Examining the Sensitivity of the Production Approach to Markup Estimation*

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Abstract

Under the production approach for markup estimation, using different flexible inputs should measure the same markup. I test the production approach by comparing markups using labor and materials for four manufacturing censuses and internal store-level data from a major nationwide US retailer. Across all five datasets, I find that markups using labor are negatively correlated with those using materials, exhibit much greater dispersion, and have different trends over time. I also find different correlations with the degree of competition faced by the store for the retailer. I examine several mechanisms for these findings, and conclude that these findings could be consistent with plant level heterogeneity in production technology. These differences thus raise questions about whether the production functions estimated in the standard implementation of this methodology can successfully be used to measure markups.

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An understanding of the markup over marginal cost, one measure of market power, is required to answer policy questions across fields in economics. In macroeconomics, rising markups are one explanation for the decline in the labor share of income. Economists have used the aggregate trend in markups as a proxy for whether the economy has become less competitive over time.[1] In industrial organization, measuring markups is important to evaluate past mergers, as well as to predict the competitive harm from proposed mergers.

One of the most common approaches to estimate markups is the *production approach* pioneered by De Loecker and Warzynski (2012). They show that, given cost minimization with competitive input markets, a variable input's output elasticity divided by the input's share of revenue identifies the markup. Papers using this methodology have recently suggested a decline in competition in many industries. 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.[2]

The production approach holds for *all* flexible inputs. Thus, I assess the production approach through overidentification tests comparing the implied markups using different flexible inputs. The literature using the production approach has used labor, materials, or cost of goods sold, a combination of both, as variable inputs; I compare markups using labor, materials, or a combined variable input consisting of labor and materials.[3]

[1] Markup changes could also reflect changes in technology, and not competition.

[2] De Loecker et al. (2018) is the updated version of De Loecker and Eeckhout (2017).

[3] 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).

Implementing the production approach requires strong auxiliary assumptions on the form of the production function. As in De Loecker et al. (2018), I estimate Cobb Douglas and Translog production functions at the industry level using the Ackerberg et al. (2015) procedure. I use manufacturing censuses and surveys from Chile, Colombia, India, and Indonesia, all of which have been used in the literature estimating production functions[4], and new confidential data on all retail stores of a major nationwide US retailer for three years.

I first examine the distribution of estimated markups. I define the labor markup as the markup measured using labor as the flexible input, the materials markup as the markup measured using materials, and the combined input markup the markup measured using the combined variable input. Across all of the datasets, the dispersion in markups is much higher using the labor markup compared to the materials markup, and higher for the materials markup compared to the combined variable input.

Following De Loecker et al. (2018), I next examine trends in the average markup over time. In all of the datasets, I find substantially different trends in the markup using different inputs. For example, for Colombia, the average labor markup falls by about 28% over the sample, while the average materials markup rises by about 8%. For Indonesia, the average labor markup and materials markup move in opposite directions after the 1998 Asian crisis.

I then estimate the correlation of the labor markup with the materials markup, controlling

[4]For some examples, see Gandhi et al. (forthcoming), Oberfield (2013), Pavcnik (2002), and Levinsohn and Petrin (2003) 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.

for the time effects shown above. 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.

Finally, at the heart of research such as Blonigen and Pierce (2016) and De Loecker et al. (2018) is that markup estimates can proxy for the degree of competition faced by firms, with rising markups reflecting decreasing competition. For the retailer I have access to two internal classifications of the degree of competition that each retail store faces. For both, I find a different sign and magnitude of the relationship between competition and markups when using different flexible inputs.

I then examine several potential mechanisms for these findings. To evaluate explanations due to adjustment costs in labor or wage bargaining, I include energy and non-energy raw materials as two alternative flexible inputs and find similar differences in markups. Another explanation is measurement error. However, I find similar differences using the retailer data, which is the internal data of the firm and should be of much high quality than survey responses. A third explanation would be misspecification of the assumptions required for the Ackerberg et al. (2015) procedure. I thus also estimate output elasticities through industry cost shares, which require very different assumptions, but continue to find differences between markup estimates using different inputs.

Another explanation for these differences is the assumption of a common production function for all plants in the same broad industry.[5] I examine this assumption empirically by estimating *plant*-level Cobb-Douglas elasticities through the cost share approach; with plant-level Cobb-Douglas elasticities, I do estimate positive correlations between labor and materials markups. However, I continue to estimate substantially different time trends for the markup using different inputs.

Finally, empirical implementation of the production approach has assumed that productivity is Hicks neutral, and thus improves all factors equally. Alternatively, factor augmenting productivities could vary across time and plants, as in Acemoglu (2002), Doraszelski and Jaumandreu (2018), Oberfield and Raval (2014), and Raval (forthcoming). Non-neutral technical differences could cause the underlying differences in revenue shares behind my findings if labor augmenting productivity and materials augmenting productivity are negatively correlated within plants and on different trends over time.

Taken together, these results provide a cautionary note to those using the production approach to markup estimation. Without good estimates of the firm's production function, inferences using markups estimated with the production approach are fraught with difficulty.

Within the broad literature on production functions and markups, my paper is most similar to a couple of articles that examine differences between markup estimates using the production approach. In particular, De Loecker et al. (2018), Traina (2018), and Karabar-

[5]For example, if "hyper-productive" or "superstar" firms (Kehrig and Vincent, 2017; Autor et al., 2017) use a different production function than other firms in the same industry, the production approach would incorrectly measure their markups.

bounis and Neiman (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. Somewhat similarly, 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, and not the dispersion or correlation across markup estimates.

My evidence is also consistent with results in De Loecker et al. (2018) that compare different variable inputs. For example, when De Loecker et al. (2018) compare labor and materials using manufacturing data from the US Census, they find a 60 percentage point increase in the materials markup in the 2000s compared to no change in the labor markup, an average markup of 3 in 1987 using materials compared to 1.65 using labor, and significantly higher dispersion in the materials markup compared to the labor markup.[6]

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

[6] 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 cost of goods sold to the wage bill using Compustat, and shows opposite time trends for markups using either input between 1970 and 1990.

1 Production Approach to Markup Estimation

Below, I closely follow De Loecker and Warzynski (2012) in the derivation of the markup using the production function approach. 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.[7] 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 competitive factor markets, this implies:

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

, where X_{it} is one of the inputs in production, P_{it}^X is that input's price, and λ_{it} is the firm's marginal cost.[8] Rearranging terms[9], 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:

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

[7] I use a gross output production function as recent work has found substantial differences between gross output and value added productivity estimates (Gandhi et al., 2017).

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

[9] Formally, multiply each side by $\frac{X_{it}}{F_{it}}$, divide each side by the marginal cost, and multiply and divide the right hand 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 competitive factor market. Thus, we can examine the sensitivity of markup estimation through the use of different variable inputs.

Estimating the markup thus 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 estimated in order to recover the firm's output elasticity for input X.

1.1 Production Function Estimation

Estimating a production function requires a large set of auxiliary assumptions. De Loecker and Warzynski (2012) and the subsequent papers using the production function approach assume Hicks neutral technology and a specific functional form for the production function with common coefficients across all firms in the same industry.

Given these assumptions, the Ackerberg et al. (2015) technique, which builds upon the control function approach of Olley and Pakes (1996) and Levinsohn and Petrin (2003), can be used to estimate the production function. The ACF approach assumes that measured revenue includes additive measurement error ϵ_{it}. Since materials (or another flexible input) is assumed to be decided after the firm learns its productivity shock, it can be inverted for productivity. Thus, the first stage includes a flexible form of the flexible inputs and other inputs to approximate productivity, and recovers the additive measurement error ϵ_{it}. Formally, measured log revenue y_{it} is:

$$y_{it} = f(x_{it}) + \omega_{it} + \epsilon_{it} \tag{5}$$

$$y_{it} = g(x_{it}) + \epsilon_{it} \tag{6}$$

for inputs x_{it}, (logged) production function f, log productivity ω_{it}, and a nonparametric function of inputs g. In practice, I use a third order polynomial in inputs for the function g, and also control for year effects.

In the second stage, productivity is assumed to follow a first order AR(1) process.[10] In that case, given knowledge of the production function coefficients β, one can recover the innovation in productivity as:

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

with AR(1) coefficient ρ.

[10]This assumption can easily be generalized, such as to a first order Markov assumption on productivity.

Because the innovation in productivity is, by construction, independent of inputs chosen before time t, we can estimate the production function coefficients through moments of the innovations multiplied by inputs chosen before the productivity innovation: $E(\nu_{it}x_{i,t-1})$.

I use the ACF approach to estimate a Cobb-Douglas and Translog production function, which are the first and second order approximations for any production function around its inputs. For the Cobb-Douglas, I use capital and the first lag of materials and labor (or a combined input of the two) as instruments in the moment conditions above. For the Translog, I use capital and the first lag of materials and labor as instruments, as well as the relevant interactions in the moment conditions above, following De Loecker and Scott (2017). In addition to estimating a production function with capital, labor, and materials separately, I also estimate a production function with capital and a combined variable input of labor and materials.[11]

Finally, as in De Loecker and Warzynski (2012), I correct the value of sales in the input

[11] For the Cobb Douglas with labor and materials, the (logged) production function is:

$$f_{i,t} = \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} \tag{8}$$

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

$$\begin{aligned} f_{i,t} = \beta_k k_{i,t} \quad &+ \quad \beta_l l_{i,t} + \beta_m m_{i,t} + \beta_{kk} k_{i,t}^2 + \beta_{ll} l_{i,t}^2 + \beta_{mm} m_{i,t}^2 && (9) \\ &+ \quad \beta_{kl} k_{i,t} l_{i,t} + \beta_{km} k_{i,t} m_{i,t} + \beta_{lm} l_{i,t} m_{i,t} && (10) \end{aligned}$$

and so the output elasticity for each input will depend upon both an input's output elasticity and its cross-elasticities with other inputs. For example, the firm's output elasticity for materials would be:

$$\beta_m + 2\beta_{mm} m_{i,t} + \beta_{km} k_{i,t} + \beta_{lm} l_{i,t} \tag{11}$$

.

share of revenue for the measurement error estimated in the control function step of the ACF procedure. Thus, for input X, the estimate of the markup is:

$$\hat{\mu_{it}} = \frac{\hat{\beta_i^X}}{s_{it}^X exp(\hat{\epsilon}_{it})} \tag{12}$$

.

2 Data

In this article, I use datasets on both manufacturing plants and firms for several countries, and on the retail outlets of a major US national retailer. I summarize the characteristics of these datasets in Table I; I include further details on data construction in Appendix C.

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.[12]

[12] 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 2010. 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.

