Online Appendix for "Testing the Production Approach to Markup Estimation"*

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C Robustness to Empirical Tests

In this section, I show that the large, substantive differences between markups estimated with different inputs demonstrated in Section 3 are robust to several additional specifications. First, in Appendix C.1, I show that these patterns hold estimating production functions through several different estimation approach compared to the ACF approach in the main text. Second, in Appendix C.2, I show similar patterns estimating production functions at the subindustry or product level. Third, in Appendix C.3, I show similar patterns estimating quantity as opposed to revenue production functions using data on Indian homogeneous products. Finally, in Appendix C.4, I argue that measurement error is unlikely to explain the patterns that I find.

C.1 Alternative Production Function Estimators

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

First, the auxiliary assumptions required for the control function approach, such as a Markov assumption on productivity together with timing assumptions on when the firm determines its level of inputs, may not hold. Second, Gandhi et al. (2020) show that the ACF procedure is

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not identified when applied to gross-output production functions.[1] Third, Flynn et al. (2019), Doraszelski and Jaumandreu (2019), and Bond et al. (2020) show how the ACF procedure can fail to identify production function parameters with non-competitive output markets when the dependent variable is revenue and not quantity produced. Fourth, Rovigatti and Mollisi (2018) find that ACF estimates are quite sensitive to the initial conditions used for optimization. Empirically, Foster et al. (2017) show that estimated output elasticities can vary substantially across different estimation approaches.

To examine whether such issues explain my findings, I examine three additional approaches to production function estimation. First, I use a dynamic panel approach to estimation following Blundell and Bond (2000). Second, Flynn et al. (2019) develop a new method to estimate production functions using a similar set of auxiliary assumptions as Ackerberg et al. (2015) together with constant returns to scale. I use this new method to estimate translog production functions.[2] Finally, I use the cost share approach assuming that productivity differences are neutral using industry-year cost shares, as in De Loecker et al. (2020). The cost share estimates allow the output elasticities of the industry-level production function to change over time, but do not allow non-neutral technological differences across establishments in the same year.

Using all three methods, the time trends using different inputs estimated using (5) are very different for all cases except for cost shares for Colombia. I depict these in Figure C.1 through Figure C.3. In addition, after controlling for time trends, I show in Table C.1 that the labor markup remains negatively correlated with the materials markup, with a decline in the labor markup with a 1% increase in the materials markup ranging from -0.20% to -1% using the dynamic panel approach, -0.17% to -7.05% using the Flynn et al. (2019) approach, and from -0.21% to -1% for the cost share approach.

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

C.2 Within Industry Heterogeneity

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

I first examine this concern by estimating production functions at the subindustry level. There are 60 such subindustries for Chile, 82 for Colombia, 260 for Indonesia, 19 for the US (at NAICS 3 digit level, i.e. similar to the baseline industry definition for the other datasets), and 292 for Southern Europe. For India, industry definitions vary over time; there are 764 subindustries in the

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

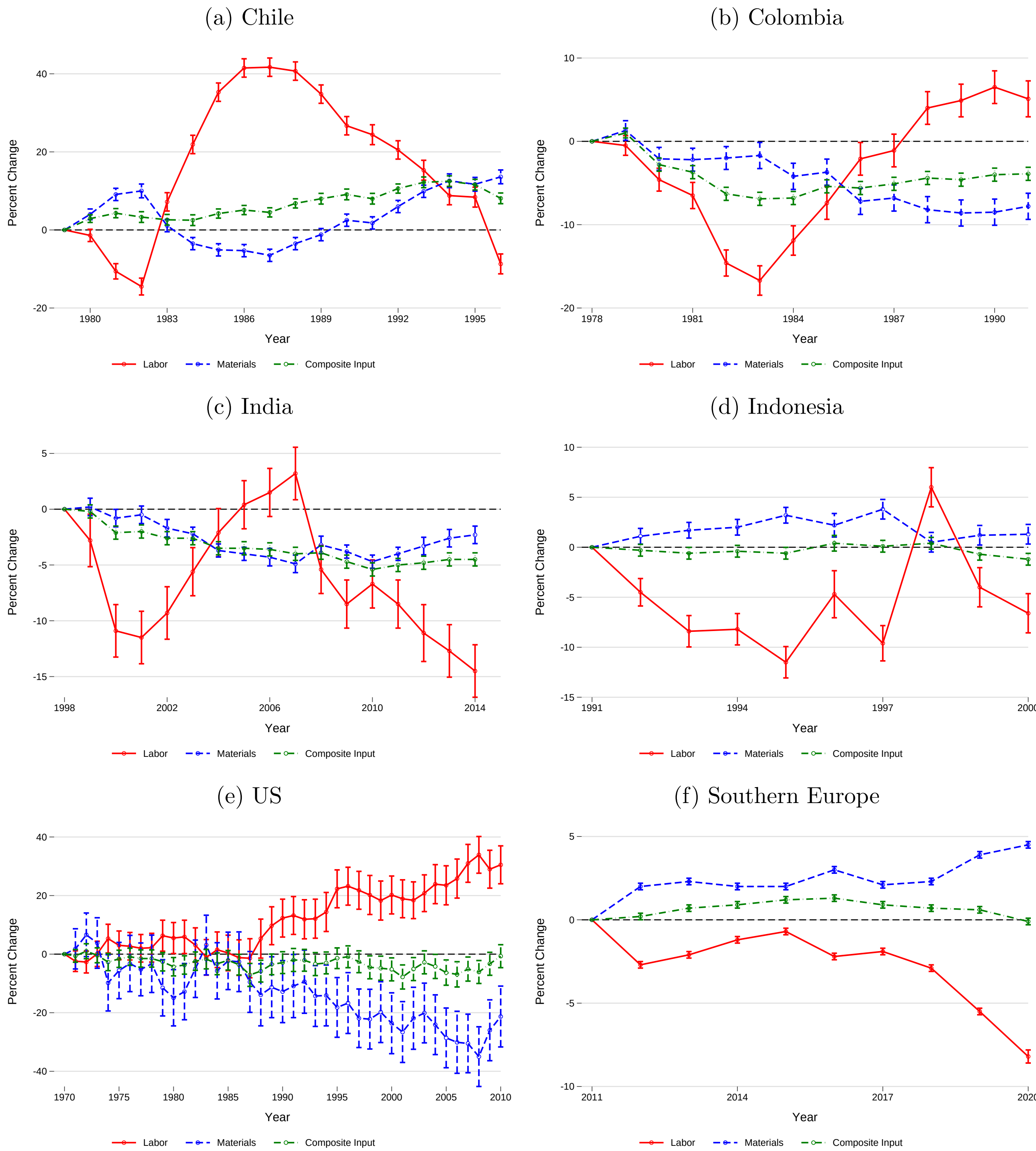
[2] This approach does not converge for one industry for Chile, Colombia, and Indonesia, and two industries for India for the labor and materials specification, as well as one industry for Indonesia, seven industries for India, and two industries for Southern Europe in the composite variable input specification.

