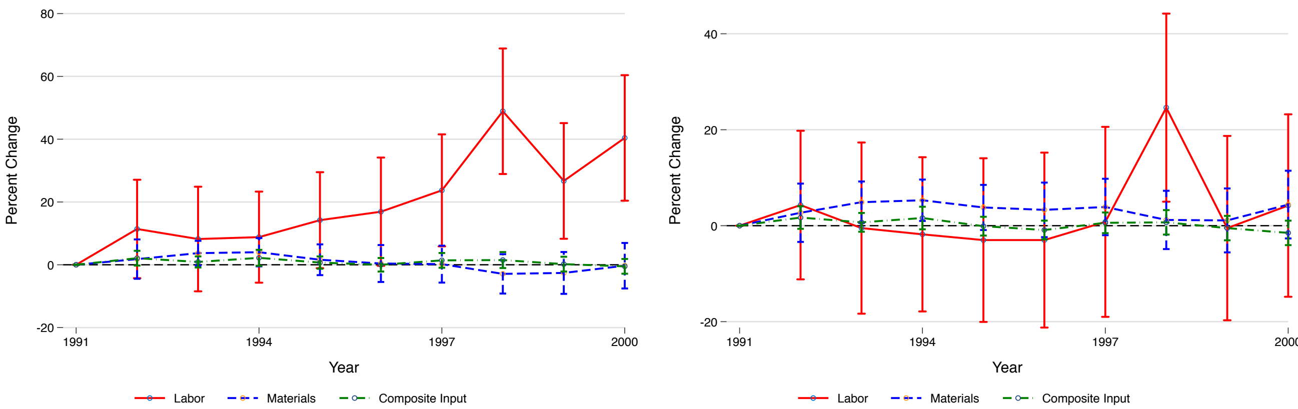
Figure 23 Change in Average Markup Over Time, Cost Weighted: India



(a) Cobb-Douglas (b) Translog

Note: Estimates based on (11), 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 24 Change in Average Markup Over Time, Cost Weighted: Indonesia



(a) Cobb-Douglas

(b) Translog

Note: Estimates based on (11), 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 XIV Correlation between Markup Estimates: Cost Weighted

	Labor on Materials		Labor on Combined Input		Materials on Combined Input	
Dataset	CD	TL	CD	TL	CD	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	-1.99	-0.30	-1.56	0.40	1.06	0.46
	(0.130)	(0.086)	(0.434)	(0.501)	(0.055)	(0.045)
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 (12) 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.

estimated by the production approach by estimating the following regression specification:

$$\log(\mu^X_{i,t}) = \alpha + \beta \log(\mu^\pi_{i,t}) + \gamma_t + \delta_n + \epsilon_{i,t} \tag{20}$$

where $\mu^\pi_{i,t}$ is the profit based markup.

Table XV Elasticity between Production Markup Estimates and Profit Based Markup

	Labor		Materials		Composite Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	-0.03	-0.06	0.37	0.35	0.09	0.08
	(0.016)	(0.014)	(0.010)	(0.009)	(0.003)	(0.003)
Colombia	-0.15	-0.16	0.01	0.05	-0.00	0.01
	(0.018)	(0.014)	(0.013)	(0.007)	(0.004)	(0.003)
India	0.21	-0.05	0.15	0.18	0.02	-0.01
	(0.010)	(0.008)	(0.003)	(0.004)	(0.001)	(0.001)
Indonesia	0.06	-0.09	-0.12	-0.09	-0.03	-0.04
	(0.011)	(0.011)	(0.006)	(0.005)	(0.002)	(0.002)
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 (20). CD is Cobb-Douglas and TL Translog. 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 report these estimates in Table XV. For the manufacturing datasets, I do not find strong positive correlations between the profit based markup and production based markup across any of the inputs. The correlation is *negative* for labor markups for Chile and Colombia, materials markups for Indonesia, and translog labor markups for India and Indonesia.

For the retailer, estimates using the accounting profit based markup, and factor cost profit based markup, are similar, except for translog labor markups. For the retailer, labor markups are highly correlated with the profit share based markups (except for translog and the accounting profit case), but materials markups are negatively correlated with the profit share based markups. Thus, in general, production based markups are not highly positively correlated with profit share based markups.

A.6 Correlations with Competition

In Section 4.6, 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 XVI. 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. Moving from 0-1 to 10+ competitors lowers the markup by an insignificant 0.3% using the Cobb-Douglas labor markups, compared to a rise of 0.4% using the Cobb-Douglas materials estimates and 0.7% using the combined input estimates. For the Translog production function, moving from 0-1 to 10+ competitors lowers the markup by 8.5% using the labor markup compared to an insignificant rise of 0.1% using the materials markup and a smaller decline of 1.5% using the combined input markups.

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.[26]

I thus re-estimate (14) replacing the year fixed effects with MSA year fixed effects. Table XVII and Table XVIII contain these estimates; I continue to find sharp differences in magnitude and sign of the relationship between competition and markups after controlling for market size through MSA-year fixed effects.

Table XVI Percent Change in Markup with Competition for Company 1: Number of Competitors

	Labor		Materials		Combined Input	
Number of Competitors	CD	TL	CD	TL	CD	TL
2	0.006	0.024	-0.001	-0.003	0.000	-0.001
	(0.007)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
3	-0.002	0.013	-0.000	-0.002	0.000	-0.001
	(0.007)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
4	-0.002	0.007	-0.001	-0.003	0.001	-0.004
	(0.007)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
5-9	-0.005	-0.031	0.001	-0.002	0.003	-0.007
	(0.006)	(0.008)	(0.001)	(0.001)	(0.000)	(0.001)
10+	-0.003	-0.085	0.004	0.001	0.007	-0.015
	(0.009)	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Estimates are based on (13) and are relative to a retail store with 0-1 competitors. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level.

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

Table XVII Percent Change in Markup with Competition for Company 1: Competition Band, MSA-Year Controls

	Labor		Materials		Combined Input	
Level of Competition	CD	TL	CD	TL	CD	TL
Medium Competition	0.02	-0.01	-0.00	-0.00	0.00	-0.01
	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
High Competition	0.04	-0.08	0.00	-0.00	0.01	-0.02
	(0.006)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Estimates are based on (14), 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. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level.

Table XVIII Percent Change in Markup with Competition for Company 1: Number of Competitors, MSA-Year Controls

	Labor		Materials		Combined Input	
Number of Competitors	CD	TL	CD	TL	CD	TL
2	0.01	0.02	-0.00	-0.00	0.00	-0.00
	(0.006)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
3	0.02	0.01	-0.00	-0.00	0.00	-0.00
	(0.006)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
4	0.02	0.01	-0.00	-0.00	0.00	-0.01
	(0.006)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
5-9	0.03	-0.03	-0.00	-0.00	0.01	-0.01
	(0.005)	(0.008)	(0.000)	(0.001)	(0.000)	(0.001)
10+	0.05	-0.08	-0.00	-0.00	0.01	-0.02
	(0.008)	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Estimates are based on (13), 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. CD is Cobb-Douglas and TL Translog. 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.

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.[27]

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 depre-

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

ciation rate to 0.19.[28]

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.[29] 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.[30] 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 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.[31]

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[28] 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%.

[29] 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.

[30] 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.

[31] 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.

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.

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.