The last dataset is data for three years from a major US nationwide retailer, which I will call "Company 1", at the retail store level. This retailer has thousands of stores across the United States.[13]

Table I Datasets

Dataset	Industry	Time Period	Number of Establishments
Chile	Manufacturing	1979-1996	5,000 / year
Colombia	Manufacturing	1978-1991	7,000 / year
India	Manufacturing	1998-2014	30,000 / year
Indonesia	Manufacturing	1991-2000	14,000 / year
Company 1	Retail	3 years	Thousands / year

In order to estimate production functions, I require data on capital, labor, and materials, as well as sales. For each dataset, I obtain capital, materials, and output deflators in order to construct consistent measures over time, and drop any observations with zero or negative capital, labor, materials, sales, or labor costs. I also trim the bottom 1% and top 1% of

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

labor's share of revenue, materials's share of revenue, and the combined variable input share of revenue for each industry to remove outliers.

For labor, I use the number of workers in Chile, Colombia, and Indonesia. 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 materials, I construct separate measures of materials for non-energy raw materials and energy (which includes electricity and fuels) for the manufacturing datasets. Materials is the sum of raw materials and energy. 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 combined variable input is the sum of materials and labor costs; I deflare this input using the output deflator to match De Loecker et al. (2018)'s treatment of cost of goods sold.

Capital is the most involved variable to construct. For each dataset, I construct a perpetual inventory measure of capital for each type of capital. I then construct rental rates of capital based on an average real interest rate over time plus depreciation for that type of capital, and sum capital stocks times their rental rates, plus any rental payments for capital, as my measure of capital. This provides an approximation to a Divisia index for capital given different types of capital.[14]

For the manufacturing datasets, I estimate production functions at the industry level. I define industries at a similar level to two digit US SIC; for Chile, Colombia, and Indonesia

[14] 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.

this is at the three digit ISIC (Rev.2) level, and for India at the two digit NIC 87 level.[15] I only include industries with at least 1,000 observations over the entire dataset.

3 Results

In this section, I estimate markups using different variable inputs. Under the assumptions of the production approach, the markup using any variable input should be the same. I examine several features of the markup distribution, including how average markups, dispersion of markup estimates, and trends in aggregate markups compare, how the different markup estimates are correlated with each other, and how the different markup estimates are correlated with the degree of competition.[16]

3.1 Average Markups

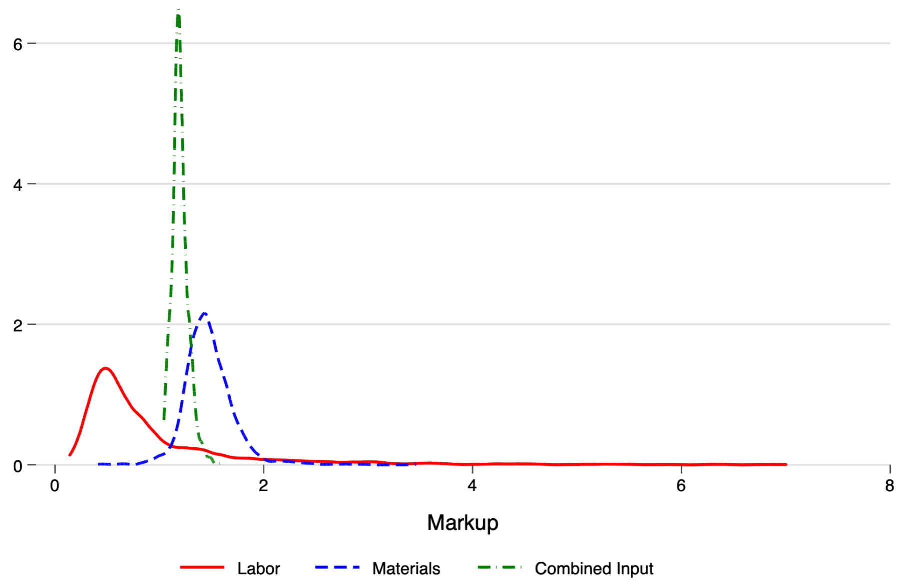
I first examine average markups; De Loecker and Warzynski (2012) and De Loecker and Scott (2017) have found similar average markups using different variable inputs. I find similar average markups in some, but not all, of the datasets.

[15] This industry definition 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.

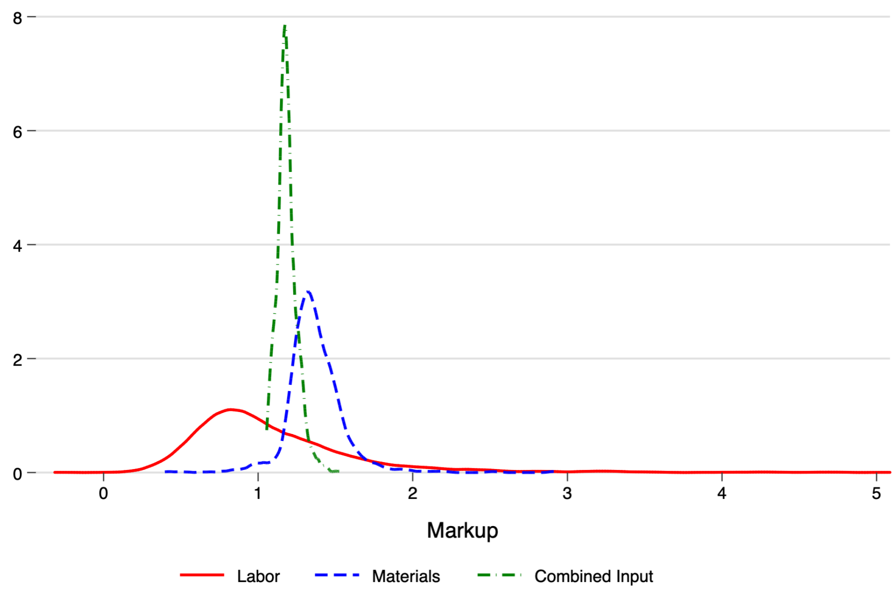
[16] In this section, all of my estimates are unweighted, except using sample probability weights for India. My overidentification tests should hold for any set of weights on firm markups. De Loecker et al. (2018) weight markups by sales, while Edmond et al. (2018) argue that, for welfare calculations, markups should be weighted by share of cost. I examine both in Appendix B, and find qualitatively similar findings to the unweighted results below.

To show how the average markup varies between measures, I plot the distribution of the labor, materials, and combined input markup in Figure 1 for Chilean Food Products in 1996; 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 sets of estimates, the mode of the distribution is larger using the materials markup compared to the labor markup; the combined input lies in the middle. The average labor markup is 0.94 using the Cobb-Douglas estimates and 1.10 using the Translog estimates, the average materials markup is 1.37 using the Cobb-Douglas estimates and 1.47 using the Translog estimates, and the average combined input markup 1.20 using the Cobb-Douglas estimates and 1.19 using the Translog estimates. Thus, for Chilean Food Products in 1996, the average estimated materials markup is 25 to 60% higher than the average labor markup, and 15 to 25% higher than the average combined input markup.

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 II. The average labor markup is 9% higher than the 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, 4% higher for India, 69% higher for Indonesia, and 5% lower for Company 1. Thus, the average markups are close to each



(a) Cobb-Douglas



(b) Translog

Figure 1 Distribution of Markups for Chilean Food Products, 1996 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 II 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.

Table II 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	1.11	1.03	1.48	1.09	1.33	1.06
	(0.016)	(0.014)	(0.015)	(0.011)	(0.010)	(0.005)
India	2.27	1.05	2.43	1.13	1.07	1.07
	(0.009)	(0.009)	(0.010)	(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.

3.2 Dispersion in Markup Estimates

I next look at the dispersion in markup estimates. In Figure 1, we can see that the labor markups are much more disperse than the materials markup, which are in turn more disperse than the combined input markups, for both the Cobb-Douglas and Translog estimates for Chilean Food Products in 1996. For example, for the Translog estimates, the 10th percentile markup is 0.49 using labor, 1.21 using materials, and 1.11 using the combined input. Similarly, the 90th percentile markup is 1.71 using labor, 1.56 using materials, and 1.27 using the combined input.

For all the datasets, I measure dispersion by calculating the 75/25 ratio and 90/10 ratio of the markup estimates, which I report in Table III and Table IV. Just as in Figure 1, labor markups are more disperse than materials markups, which are more disperse than combined input markups. For example, using the Translog estimates, the 75th percentile markup is 106% higher than the 25th percentile markup for Chile using labor, 32% higher using materials, and 15% using the combined input, 78% higher for Colombia using labor, 24% higher using materials, and 14% using the combined input, 543% higher for India using labor, 36% using materials, and 29% using the combined input, and 165% higher for Indonesia using labor, 37% higher using materials, and 13% using the combined input. These differences are even more extreme using the 90/10 ratio.

For the retailer, there is hardly any dispersion in materials markups – the 90th percentile markup is only 6% higher than the 10th percentile – but substantial dispersion in the labor markup. The dispersion in the combined input markup is similar to the materials markup. For the labor markup, the 75th percentile is 35% higher than the 25th percentile and the 90th percentile is 76% higher than the 10th percentile.

Table III Dispersion in the 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
	(0.014)	(0.007)	(0.003)	(0.002)	(0.001)	(0.001)
Colombia	2.72	1.78	1.64	1.24	1.14	1.14
	(0.012)	(0.007)	(0.004)	(0.001)	(0.001)	(0.001)
India	5.15	6.43	1.40	1.36	1.27	1.29
	(0.017)	(0.041)	(0.001)	(0.001)	(0.001)	(0.001)
Indonesia	3.82	2.65	1.55	1.37	1.12	1.13
	(0.020)	(0.010)	(0.002)	(0.001)	(0.000)	(0.001)
Company 1	1.28	1.35	1.03	1.03	1.02	1.03
	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)

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

3.3 Changes Over Time

Much of the interest in the production approach has been to examine the aggregate markup over time, as De Loecker et al. (2018) do. I thus look at changes in the average markup over time by estimating the following specification:

Table IV Dispersion in the 90/10 Ratio of Markup Estimates

	Labor		Materials		Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	6.25	4.04	2.08	1.81	1.33	1.31
	(0.036)	(0.018)	(0.007)	(0.005)	(0.001)	(0.001)
Colombia	7.82	4.06	2.76	1.71	1.31	1.30
	(0.060)	(0.043)	(0.010)	(0.006)	(0.001)	(0.001)
India	22.56	-6.03	1.89	1.91	1.57	1.56
	(0.101)	(0.066)	(0.002)	(0.002)	(0.001)	(0.001)
Indonesia	17.05	8.16	2.34	1.97	1.25	1.28
	(0.145)	(0.054)	(0.006)	(0.004)	(0.001)	(0.001)
Company 1	1.59	1.76	1.05	1.06	1.04	1.05
	(0.005)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)

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

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

where $\mu_{i,t}^X$ is the markup using input X, and γ_t and δ_n are year and industry fixed effects. I then plot the year effects using either the Cobb-Douglas or Translog estimates in Figure 2 through Figure 5, 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 combined input markups. For all of the four countries, I find very different patterns over time using different measures of the markup.