Table C.1 Relationship between Markup Estimates: Alternative Estimators

Dataset	Dynamic Panel	FGT	CostShare Ind	CostShare SubInd
Chile	-0.25	-0.69	-0.24	-0.20
	(0.015)	(0.018)	(0.015)	(0.014)
Colombia	-0.65	-1.06	-0.65	-0.61
	(0.008)	(0.020)	(0.008)	(0.009)
India	-0.89	-0.17	-0.89	-0.66
	(0.008)	(0.007)	(0.008)	(0.008)
Indonesia	-0.70	-0.82	-0.51	0.02
	(0.011)	(0.020)	(0.010)	(0.016)
US	-0.20	-0.18	-0.21	-0.21
	(0.021)	(0.032)	(0.021)	(0.022)
S Europe	-0.55	-0.83	-0.55	-0.50
	(0.003)	(0.006)	(0.003)	(0.003)
Retailer	-1.00	-7.05	-1.00	-1.00
	(0.055)	(0.151)	(0.055)	(0.055)

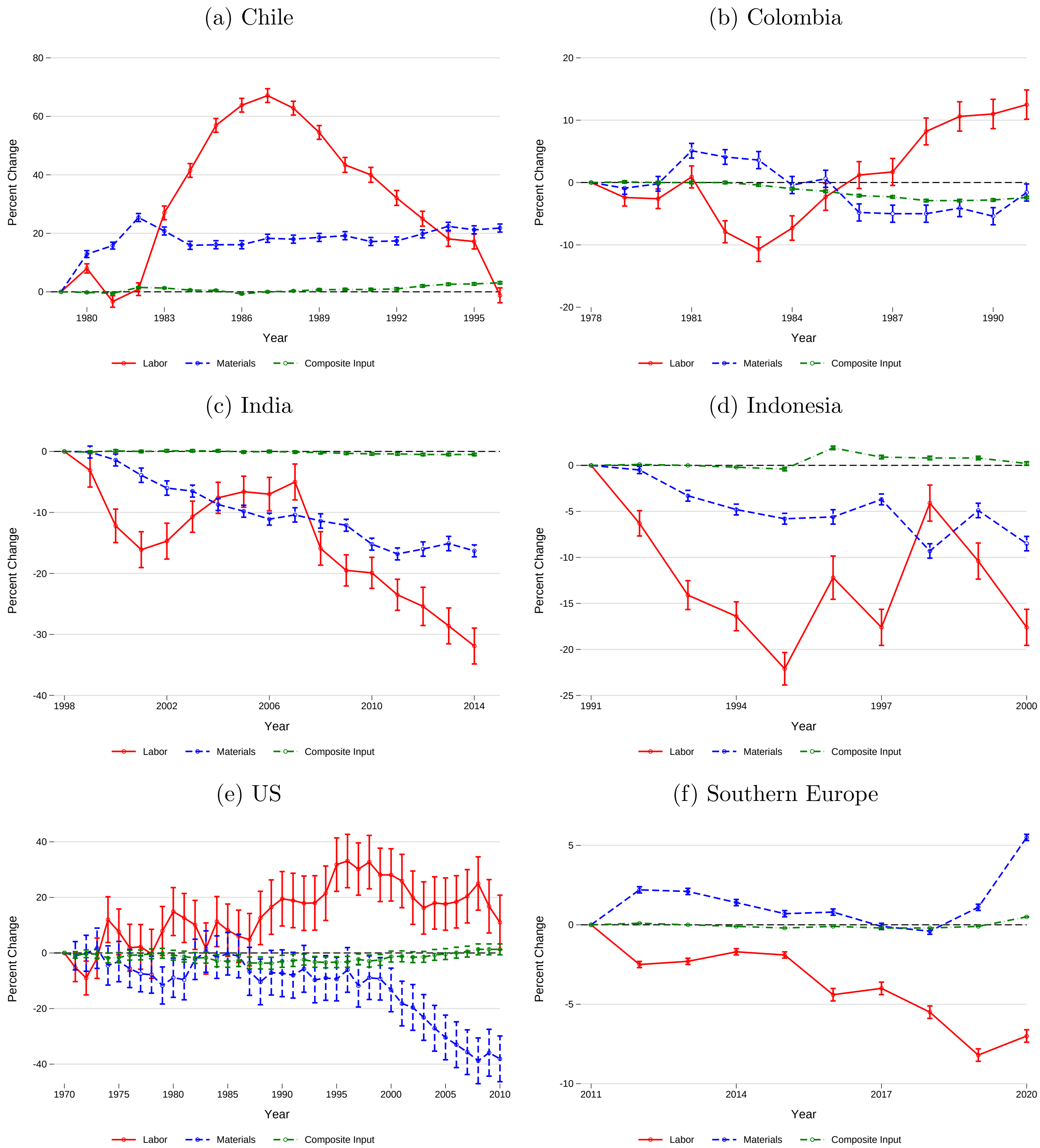
Note: Estimates based on (6) where the labor markup is the dependent variable and materials markup the independent variable. Columns labeled Dynamic Panel are markups based on Blundell and Bond (2000), and labeled FGT based on Flynn et al. (2019), as described in the text. Columns labeled CostShare Ind are markups based on industry-year level cost shares, and CostShare SubInd are markups based on subindustry-year level cost shares, as described in the text. Standard errors are clustered at the establishment level.

Figure C.1 Markup Time Trends using Dynamic Panel Estimates



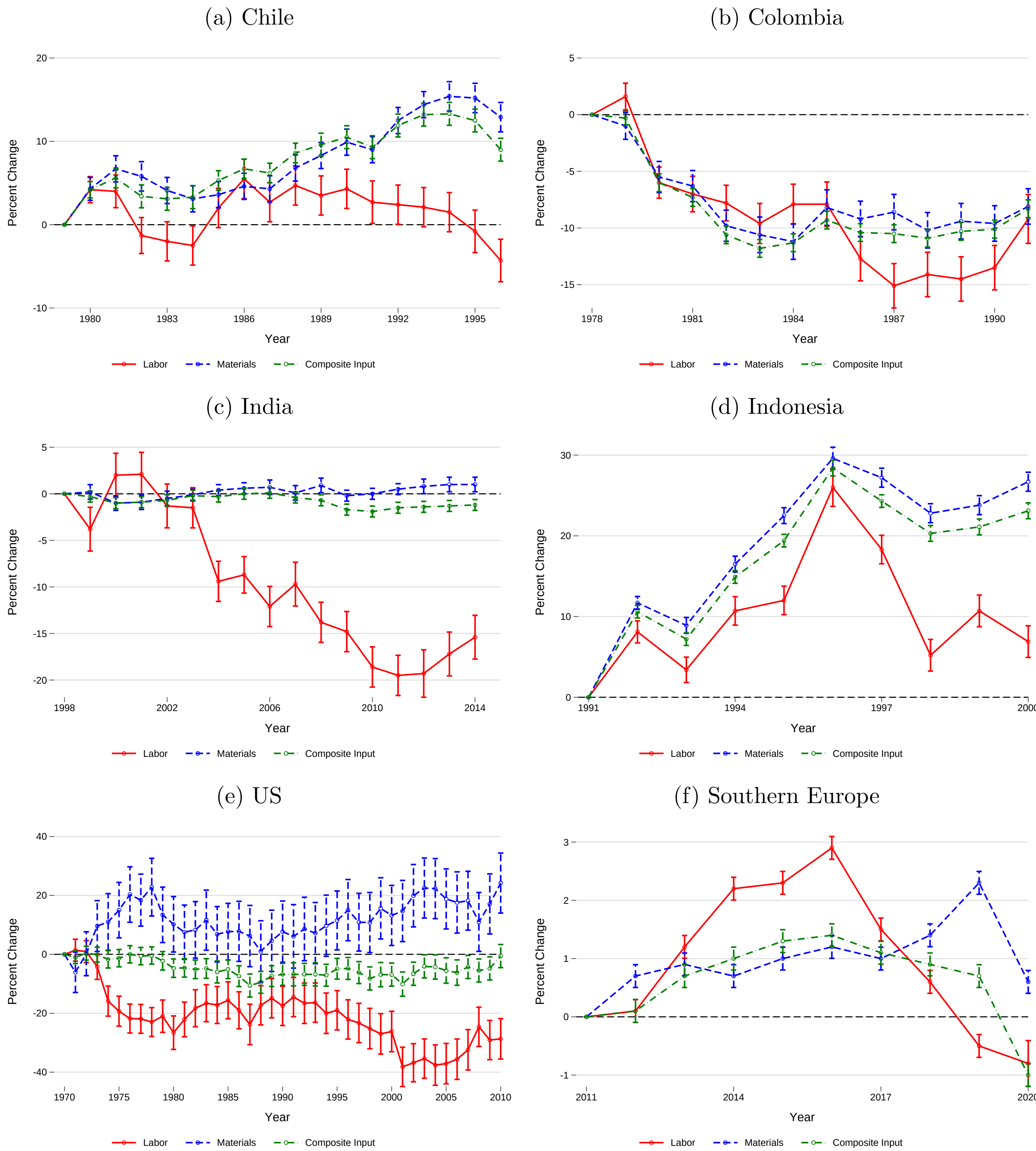
Note: Estimates based on (5), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure C.2 Markup Time Trends using Flynn, Gandhi, Traina Estimates



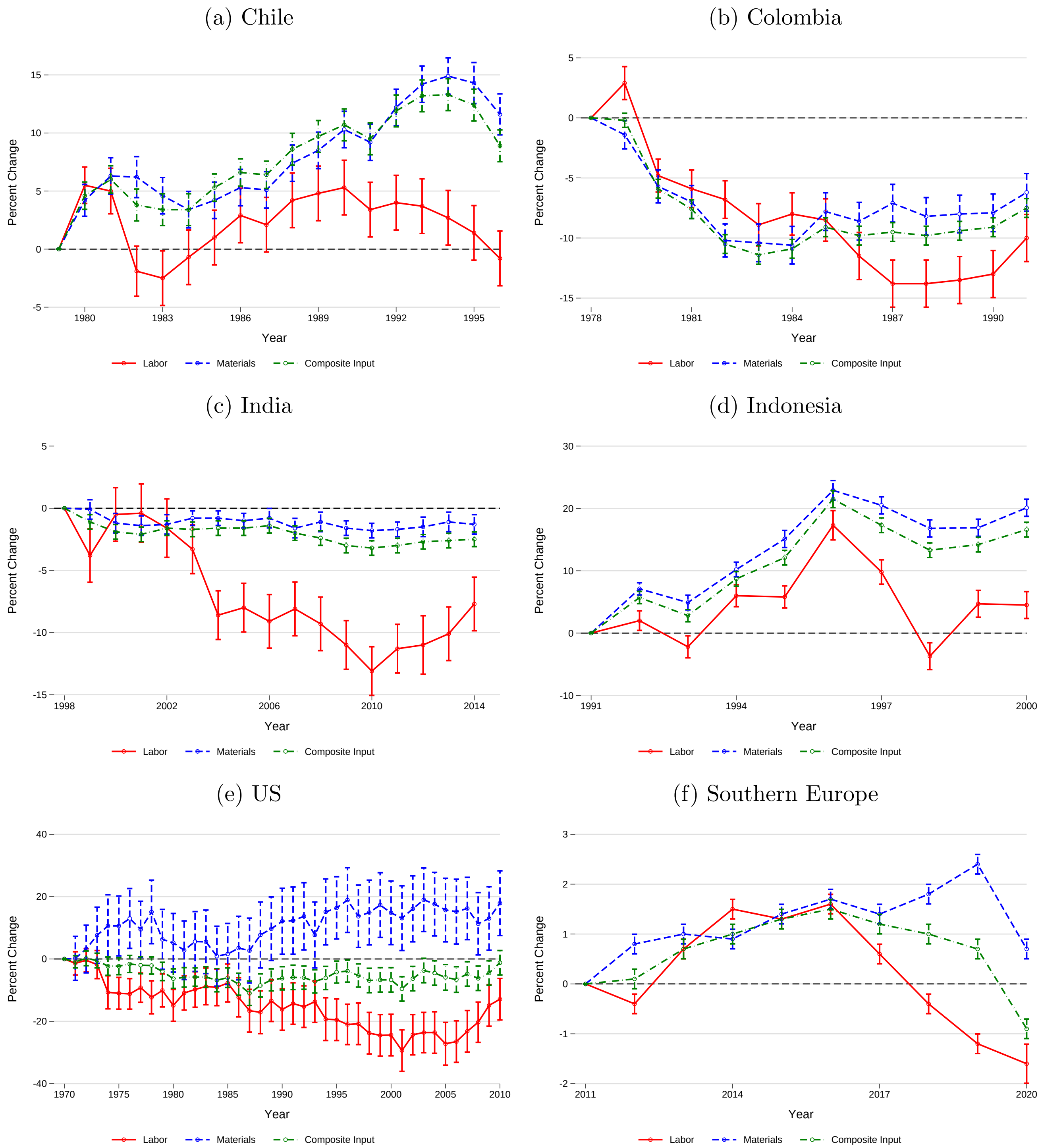
Note: Estimates based on (5), and include 95% Confidence Intervals (vertical bars) based on clustering at the establishment level. All estimates relative to the first year, which is set to zero.

Figure C.3 Markup Time Trends using Industry Cost Share Estimates



Note: Estimates based on (5), 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 C.4 Markup Time Trends using Subindustry Cost Share Estimates



Note: Estimates based on (5), 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.

period before 2004, 684 between 2004 and 2007, and 586 in the period after 2007.[3]

I estimate production functions at the subindustry level using subindustry-year cost shares. Time trends, reported in Figure C.4, continue to be very different across inputs. The magnitude of the negative cross-sectional correlation between the labor and materials markup is smaller at the subindustry level; the labor markup is uncorrelated with the materials markup for Indonesia, and is negatively correlated with the materials markup in the other datasets, with a 1% increase in the materials markup decreasing the labor markup by −0.20% to −1%. See the CostShare SubInd column of Table C.1.

For India, I also have access to product-level data and so can estimate product level production functions. I only include manufacturing plants that report only one product within a given year; in 2014, this dataset includes about 25,000 plants and 3,000 products. I then estimate production functions at the product-year level using product-year cost shares. The labor markup is negatively correlated with the materials markup, with a decline in the labor markup of −0.45% with a 1% increase in the materials markup using product-year cost shares, compared to −0.85% estimating production functions using industry-year cost shares on the same data.

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

C.3 Revenue Production Functions

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

I examine this issue by using data on ten Indian homogenous products for which I have the quantity produced and price of the good, in the spirit of Foster et al. (2008).[4] For these products, I estimate product-level quantity production functions using the control function estimator. I only include plants for which at least 75% of their revenue comes from one of these products. The labor markup and materials markup are negatively correlated for these products, with a decline in the labor markup of −0.42% and −0.83% with a 1% increase in the materials markup using Cobb-Douglas and translog production functions. Thus, problems with revenue as opposed To production functions alone cannot explain my findings.

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

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

C.4 Measurement Error

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

Measurement error may be more of an issue for smaller, less sophisticated plants compared to large plants. All of my baseline estimates do not weight by size. I examine sales and cost weights, as in De Loecker et al. (2020) and Edmond et al. (2018) in Appendix E.4, and find qualitatively similar findings to the unweighted results.

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

D Markup Stylized Facts

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

$$\log(\mu_{it}^{X}) = \alpha + \beta Z_{it} + \gamma_t + \delta_n + \epsilon_{it} \tag{D.1}$$

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

Estimates of all of the stylized facts vary in sign and magnitude across inputs and datasets using both the Cobb-Douglas and translog control function estimators, and often conflict with predictions from theory.

D.1 Size

Multiple theories of variable markups (Atkeson and Burstein, 2008; Melitz and Ottaviano, 2008) predict markups increasing in firm size. I examine this prediction by estimating (D.1) regressing markups on the logarithm of deflated sales, and report these estimates in Table D.1. With the Cobb-Douglas estimates, markups estimated using labor are substantially higher for bigger firms, while markups estimated using materials are negatively correlated with firm size in all datasets. Using the translog estimates, this correlation is negative for materials for six of seven datasets and negative for labor for four datasets.