Below, I describe changes in aggregate markups using the Translog estimates; markups using the Cobb-Douglas are qualitatively similar for Chile and Indonesia, but not for Colombia and India. I find substantially different patterns in average markups for labor and materials. The combined input markups lie between the two, but much closer to materials, and exhibit less extreme movements.

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

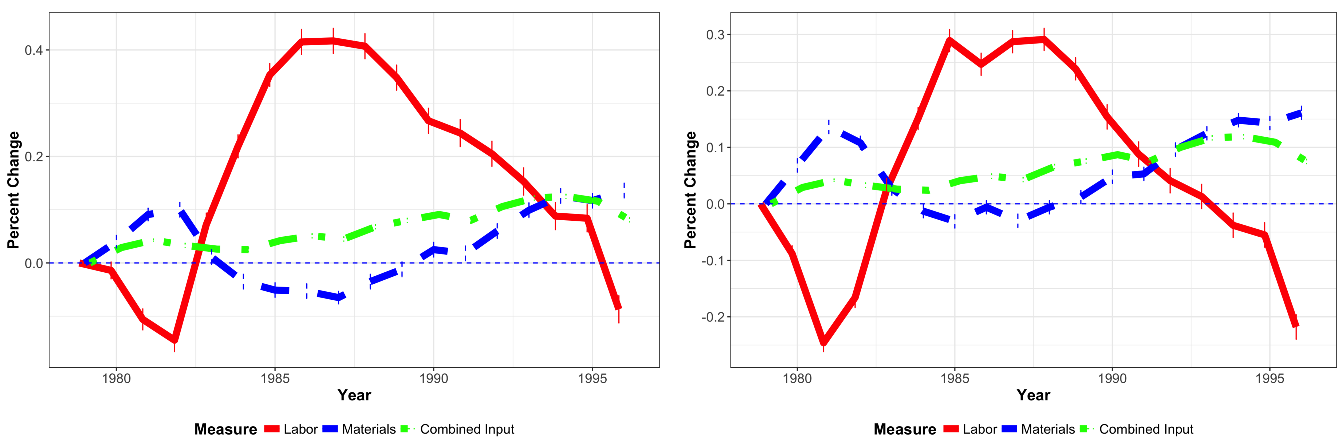
For Colombia, the average labor markup falls substantially at the beginning of the sample using labor, and remains about 28% lower at the end of the sample compared to the beginning of the sample. The average materials markup rises over time and is about 8% higher at the end of the sample. The combined 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 39% 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 combined input markup exhibits a decline of 7%, much smaller than for labor and 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 combined 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 combined 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: Chile

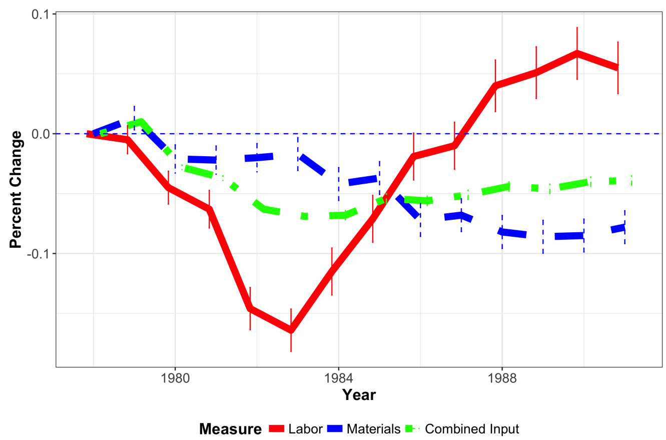


(a) Cobb-Douglas

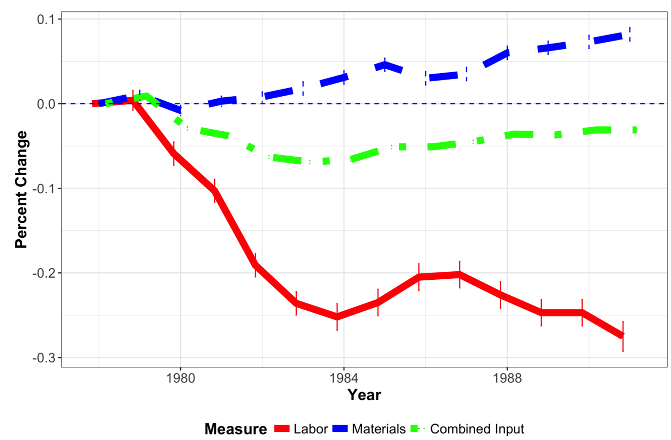
(b) Translog

Note: Estimates based on equation (13), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure 3 Change in Average Markup Over Time: Colombia



(a) Cobb-Douglas

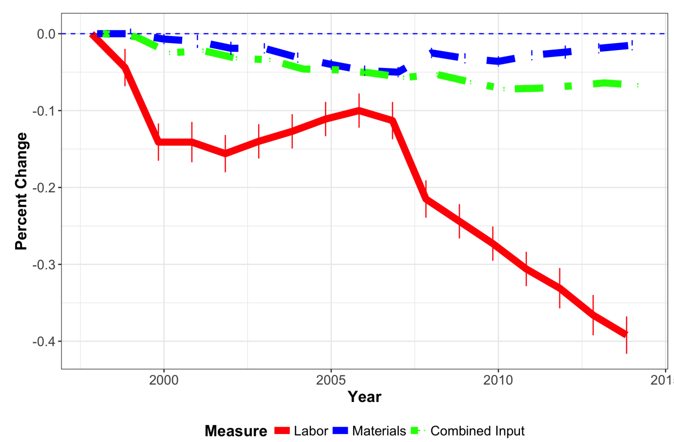


(b) Translog

Note: Estimates based on equation (13), 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 4 Change in Average Markup Over Time: India

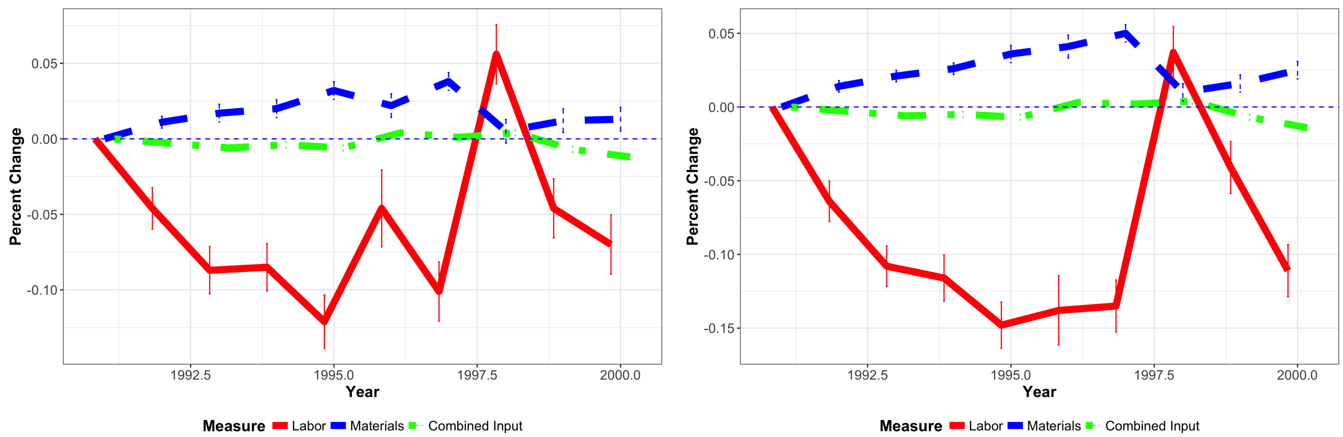
(a) Cobb-Douglas



(b) Translog

Note: Estimates based on equation (13), 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 5 Change in Average Markup Over Time: Indonesia

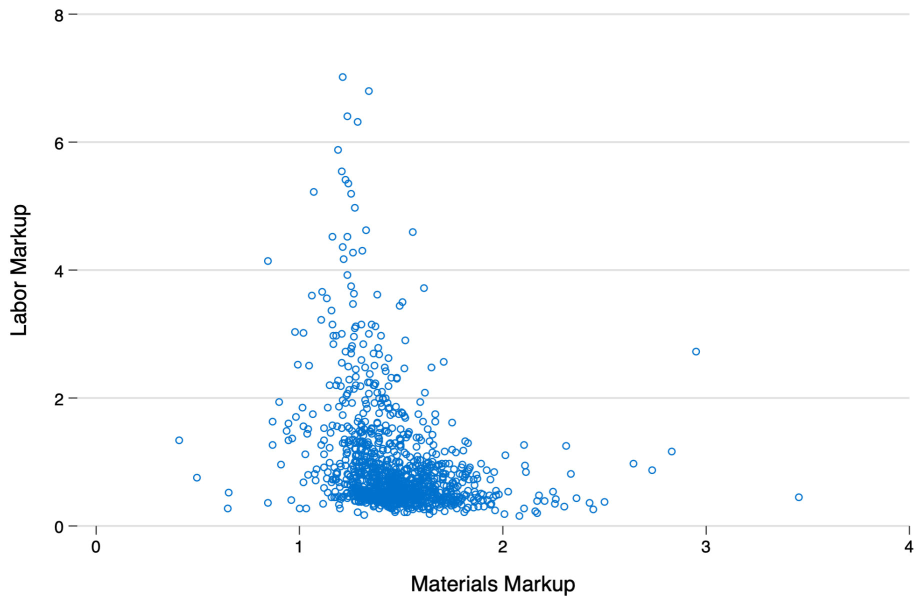


(a) Cobb-Douglas (b) Translog

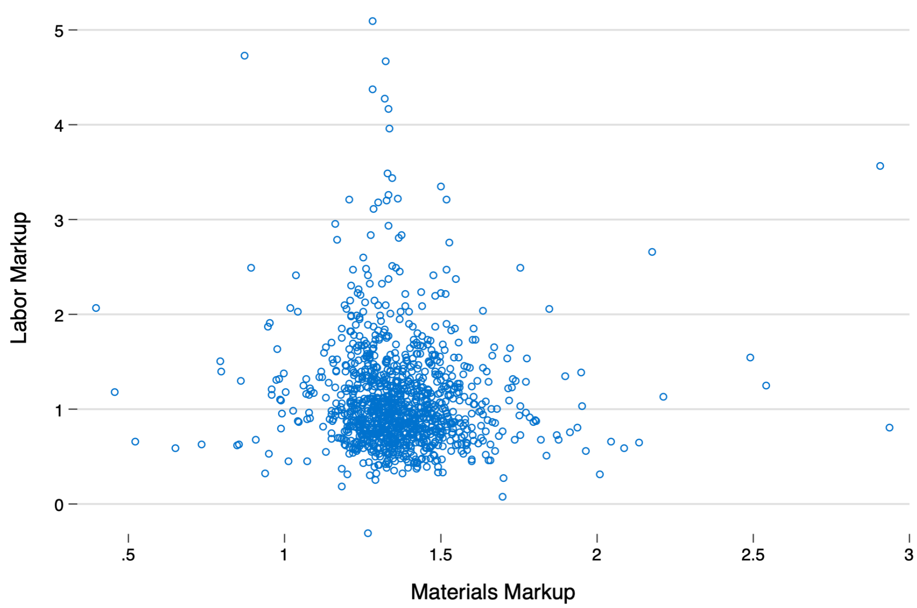
Note: Estimates based on equation (13), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