Table D.1 Markups and Sales

Dataset	Labor Cobb-Douglas	Labor Translog	Materials Cobb-Douglas	Materials Translog	Composite Input Cobb-Douglas	Composite Input Translog
Chile	0.12	-0.03	-0.02	-0.00	0.01	0.00
	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Colombia	0.16	-0.01	-0.07	-0.00	0.00	0.01
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
India	0.21	0.05	-0.02	-0.00	0.01	0.01
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	0.20	0.04	-0.06	-0.03	0.01	0.01
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
US	0.05	-0.01	-0.01	0.06	0.06	0.05
	(0.007)	(0.009)	(0.008)	(0.007)	(0.002)	(0.003)
S Europe	0.13	-0.03	-0.13	-0.05	-0.01	-0.01
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Retailer	0.31	0.09	-0.01	-0.02	0.03	-0.04
	(0.004)	(0.008)	(0.000)	(0.001)	(0.000)	(0.001)

Note: Estimates are based on (D.1) where the independent variable is deflated sales. Standard errors are clustered at the establishment level.

D.2 Exporting

Atkeson and Burstein (2008) and Melitz and Ottaviano (2008) also predict that exporters, being more productive than the typical firm, will have larger markups; De Loecker and Warzynski (2012) focused on this question. I examine this question using an indicator variable for whether the establishment exports using the manufacturing census datasets.[5] Table D.2 contains these estimates. The correlation of markups estimated using the Cobb-Douglas estimator with exporting are positive for Chile, Colombia, and Indonesia using labor and for Colombia and Indonesia using materials. Using the translog estimates, this correlation is negative for labor for two of the four datasets, and positive albeit with a small magnitude for materials in all of the datasets.

D.3 Profit Share Markups

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

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

Table D.2 Markups and Exporting

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

Note: Estimates are based on (D.1) where the independent variable is an indicator for whether the establishment exports. Standard errors are clustered at the establishment level.

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

I then regress the log production based markup on the log profit share based markup using (D.1). I report these estimates in Table D.3. Using the Cobb-Douglas estimates, this correlation is negative for materials for three of eight datasets and negative for labor for four of eight datasets. Using the translog estimates, this correlation is negative for materials for three of eight datasets and negative for labor for seven of eight datasets.

D.4 Competition

One explanation for high markups is less competition. I examine how markups correlate with competition for the retailer using its own classification of the degree of competition. The retailer classifies each store as facing either Low, Medium, or High competition, and records the number of competitors for each store. I examine the competition band in this section in Table D.4, and a discretized number of competitors in Table D.5.

With the Cobb-Douglas estimates, labor markups are slightly lower with mroe competition, and materials markups are slightly higher. With the translog estimates, labor markups are substantially (9%) lower on average with competition, while materials markups rise slightly.

Here, theory is not as clear cut. On the one hand, we might expect from canonical models of competition that markups would decline with competition. On the other hand, uniform or near-uniform pricing by many large retailers (DellaVigna and Gentzkow, 2017) might lead to the same

Table D.3 Production Markup Estimates and Profit Based Markup

	Labor		Materials		Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
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)
US	-0.01	-0.27	0.77	0.72	0.33	0.31
	(0.040)	(0.042)	(0.055)	(0.040)	(0.018)	(0.019)
S Europe	-0.41	-0.24	0.12	0.04	0.00	0.00
	(0.007)	(0.005)	(0.006)	(0.002)	(0.001)	(0.001)
Retailer	1.81	-0.09	-0.08	-0.01	0.15	-0.17
	(0.027)	(0.041)	(0.003)	(0.003)	(0.003)	(0.003)
Retailer (EBIT)	2.00	0.85	-0.09	-0.09	0.16	-0.16
	(0.028)	(0.045)	(0.003)	(0.004)	(0.003)	(0.003)

Note: Estimates are based on (D.1) where the independent variable is the profit share based markup. 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.

markups across stores facing different competition, and the retailer's own data shows that it uses only a small number of pricing zones.

Table D.4 Markups and Competition

	Labor		Materials		Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Medium	-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	-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 (D.1) where the independent variable is the company-derived measure of competition; all estimates are relative to a retail store facing Low Competition. Standard errors are clustered at the establishment level.

Table D.5 Markup and Number of Competitors

	Labor		Materials		Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
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 (D.1) and are relative to a retail store with 0-1 competitors. Standard errors are clustered at the establishment level.

E Additional Empirical Results

E.1 Trends over Time

In Figure E.1, I depict aggregate markup trends based on labor, materials, or the combined input of both as flexible inputs estimated using Cobb-Douglas production functions. In Figure E.2, I depict aggregate markup trends based on labor, raw materials, or energy as flexible inputs estimated using Cobb-Douglas production functions.

E.2 Markup Dispersion

In Table E.1 and Table E.2, I report the 75/25 ratio and 90/10 ratio of markup estimates.

Table E.1 75/25 Ratio of Markup Estimates

	Labor		Materials		Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Chile	2.68	2.06	1.41	1.32	1.16	1.15
	(0.009)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
Colombia	2.69	1.87	1.63	1.24	1.14	1.14
	(0.013)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)
India	4.25	3.16	1.32	1.25	1.13	1.12
	(0.011)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)
Indonesia	3.82	2.65	1.55	1.37	1.12	1.13
	(0.022)	(0.010)	(0.002)	(0.002)	(0.000)	(0.000)
US	2.45	4.04	3.81	1.93	1.29	1.54
	(0.018)	(0.051)	(0.436)	(0.014)	(0.003)	(0.008)
S Europe	2.37	1.74	1.65	1.23	1.10	1.10
	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Retailer	1.28	1.35	1.03	1.03	1.02	1.03
	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)

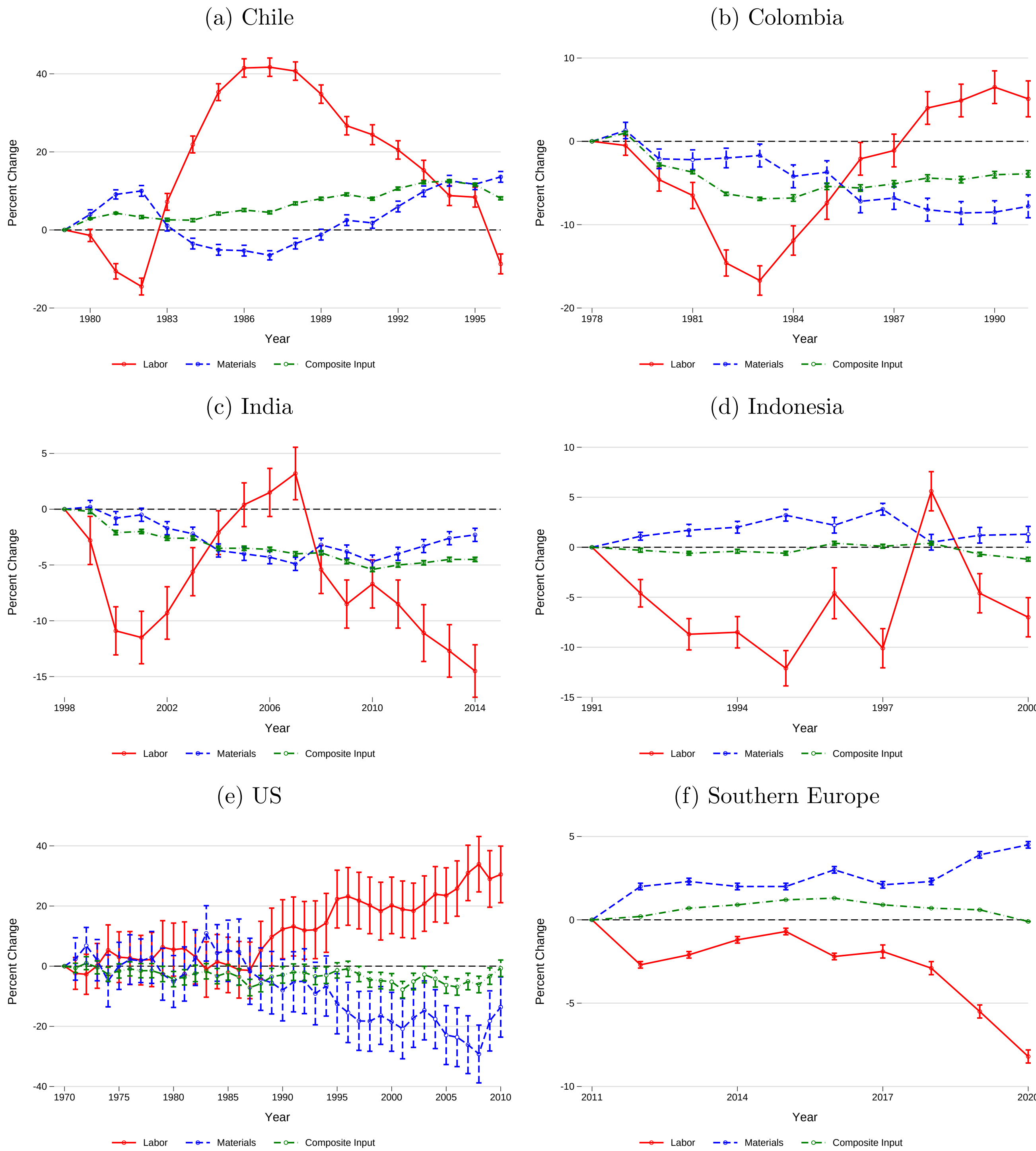
Note: Estimates use all establishments and years. Standard errors are based on 20 bootstrap simulations. For India, these estimates ignore the sample weights.

E.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 E.3. The average labor markup is 9% higher than the average materials markup for Chile, 18% higher for Colombia, 98% higher for India, 72% higher for Indonesia, 137% higher for the US, 19% higher for Southern Europe, and 106% higher for the retailer under the Cobb-Douglas estimates. Under the translog estimates, the average labor markup is 50% higher than the average materials markup for Chile, 5% lower for Colombia, 46% higher for India, 69% higher for Indonesia, 124% higher for the US, 1% lower for Southern Europe, and 5% lower

Figure E.1 Markup Time Trends using Cobb-Douglas Estimates



Note: Estimates based on (5), 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.

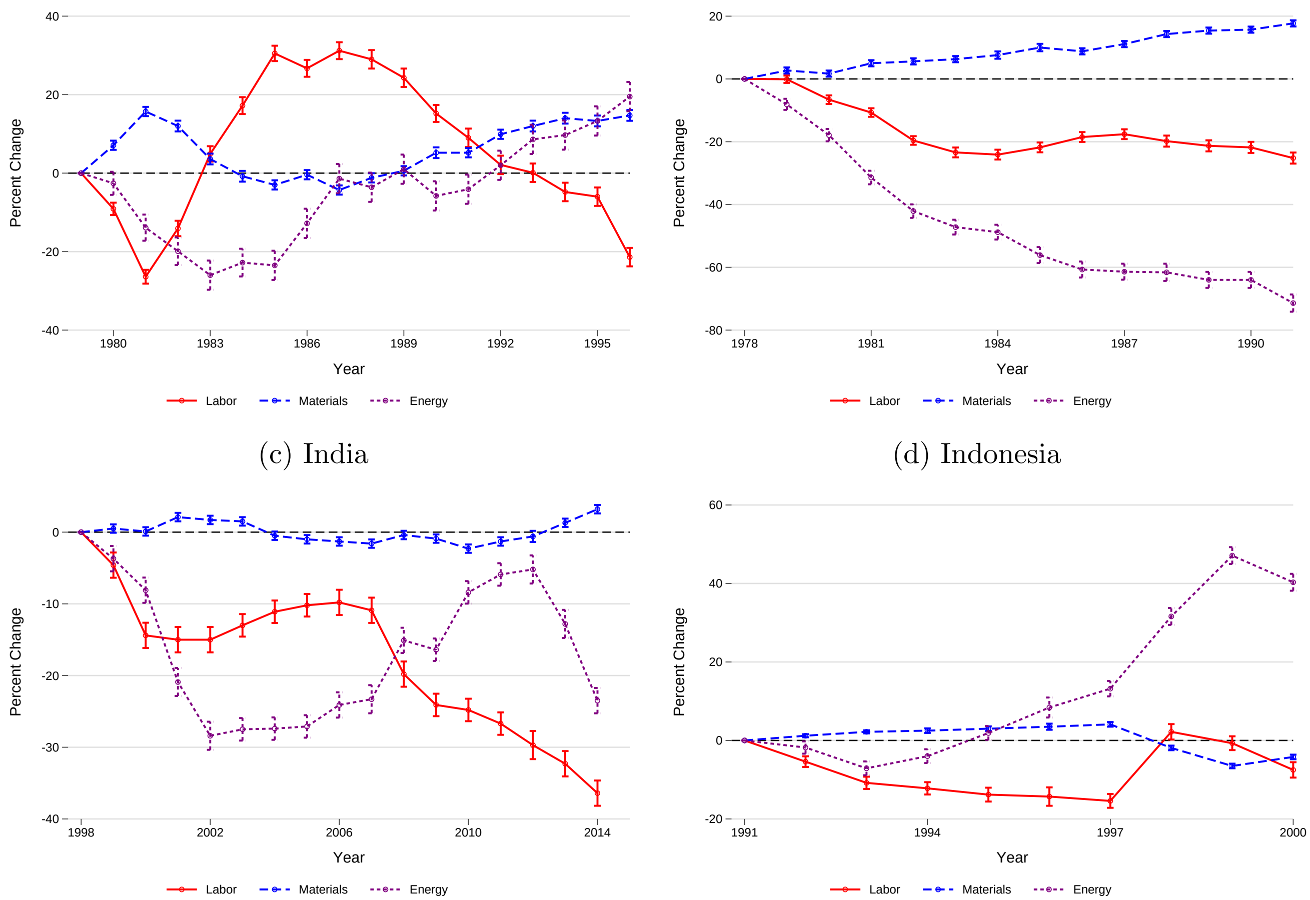
Figure E.2 Markup Time Trends using Cobb-Douglas Estimates, with Energy

(a) Chile

(b) Colombia

(c) India

(d) Indonesia



Note: Estimates based on (5), 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 E.2 90/10 Ratio of Markup Estimates

	Labor		Materials		Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Chile	6.25	4.04	2.08	1.81	1.33	1.31
	(0.032)	(0.020)	(0.004)	(0.006)	(0.002)	(0.001)
Colombia	7.87	7.43	2.71	1.68	1.31	1.30
	(0.076)	(0.304)	(0.010)	(0.006)	(0.001)	(0.001)
India	15.81	10.08	1.75	1.58	1.27	1.27
	(0.063)	(0.044)	(0.001)	(0.001)	(0.000)	(0.000)
Indonesia	17.05	8.16	2.34	1.97	1.25	1.28
	(0.142)	(0.061)	(0.005)	(0.004)	(0.001)	(0.001)
US	6.42	14.51	-15.82	4.84	1.62	2.66
	(0.093)	(0.201)	(0.354)	(0.067)	(0.006)	(0.013)
S Europe	5.45	3.13	2.75	1.49	1.22	1.21
	(0.011)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)
Retailer	1.59	1.76	1.05	1.06	1.04	1.05
	(0.004)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)