3.4 Correlations of Markup Estimates

I next look at how the different markup estimates are correlated with each other beyond differences in markup movements over time. If both estimates are good measures of the firm markup, they should be highly correlated with each other. In Figure 6, I plot scatter plots of the materials markup on the x-axis against the labor markup on the y-axis for the Chilean Food Products industry in 1996. The upper plot uses Cobb-Douglas estimates of the production function, and the lower plot uses Translog estimates of the production function. 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.



(a) Cobb-Douglas



(b) Translog

Figure 6 Correlation of Markups for Chilean Food Products, 1996

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

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

where $\mu_{i,t}^{Y}$ and $\mu_{i,t}^{X}$ are the markups using input Y and X. I also include controls γ_t and δ_n, which are year and industry fixed effects, so estimated correlations do not reflect the yearly trends discussed in the previous section. In this specification, β represents the elasticity of the markup using input Y with respect to the markup using input X.

I report these correlations between markup measures in Table V; 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. An establishment with a 100% higher materials markup has, on average, a 66% lower labor markup for Chile, 99% lower for Colombia, 176% 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 15% lower labor markup for Chile, 30% lower for Colombia, 63% lower for India, 48% lower for Indonesia, and 1008% lower for Company 1. The large magnitude of the elasticities for Company 1 likely reflect the small dispersion in materials markups, relative to labor markups, reported in Section 3.2.

In Table V, the third and fourth columns are the elasticity of the labor markup to the combined input markup, and the fifth and sixth columns the elasticity of the materials markup to the combined input markup. Under the Translog estimates, these elasticities are positive, but vary substantially in magnitude across datasets. The elasticity of the labor markup to the combined input markup varies from 28% to 136% across datasets, while the elasticity of the materials markup to the combined input markup varies from 26% to 157% across datasets.

Table V Correlation between Markup Estimates

	Labor on Materials		Labor on Combined Input		Materials on Combined 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	-0.30	-1.12	0.83	2.11	1.06
	(0.014)	(0.019)	(0.061)	(0.049)	(0.032)	(0.019)
India	-1.76	-0.67	-0.29	1.70	1.13	-0.35
	(0.012)	(0.012)	(0.042)	(0.055)	(0.009)	(0.015)
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 equation (14) 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.

3.5 Markups and the Degree of Competition

A key focus of papers such as De Loecker et al. (2018) and Blonigen and Pierce (2016) using the production approach has been how markups vary with competition. For Company 1, I can also examine this question as I have two different company provided measures of the degree of competition.[17] Company 1 has both provided 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 discretize the number of competitors provided by the company into bins of 0-1, 2, 3, 4, 5-9, or 10 or more competitors. In order to examine these correlations, I estimate the following regression specification:

$$\log(\mu_{i,t}^X) = \alpha + \beta \log(Comp_i) + \gamma_t + \delta_n + \epsilon_{i,t} \tag{15}$$

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

In Table VI and Table VII, 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 combined 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 combined input

[17] Note that any measures of the degree of competition are endogenous, and may reflect other underlying determinants of market structure.

markups.

I find very similar patterns using the number of competitors instead of the company's competition band. 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. Thus, the relationship between the degree of competition and markup can change dramatically depending upon the measure of markups used.

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

	Labor		Materials		Combined 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 equation (15) and relative to a retail store facing Low Competition. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level.

Table VII 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 equation (15) 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.

4 Mechanisms

In this section, I investigate several explanations for the differences between markups measured with different inputs documented in Section 3. I do not find that alternative production function estimators to the ACF procedure, adjustment costs in labor or wage bargaining, or measurement error can explain the differences between labor and materials markups. Estimating plant-level Cobb-Douglas production functions leads to similar average markups, and positive correlations between labor and materials markups, but different flexible inputs continue to lead to different time trends in markups. A model with factor augmenting productivites could, however, explain these findings.

4.1 Alternative Production Function Estimators

One explanation for the findings in Section 3 is that the auxiliary assumptions required for the Ackerberg et al. (2015) procedure are misspecified. The ACF procedure places a Markov assumption on productivity together with timing assumptions on when the firm determines its level of inputs. Foster et al. (2017) compare TFP estimates using different approaches to estimate Cobb-Douglas output elasticities, and find substantially different output elasticities using different techniques, with double the average capital elasticity using an ACF like estimation approach compared to a cost share approach.

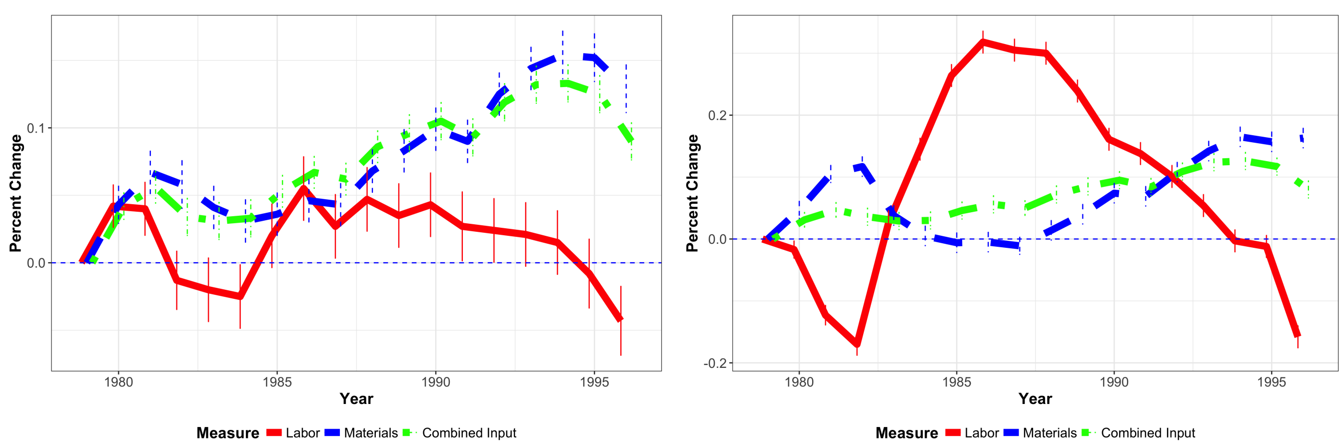
I thus also estimate production functions by setting output elasticities equal to their industry cost shares. The cost share method has been used in productivity analysis (Foster et al., 2001, 2008) and does not require the Markov assumptions on productivity or timing assumptions on inputs, or in fact 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.

While average markups using different variable inputs are closer to each other using the cost share approach, I continue to find different time trends in the markup using different inputs and negative correlations between the labor and materials markup.

In Table VIII, the columns labeled Industry report the ratio of average markups using this cost share approach. In general, the average markups using different inputs are close to each other – in all cases, within 40% of each other, and often much closer.

However, the time trends using different inputs, estimated using equation (13), are very different for all cases except Colombia. I depict these in the left figures in Figure 7 through Figure 10.[18] In addition, after controlling for time trends, I show in the columns of Table IX labeled Industry that the labor markup remains negatively correlated with the materials markup, with correlations ranging from -0.24 to -1.00. Thus, it does not appear that an alternative estimation strategy for an industry wide production function can explain the differences in markups using different inputs.

Figure 7 Change in Average Markup Over Time, Cost Share Estimates: Chile



(a) Industry Cost Share (b) Plant Cost Share

Note: Estimates based on equation (13), 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.

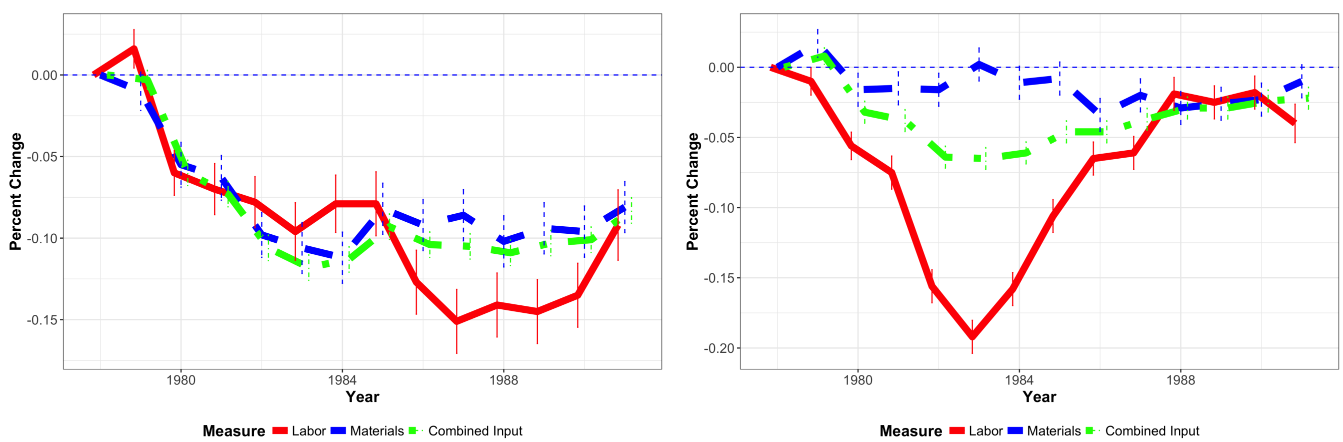
[18]For the retailer Company 1, the time trends using labor, materials, or the combined input are similar, with about a 1% decline in the markup over 3 years.