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

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

E.4 Weighted Estimates

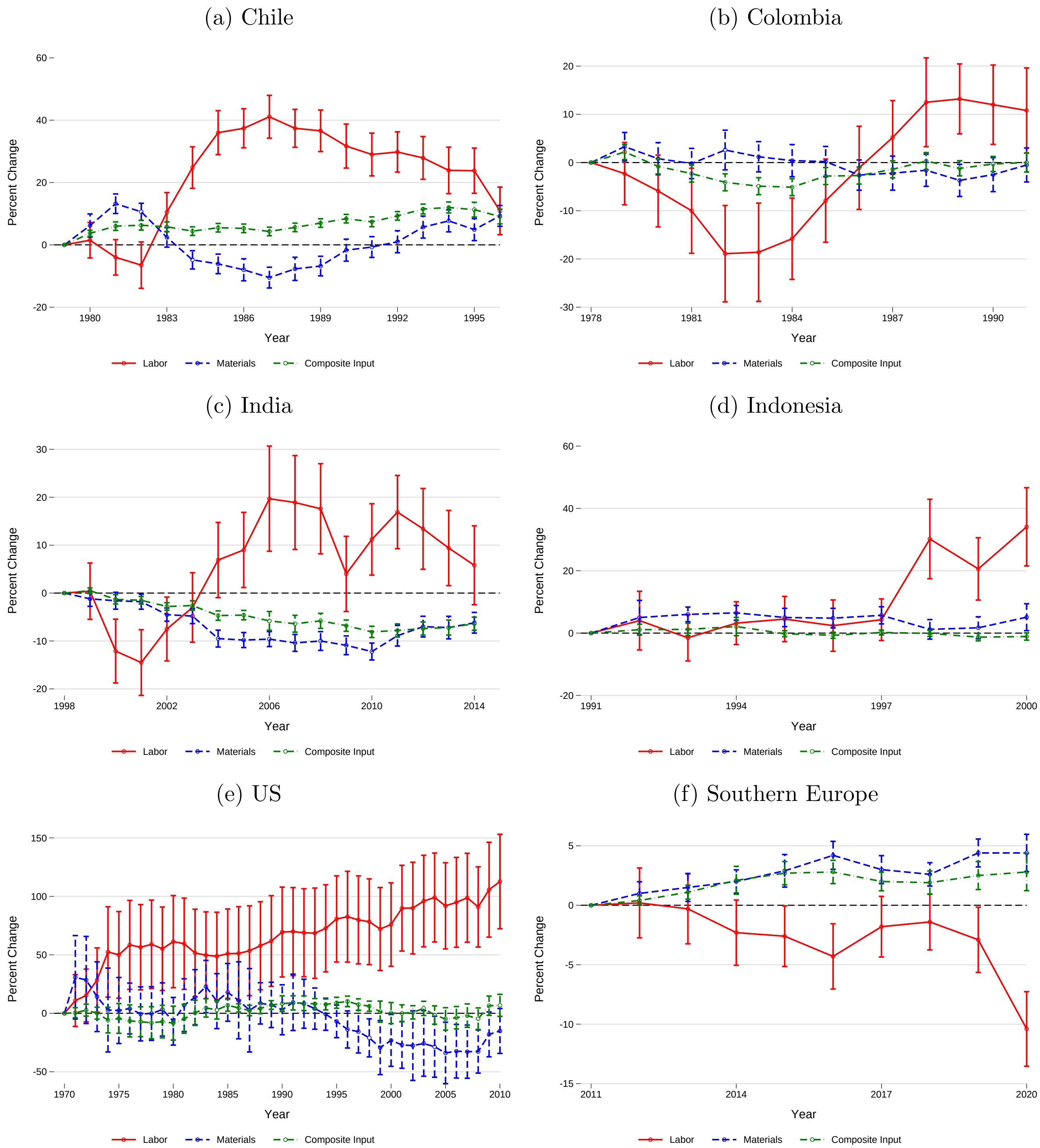
De Loecker et al. (2020) weight markups by sales, while Edmond et al. (2018) argue that cost weights are the right benchmark for welfare calculations. In this section, I weight all observations using sales weights (the plant's share of total sales in the year), or cost weights (the plant's share of total costs in the year). I then report the ratio of average markups, trends over time, and correlations between markups, using either labor, materials, or the combined variable input to compute markups. In some of the manufacturing datasets, a few plants have very large sales and cost shares (for example, petroleum refineries in India), so weighted estimates can differ from unweighted estimates substantially. Nevertheless, I continue to find negative correlations between labor markups and materials markups and different trends over time after weighting using sales or cost weights.

Table E.3 Ratio of Average Markup Estimates

	Labor/Materials		Labor/Composite Input		Materials/Composite Input	
Dataset	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Chile	1.09	1.50	1.30	1.63	1.19	1.09
	(0.012)	(0.012)	(0.012)	(0.012)	(0.003)	(0.002)
Colombia	1.18	0.95	1.53	1.02	1.30	1.08
	(0.016)	(0.015)	(0.016)	(0.013)	(0.010)	(0.005)
India	1.98	1.46	2.17	1.56	1.10	1.07
	(0.008)	(0.005)	(0.008)	(0.005)	(0.001)	(0.001)
Indonesia	1.72	1.69	2.00	1.89	1.17	1.11
	(0.018)	(0.019)	(0.019)	(0.021)	(0.003)	(0.002)
US	2.37	2.24	1.40	2.05	0.59	0.92
	(0.125)	(0.105)	(0.035)	(0.090)	(0.023)	(0.034)
S Europe	1.19	0.99	1.56	1.08	1.31	1.09
	(0.006)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)
Retailer	2.06	0.95	1.32	0.95	0.64	1.00
	(0.004)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)

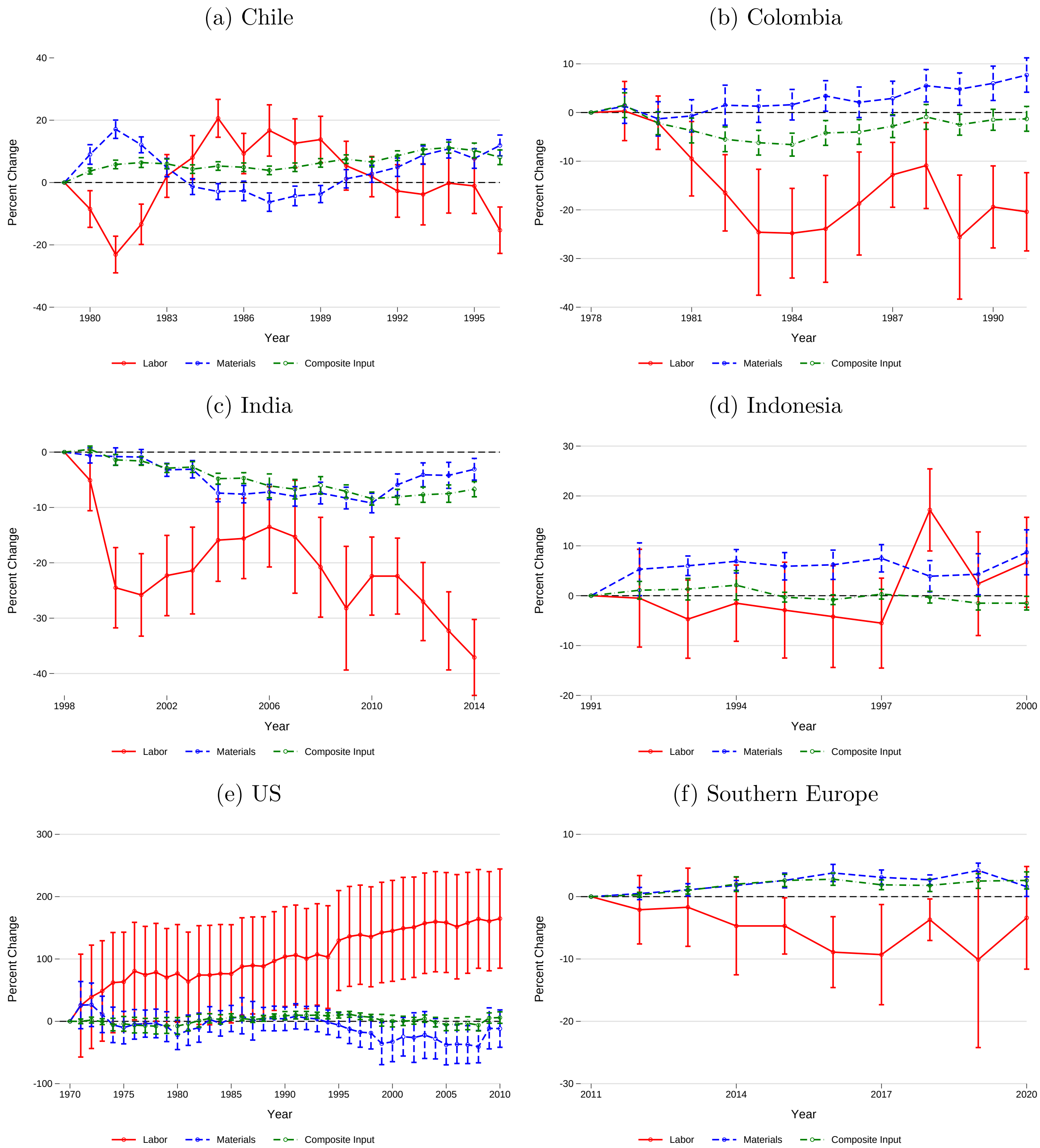
Note: Estimates are the ratio of the average markup between two flexible inputs across all establishments and years, so Labor/Materials indicates the ratio of the average labor markup to average materials markup. Standard errors are clustered at the establishment level.

Figure E.3 Markup Time Trends using Cobb-Douglas Estimates, Sales Weighted



Note: Estimates based on (5), 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 E.4 Markup Time Trends using Translog Estimates, Sales Weighted



Note: Estimates based on (5), 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 E.4 Relationship between Markup Estimates: Sales Weighted

Dataset	Cobb-Douglas	Translog
Chile	-0.83	-0.30
	(0.060)	(0.076)
Colombia	-1.37	-0.09
	(0.087)	(0.199)
India	-1.89	-0.73
	(0.127)	(0.117)
Indonesia	-0.65	-0.30
	(0.094)	(0.111)
US	-0.21	-0.61
	(0.070)	(0.060)
S Europe	-1.47	-0.20
	(0.036)	(0.116)
Retailer	-7.06	-9.70
	(0.152)	(0.121)

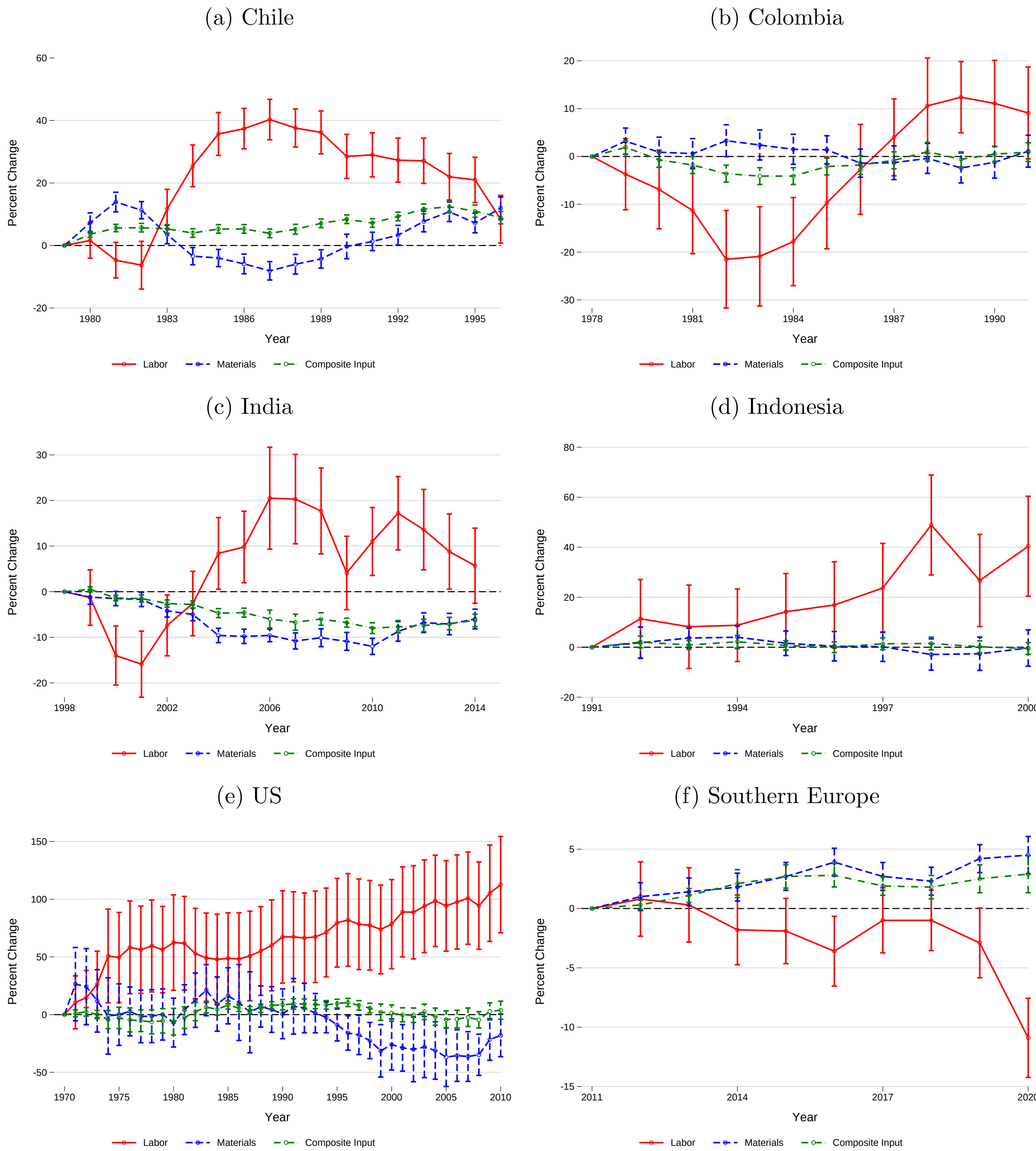
Note: Estimates based on (6) where the labor markup is the dependent variable and materials markup the independent variable. Standard errors are clustered at the establishment level. Estimates weighted with sales weights.

Table E.5 Relationship between Markup Estimates: Cost Weighted

Dataset	Cobb-Douglas	Translog
Chile	-0.83	-0.29
	(0.059)	(0.069)
Colombia	-1.42	-0.08
	(0.068)	(0.161)
India	-1.98	-0.77
	(0.120)	(0.112)
Indonesia	-0.86	-0.46
	(0.116)	(0.126)
US	-0.23	-0.64
	(0.074)	(0.062)
S Europe	-1.53	-0.18
	(0.038)	(0.131)
Retailer	-7.07	-9.71
	(0.155)	(0.119)