Table VIII Ratio of Average Markup Estimates: Cost Share Estimation

Dataset	Labor/Materials Industry	Labor/Materials Plant	Labor/Combined Input Industry	Labor/Combined Input Plant	Materials/Combined Input Industry	Materials/Combined Input Plant
Chile	0.96	1.01	1.07	1.04	1.11	1.03
	(0.010)	(0.002)	(0.009)	(0.002)	(0.003)	(0.001)
Colombia	0.79	0.98	1.05	1.04	1.32	1.06
	(0.008)	(0.002)	(0.007)	(0.002)	(0.008)	(0.002)
India	1.26	1.08	1.37	1.09	1.09	1.01
	(0.005)	(0.001)	(0.005)	(0.001)	(0.001)	(0.000)
Indonesia	0.73	1.07	0.92	1.10	1.27	1.03
	(0.006)	(0.003)	(0.006)	(0.002)	(0.004)	(0.001)
Company 1	0.99	1.00	0.99	1.00	1.01	1.00
	(0.002)	(0.000)	(0.002)	(0.000)	(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. Columns labeled Industry are markups based on industry level cost shares, and labeled Plant based on plant-level cost shares, as described in the text. Standard errors are clustered at the establishment level.

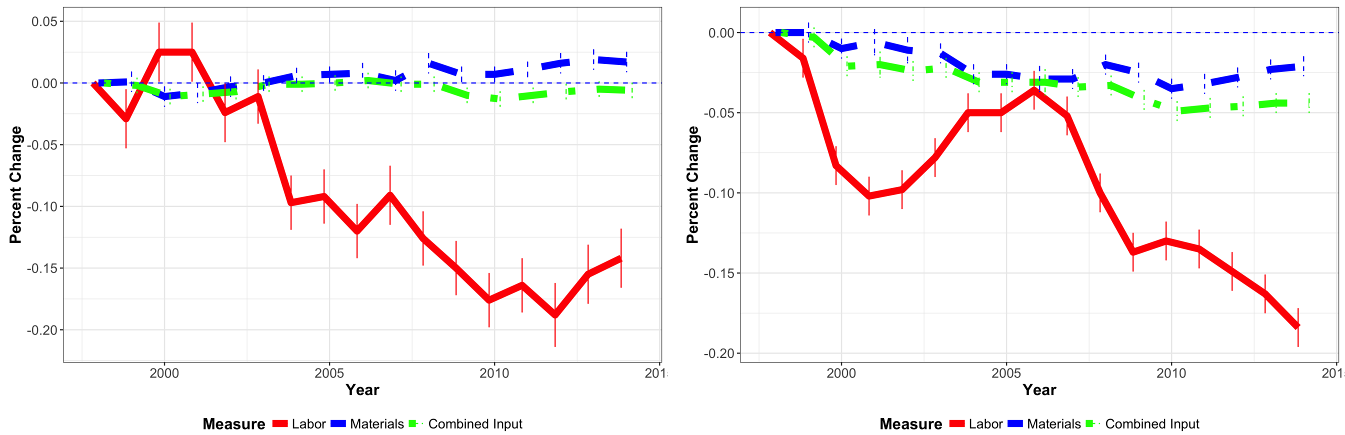
Figure 8 Change in Average Markup Over Time, Cost Share Estimates: Colombia



(a) Industry Cost Share (b) Plant Cost Share

Note: Estimates based on equation (13), 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.

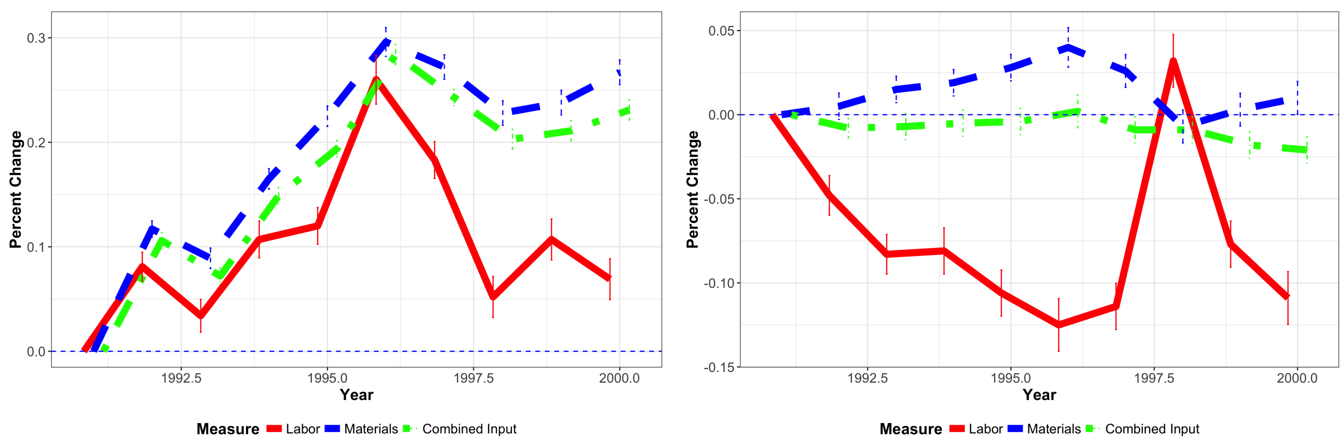
Figure 9 Change in Average Markup Over Time, Cost Share Estimates: India



(a) Industry Cost Share (b) Plant Cost Share

Note: Estimates based on equation (13), 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, Cost Share Estimates: Indonesia



(a) Industry Cost Share (b) Plant Cost Share

Note: Estimates based on equation (13), 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 IX Correlation between Markup Estimates: Cost Share Estimates

	Labor on Materials		Labor on Combined Input		Materials on Combined Input	
Dataset	Industry	Plant	Industry	Plant	Industry	Plant
Chile	-0.24	0.37	0.59	0.77	1.11	1.06
	(0.015)	(0.010)	(0.017)	(0.007)	(0.006)	(0.003)
Colombia	-0.65	0.02	0.38	0.71	1.28	1.16
	(0.008)	(0.010)	(0.017)	(0.009)	(0.010)	(0.005)
India	-0.94	0.58	0.65	0.94	1.02	1.00
	(0.009)	(0.005)	(0.010)	(0.003)	(0.002)	(0.001)
Indonesia	-0.51	0.48	0.72	0.94	1.07	1.01
	(0.010)	(0.019)	(0.010)	(0.005)	(0.004)	(0.002)
Company 1	-1.00	0.94	2.88	1.04	0.70	0.99
	(0.055)	(0.005)	(0.047)	(0.005)	(0.008)	(0.001)

Note: Estimates based on equation (14) 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 Industry are markups based on industry level cost shares, and labeled Plant based on plant-level cost shares, as described in the text. Standard errors are clustered at the establishment level.

4.2 Heterogeneous Production Technology

Another potential explanation for the differences in markups using different inputs is that the production function varies across plants within a given industry. One possibility is that each plant has its own Cobb-Douglas production function, with output elasticities varying across plants.

I examine this approach empirically by estimating plant-level output elasticities by the median plant-level cost share for a given plant over time.[19] I report the ratio of average markups and correlation between markups in the columns labeled Plant in Table VIII and

[19]Plant cost shares at the plant-year level would mean that the markup is the ratio of total sales to total cost, and so would be the same for any input by definition.

Table IX. Using the plant-level cost shares for Cobb-Douglas output elasticities, the elasticities between the labor markup and materials markup are all positive – between 0.02 and 0.94 – and the average markups are within 10% of each other for all of the inputs.

However, as the right figures in Figure 7 through Figure 10 show, the time trends for the labor markup and materials markup continue to be quite different.[20] Except for Colombia, the time trends in the markup using plant-level cost shares are similar to the time trends using the ACF translog estimates detailed in Section 3.3. Thus, even plant-level Cobb-Douglas output elasticities cannot yield similar time trends using different variable inputs to calculate the markup.

For the Cobb-Douglas results, the underlying data facts behind the markup differences are a negative correlation in the labor and materials share of sales, and different time trends in the labor and materials share of sales.[21] An alternative production technology would have to yield both facts. Allowing factor augmenting productivities, as in Doraszelski and Jaumandreu (2018), Oberfield and Raval (2014), and Raval (forthcoming), can do so. Take a CES production function with elasticity of substitution σ and factor augmenting productivities A_K, A_L, and A_M for capital, labor, and materials respectively:

[20] For the retailer Company 1, the time trend using labor indicates a 9% rise in the markup, using materials a 3% decline in the markup, and using the combined input a 2% decline in the markup, over 3 years.

[21] Since, for the Cobb-Douglas, the output elasticity for an input is a constant, the markup using a given flexible input is inversely proportional to the input's share of sales. See equation (4).

$$Y = ((A_K K)^{\frac{\sigma-1}{\sigma}} + (A_L L)^{\frac{\sigma-1}{\sigma}} + (A_M M)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{16}$$

. Assuming competitive factor markets and cost minimization, the inverse of the labor and materials shares of revenue are:

$$\frac{PY}{wL} = \mu(\frac{w}{C})^{\sigma-1}(A_L)^{1-\sigma} \tag{17}$$

$$\frac{PY}{p_m M} = \mu(\frac{p_m}{C})^{\sigma-1}(A_M)^{1-\sigma} \tag{18}$$

where μ is the markup, C the marginal cost, w the wage, and p_m is the price of materials. Thus, different time trends in the labor and materials shares can be rationalized by differing trends in labor augmenting productivity A_L and materials augmenting productivity A_M. A negative correlation between the labor and materials shares of revenue would require a negative correlation between A_L and A_M. Plants choosing between a more labor intensive or materials intensive technology could generate such a negative correlation.[22]

[22] Dinlersoz and Wolf (2018) estimate a similar model in which firms can choose the technology parameter on production labor vs. capital.

4.3 Violations of the Static FOC

One potential reason for these differences in markup estimates using different flexible inputs is that the static cost minimization first order conditions are violated, either because firms face adjustment costs when adjusting inputs or because firms are not price takers in the input market. These violations are likely to be more severe for labor, either due to hiring and firing costs when adjusting labor, as in Petrin and Sivadasan (2013), or wages determined by bargaining with unions.

In order to examine whether concerns of adjustment costs in labor or wage bargaining can explain my findings, I augment the production function by separating materials into raw materials and energy, where energy includes both electricity and fuel expenditure. I thus examine energy and raw materials as flexible inputs matching the static first order conditions. I exclude the retailer as energy is not a major input into the output of a retail output. I find that the raw materials markup has a different average markup and different trends over time compared to the energy markup, and is negatively correlated with the energy markup.

I report the ratio of average markups using different inputs in Table X. In general, the average markup is very different using energy compared to using labor or materials, with larger differences than between labor and materials. For example, using the translog estimates, the average materials markup is 85% lower than the average energy markup for Chile and 77% lower for Indonesia. The ratio of average markups is negative for Colombia and India.

Table X Ratio of Average Markup Estimates: Energy and Raw Materials Separated

Dataset	Labor/Raw Materials CD	Labor/Raw Materials TL	Labor/Energy CD	Labor/Energy TL	Raw Materials/Energy CD	Raw Materials/Energy TL
Chile	1.08	1.30	0.06	0.34	0.05	0.26
	(0.068)	(0.012)	(0.004)	(0.008)	(0.002)	(0.006)
Colombia	-1.35	-7.77	0.05	0.28	-0.03	-0.04
	(0.068)	(12.634)	(0.001)	(0.007)	(0.002)	(0.058)
India	2.46	1.00	0.92	-0.98	0.37	-0.98
	(0.011)	(0.008)	(0.006)	(0.027)	(0.002)	(0.024)
Indonesia	13.35	1.46	0.12	0.34	0.01	0.23
	(0.924)	(0.026)	(0.004)	(0.006)	(0.001)	(0.004)

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

I also examine time trends separating raw materials and energy estimating using equation (13), which I depict in Figure 11 to Figure 14. In all four datasets, the raw materials markup has a different time trend than the energy markup.

I estimate the elasticity between markup estimates using equation (14) and report these elasticities in Table XI. As before, the labor markup is negatively correlated with the raw materials markup. The raw materials markup is negatively correlated with the energy markup under the Cobb-Douglas estimates, with elasticities between -0.13 and -0.26, and has no correlation with the energy markup under the translog estimates. The labor markup is positively correlated with the energy markup under the Cobb-Douglas estimates, with elasticities between 0.16 and 0.26, but has a negative correlation with the energy markup under the translog estimates, with elasticities between -0.07 and -0.18. Thus, neither the labor or raw materials markup is highly correlated with the energy markup.

Table XI 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	-0.09	-0.13	-0.01
	(0.019)	(0.013)	(0.009)	(0.007)	(0.003)	(0.002)
Colombia	-0.69	-0.09	0.16	-0.07	-0.26	-0.00
	(0.012)	(0.013)	(0.006)	(0.005)	(0.005)	(0.003)
India	-1.02	-0.23	0.26	-0.17	-0.15	-0.01
	(0.008)	(0.009)	(0.003)	(0.004)	(0.001)	(0.001)
Indonesia	-0.75	-0.18	0.16	-0.09	-0.14	0.01
	(0.023)	(0.019)	(0.005)	(0.006)	(0.002)	(0.002)

Note: Estimates based on equation (14) 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.

4.4 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, the negative correlation between the labor markup and materials markup using the Cobb-Douglas estimates is driven by a negative correlation between the labor share of revenue and the materials share of revenue. 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.

Second, 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.

5 Conclusion

The production approach to markups implies that any flexible input can be used to measure the markup. In this article, I have executed a set of tests of the standard implementation of the production approach by using either labor or materials, or a combined variable input of both, as the input to construct the markup. I have employed five datasets – the manufacturing censuses of four countries and confidential data from a nationwide US retailer – for this purpose. My results are quite consistent across 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 the degree of competition are quite different from each other as well. I have then examined several potential explanations for these findings, and found that heterogeneity in production technology, such as due to factor augmenting technical differences, across establishments in the same industry could explain them.

Given these results, how should we measure markups? The development of the parallel demand approach to markups – exemplified by Berry et al. (1995) and Berry et al. (2004) – provide guidance. The demand approach to markups requires models of firm competition and demand, both of which depend upon a careful treatment of heterogeneity in demand across consumers and producers. Recent work on production function estimation, such as Gandhi et al. (forthcoming), Doraszelski and Jaumandreu (2018), and Raval (forthcoming), has focused on allowing more heterogeneity in production technology, and may prove fruitful in yielding better measures of markups.

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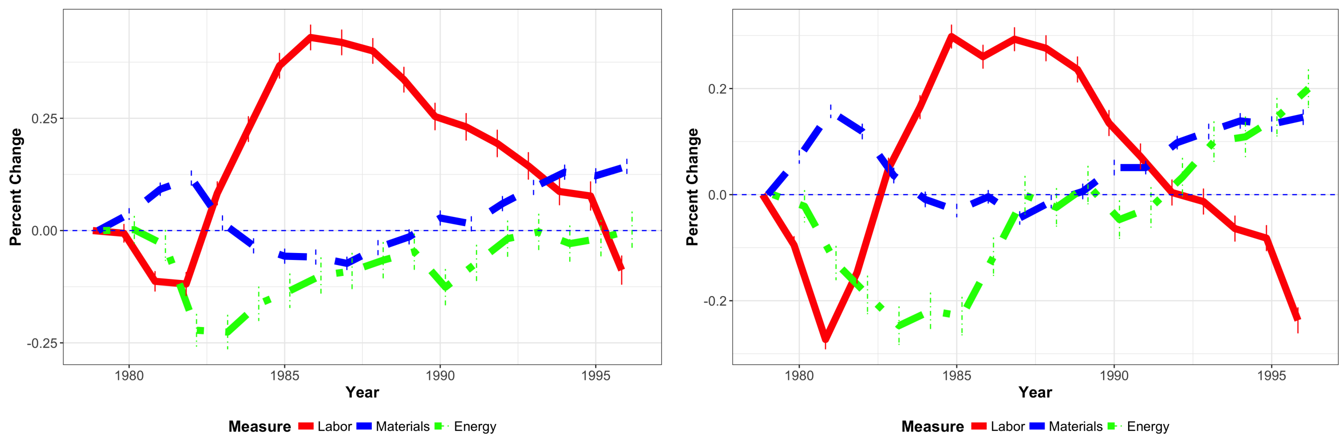
A Trends over Time, Raw Materials vs. Energy

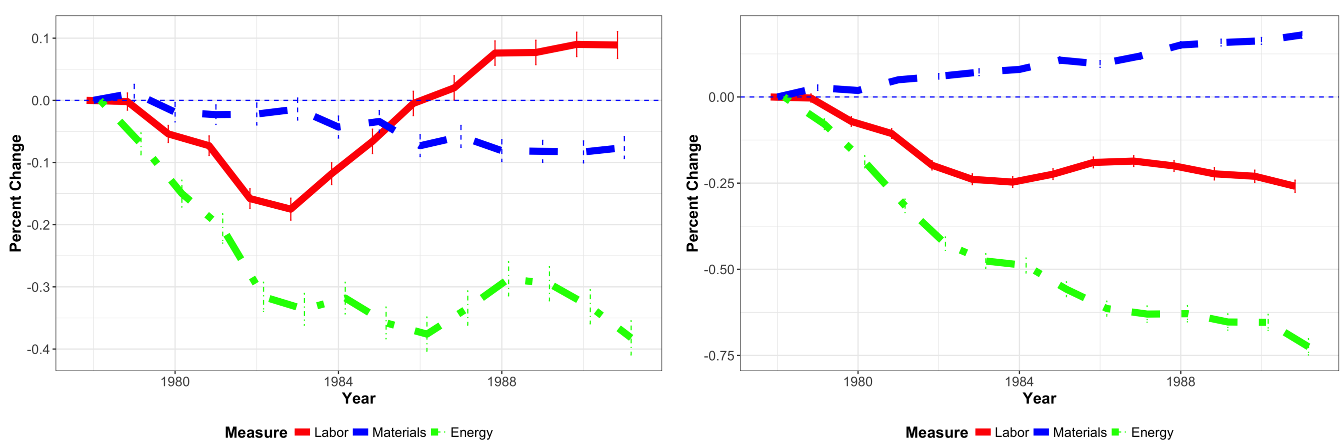
Figure 11 Change in Average Markup Over Time, with Energy: Chile



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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.

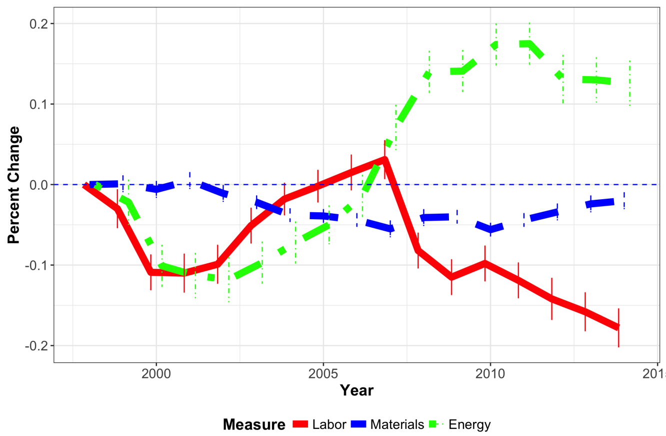
Figure 12 Change in Average Markup Over Time, with Energy: Colombia



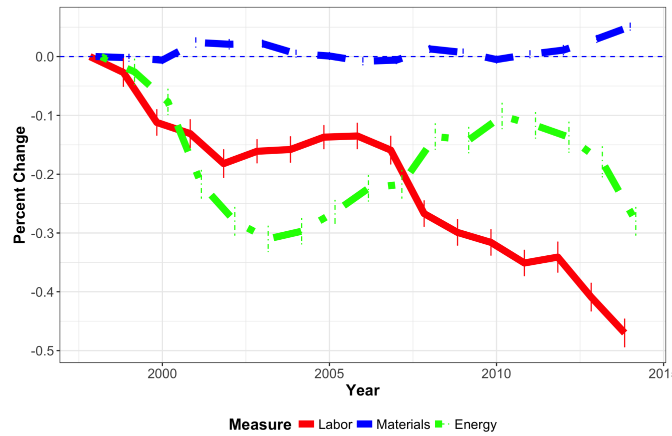
(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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, with Energy: India



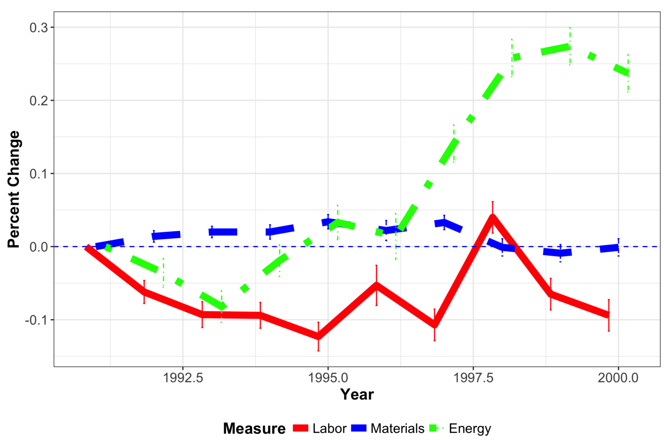
(a) Cobb-Douglas



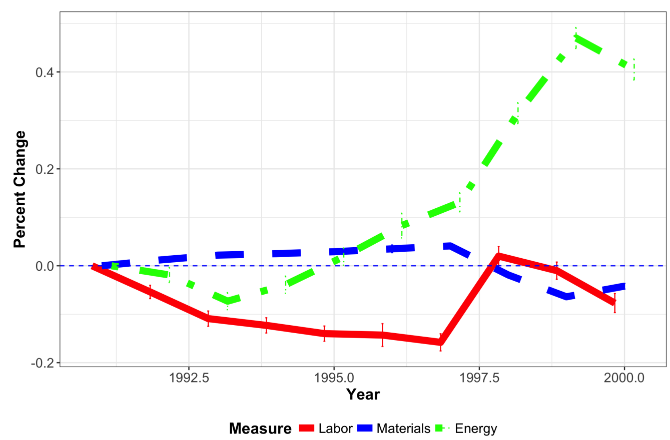
(b) Translog

Note: Estimates based on equation (13), 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, with Energy: Indonesia



(a) Cobb-Douglas



(b) Translog

Note: Estimates based on equation (13), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

B Weighted Estimates

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

Table XII Ratio of Average Markup Estimates: Sales Weighted

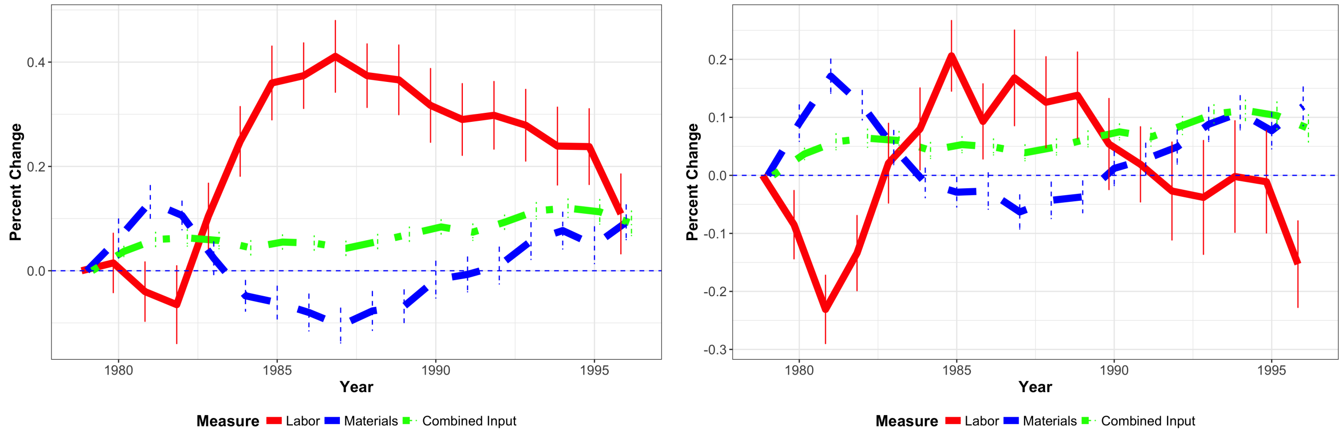
	Labor/Materials		Labor/Combined Input		Materials/Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	1.57	1.47	1.71	1.53	1.09	1.04
	(0.057)	(0.072)	(0.056)	(0.070)	(0.010)	(0.009)
Colombia	2.04	0.80	2.17	0.86	1.06	1.07
	(0.094)	(0.053)	(0.081)	(0.051)	(0.015)	(0.011)
India	4.60	0.11	4.52	0.11	0.98	1.05
	(0.211)	(0.499)	(0.195)	(0.521)	(0.004)	(0.009)
Indonesia	4.62	1.76	4.36	1.81	0.94	1.03
	(0.241)	(0.175)	(0.207)	(0.171)	(0.008)	(0.009)
Company 1	2.13	0.96	1.36	0.97	0.64	1.01
	(0.004)	(0.003)	(0.002)	(0.003)	(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. Estimates weighted with sales weights.

C Data Notes (Online Appendix)

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

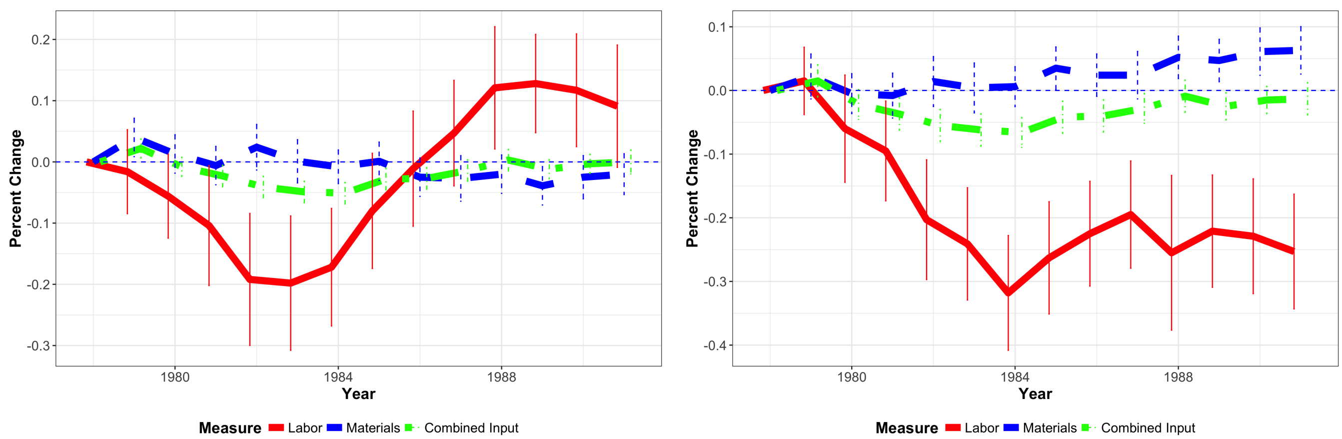
Figure 15 Change in Average Markup Over Time, Sales Weighted: Chile



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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.

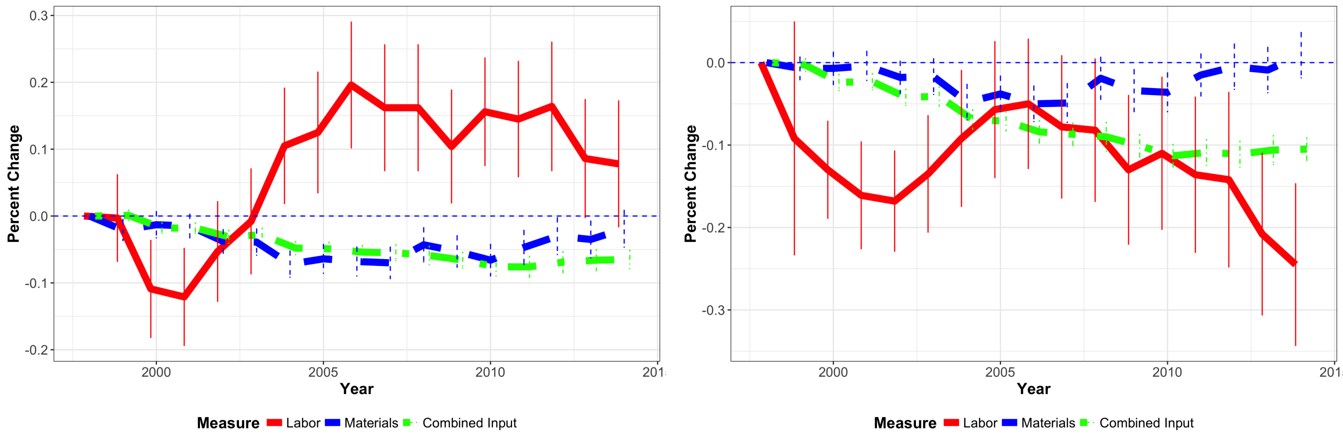
Figure 16 Change in Average Markup Over Time, Sales Weighted: Colombia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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.

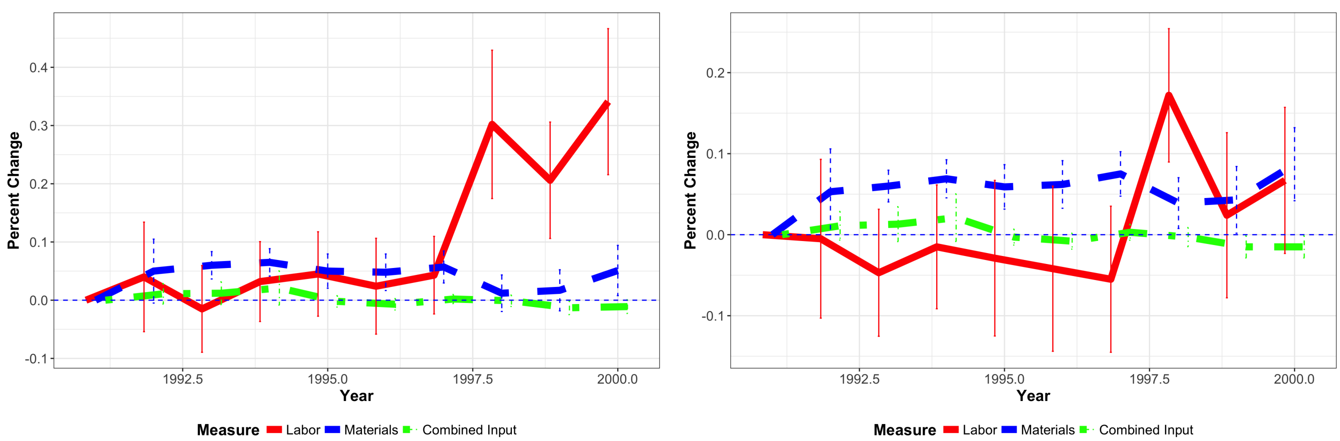
Figure 17 Change in Average Markup Over Time, Sales Weighted: India



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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: Indonesia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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	-1.20	0.31	-1.46	1.84	1.56	0.95
	(0.083)	(0.096)	(0.211)	(0.195)	(0.053)	(0.066)
India	-2.10	-0.48	-1.70	0.24	1.16	0.24
	(0.112)	(0.102)	(0.335)	(0.152)	(0.036)	(0.038)
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)

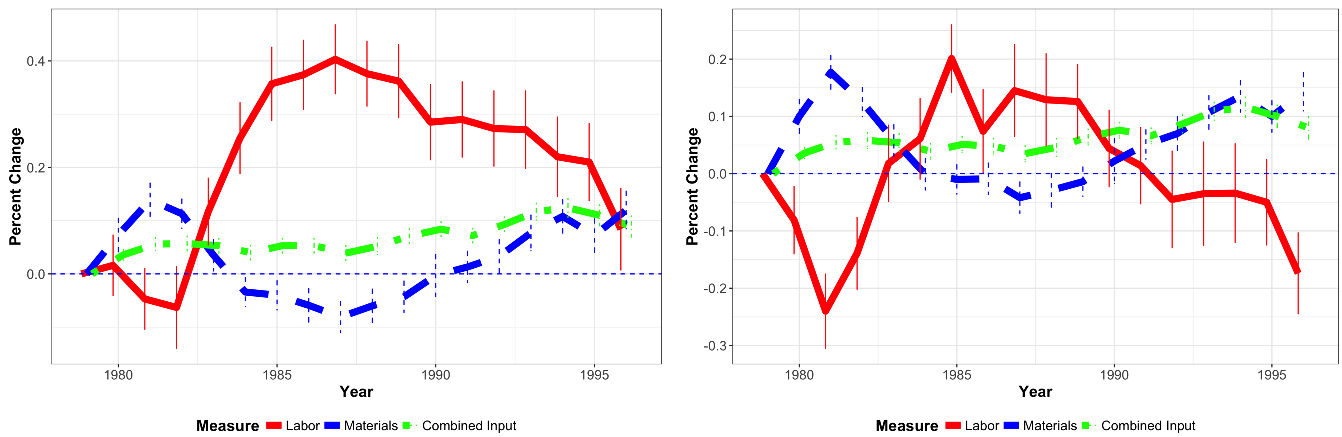
Note: Estimates based on equation (14) for markups from two flexible inputs, so Labor on Materials indicates a regression where the labor markup is the dependent variable and materials markup the independent variable. CD is Cobb-Douglas and TL Translog. Standard errors are clustered at the establishment level. Estimates weighted with sales weights.

Table XIV Ratio of Average Markup Estimates: Cost Weighted

	Labor/Materials		Labor/Combined Input		Materials/Combined Input	
Dataset	CD	TL	CD	TL	CD	TL
Chile	1.68	1.52	1.79	1.55	1.07	1.02
	(0.066)	(0.074)	(0.065)	(0.072)	(0.007)	(0.007)
Colombia	2.22	0.82	2.33	0.87	1.05	1.06
	(0.096)	(0.053)	(0.086)	(0.051)	(0.012)	(0.010)
India	4.82	-0.04	4.71	-0.04	0.98	1.05
	(0.218)	(0.531)	(0.201)	(0.556)	(0.004)	(0.010)
Indonesia	4.34	1.89	4.17	1.95	0.96	1.03
	(0.216)	(0.161)	(0.186)	(0.158)	(0.011)	(0.010)
Company 1	2.12	0.96	1.35	0.97	0.64	1.01
	(0.004)	(0.003)	(0.002)	(0.003)	(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. Estimates weighted with cost weights.

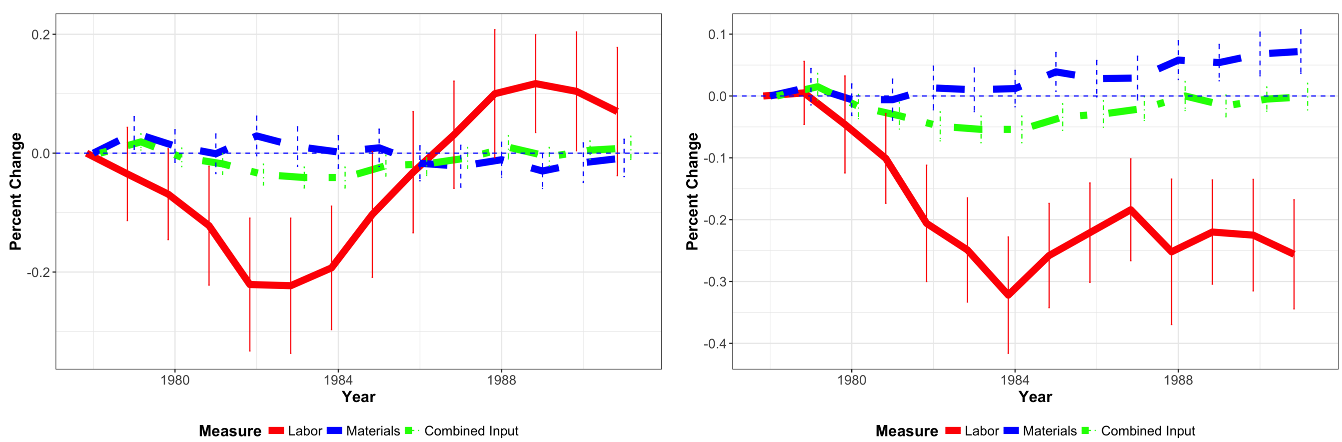
Figure 19 Change in Average Markup Over Time, Cost Weighted: Chile



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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.

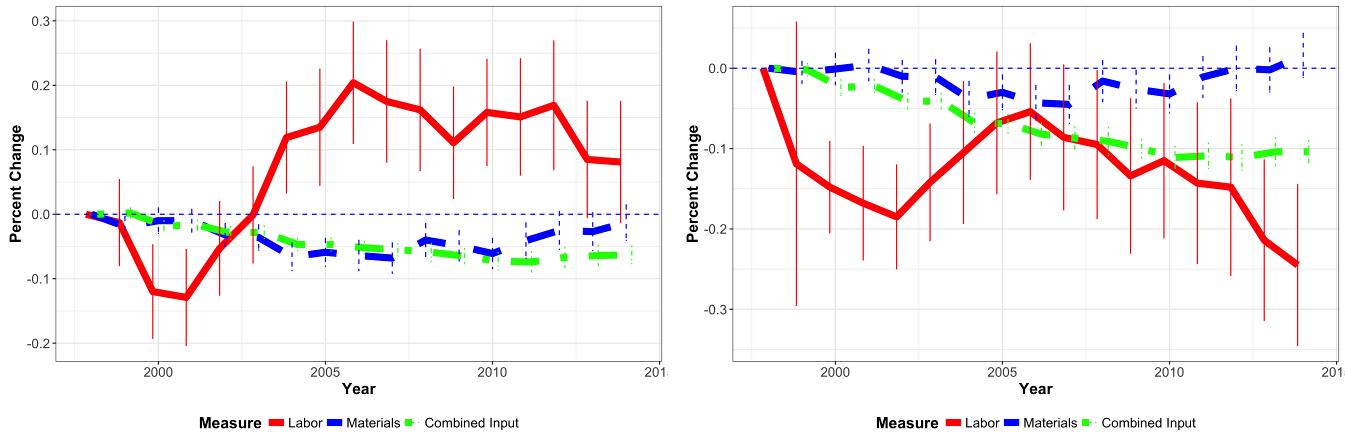
Figure 20 Change in Average Markup Over Time, Cost Weighted: Colombia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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.

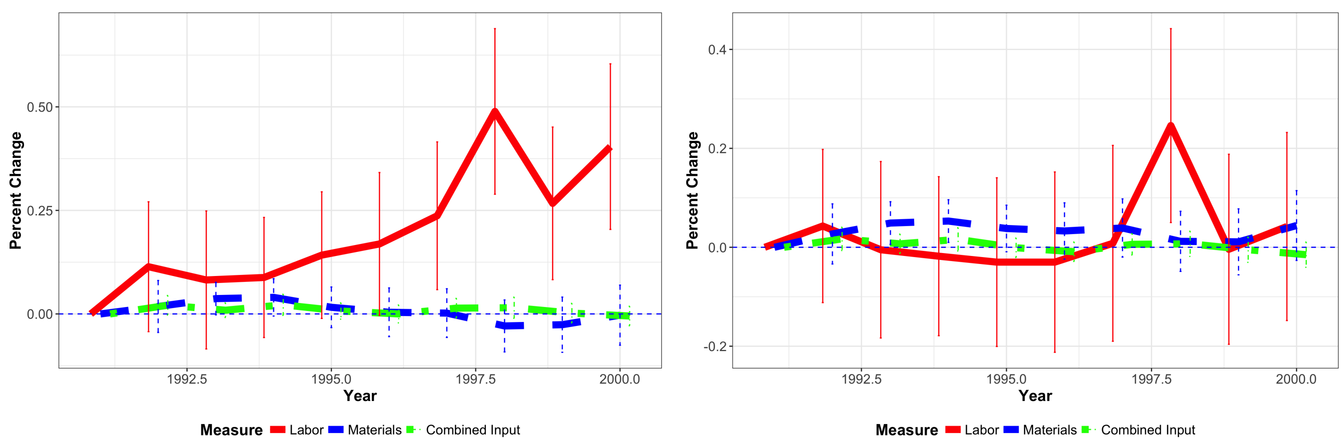
Figure 21 Change in Average Markup Over Time, Cost Weighted: India



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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: Indonesia



(a) Cobb-Douglas (b) Translog

Note: Estimates based on equation (13), 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 XV 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	0.43	1.26	0.99
	(0.059)	(0.069)	(0.178)	(0.196)	(0.058)	(0.047)
Colombia	-1.26	0.29	-1.55	1.85	1.51	0.89
	(0.068)	(0.092)	(0.200)	(0.182)	(0.054)	(0.061)
India	-2.11	-0.42	-1.89	0.47	1.17	0.25
	(0.111)	(0.116)	(0.341)	(0.174)	(0.037)	(0.034)
Indonesia	-0.86	-0.46	-1.18	0.03	1.45	1.23
	(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 equation (14) 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.

C.1 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.[23]

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.[24] 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.[25]

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-

[23]See Diewert and Lawrence (2000) and Harper et al. (1989) for details on capital rental rates and aggregation.

[24]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.

[25]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.[26]

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 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.[27] 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.[28] 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.[29]

C.2 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

[26]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%.

[27]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.

[28]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.

[29]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.

number of hours worked by all workers.

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

C.3 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 SIC level. For Indonesia, they are at the 5 digit ISIC level and for India at the 3 digit 1987 NIC 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.

C.4 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 3 digit NIC 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.

C.5 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 follow Alcott et al. (2015)'s procedure for creating a consistent 3 digit industry definition at the NIC 87 level.

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.