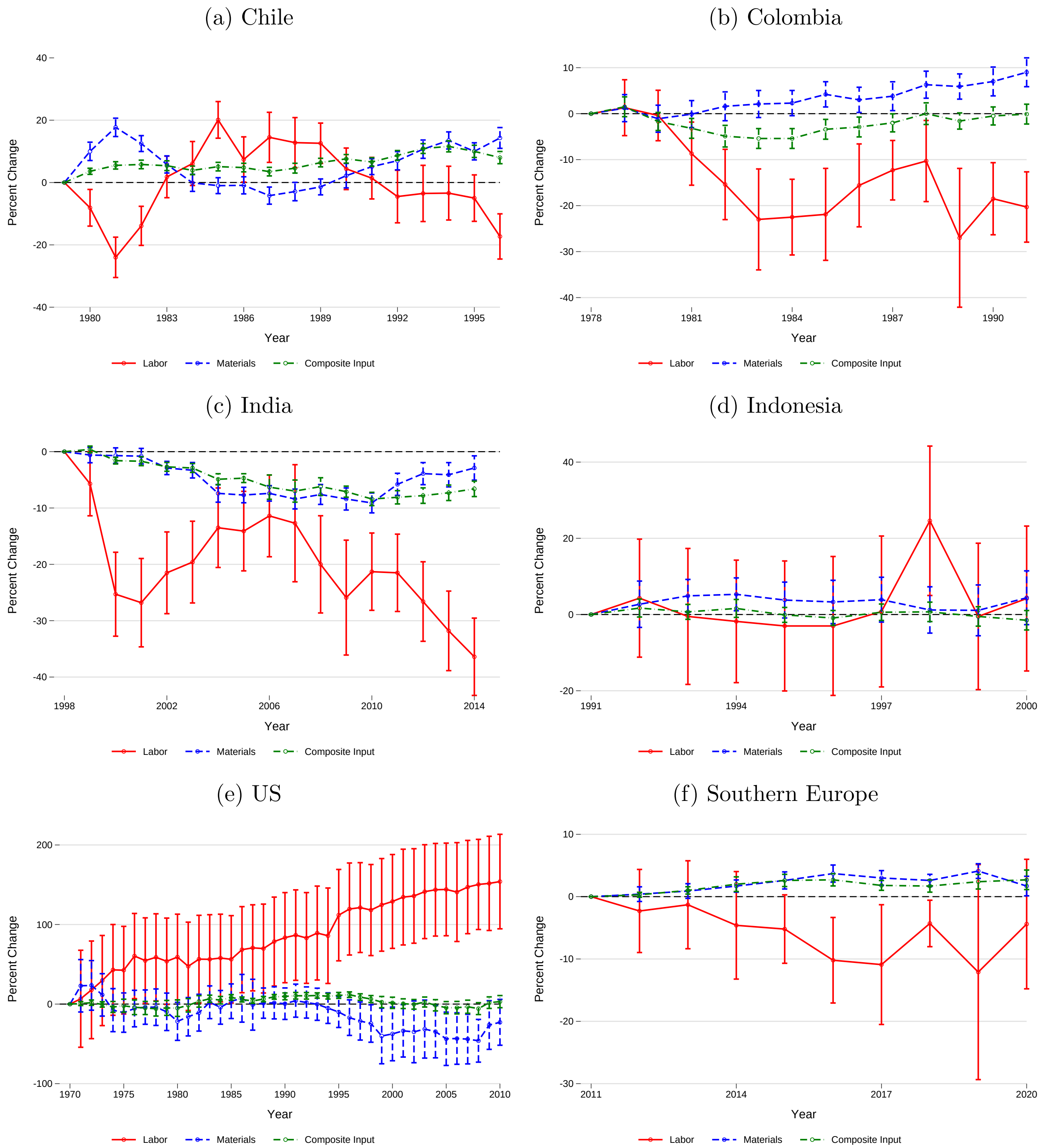
Note: Estimates based on (6) where the labor markup is the dependent variable and materials markup the independent variable. Standard errors are clustered at the establishment level. Estimates weighted with cost weights.

Figure E.5 Markup Time Trends using Cobb-Douglas Estimates, Cost Weighted



Note: Estimates based on (5), 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 E.6 Markup Time Trends using Translog Estimates, Cost Weighted



Note: Estimates based on (5), 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.

F Monte Carlo

Through a Monte Carlo exercise, I show that labor augmenting productivity differences can cause a negative correlation between markups estimated using labor and materials as flexible inputs.

I simulate an economy in which markups and labor augmenting productivity differences vary across plants. In this economy, 1000 cost minimizing plants produce for 10 years. All plants have a common CES production function, as in (8), with substitution elasticity 0.5. The logarithm of neutral productivity A and labor augmenting productivity B evolve over time through an autoregressive process with a productivity persistence parameter of 0.9 and jointly normal shocks. Productivity is thus distributed as a joint lognormal. I then calibrate the parameters of this lognormal to match moments from data on factor shares and productivity from US manufacturing plants.[6]

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

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

$$\log(\mu_{it}^{L}) = \alpha + \beta \log(\mu_{it}^{M}) + \epsilon_{it} \tag{F.1}$$

$$\log(\mu_{it}^{True}) = \alpha + \beta \log(\mu_{it}^{X}) + \epsilon_{it}. \tag{F.2}$$

First, I compare the labor markup to the materials markup using (F.1). Second, I examine how the true markup based on the demand elasticity the plant faces is correlated with different production based markups for input X using (F.2). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table F.1, I report the average of β across 200 Monte Carlo simulations, with standard deviations across simulations in parentheses. I examine Cobb Douglas and translog control function estimators, for which B is assumed not to vary across plants.[7]

As I found in Section 3, labor markups are negatively correlated with materials markups. A 1% increase in the materials markup decreases the labor markup on average by 1.15% using the

[6] I initialize productivities in their first year to the stationary distribution given the persistence process. I normalize the mean of the stationary distribution of $\log A$ to 1, and calibrate the mean of the stationary distribution of $\log B$ and the variances and covariance of $\log A$ and $\log B$ through moment-matching. I match the following six moments: an aggregate capital share of capital and labor cost of 0.3, a value of the weighted variance of capital shares of capital and labor of 0.1, and the aggregate materials share of total cost of 0.55 (all from Oberfield and Raval (2021)) the 90-10 ratio of marginal cost across plants to 2.7 (from Syverson (2004)), the coefficient of a regression of the capital cost to labor cost ratio on the log of the plant's total cost of capital and labor (weighting by the plant's total cost of capital and labor) of 0.08 from Raval (2019), and a log of total industry cost of $\log(10,000)$ (to keep the same size industry across simulations). Distribution parameters are 0.1 for capital, 0.3 for labor, and 0.6 for materials.

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

Cobb-Douglas control function estimator and 0.08% using the translog control function estimator.

In addition, both labor and materials markups are only slightly correlated with the true markup using the control function estimators; on average, the true markup is only 0.12% higher using the Cobb-Douglas estimator, or 0.05% higher using the translog estimator, after a 1% increase in the labor markup. The true markup is 0.36% higher using the Cobb-Douglas estimator, or 0.03% lower using the translog estimator, after a 1% increase in the materials markup.

Table F.1 Relationship between Markup Estimates: Monte Carlo Estimates

Estimator	Labor on Materials	True Markup on Labor	True Markup on Materials	True Markup on Composite Input
Cobb-Douglas CF	-1.15	0.12	0.36	0.79
	(0.97)	(0.16)	(0.33)	(0.23)
Translog CF	-0.08	0.05	-0.03	0.27
	(0.33)	(0.10)	(0.02)	(0.21)

Note: Estimates based on 200 Monte Carlo simulations, using (F.1) and (F.2). For example, True Markup on Materials indicates a regression where the true markup is the dependent variable and materials markup the independent variable. True markup is the actual markup set by the firm based on its demand elasticity in the Monte Carlo simulations. Markup estimates are based on ACF control function estimators.

In all specifications, the composite input markup is more highly correlated with the true markup than labor or materials, as might be expected as the composite input combines two negatively correlated inputs. However, a 1% increase in the composite input markup increases the true markup by only 0.79% using the Cobb-Douglas estimates, and 0.27% using the translog estimates.

G Data Notes

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

G.1 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.

The fifth dataset is Compustat, which comprises US public firms. I restrict the data to include only firms reporting a NAICS code for manufacturing between 1970 and 2010. This data contains about 500 firms per year, increasing from about 200 per year at the beginning of the sample to 1,000 per year at the end of the sample.

The sixth dataset is the ORBIS data from Bureau Van Dijk for manufacturing firms, defined as NACE Rev. 2 industry codes between 10 and 33, located in Italy, Spain, or Portugal ("Southern Europe"). The ORBIS data includes both public and private firms. Because my access to this data only includes firms active when I accessed the data, and up to 10 years of records for each firm, I only include the balanced panel of firms present in all years from 2011 to 2020. After data cleaning, this data contains about 100,000 firms per year, with about 30,000 firms per year in Spain, 54,000 firms per year in Italy, and 13,000 firms per year in Portugal.

I then compare total turnover and employment in this balanced panel to total turnover and employment for the manufacturing sector available from Eurostat. In 2019, the balanced panel comprises 67% of turnover and 56% of employment for Spain, 69% of turnover and 62% of employment for Italy, and 78% of turnover and 65% of employment for Portugal.[8]

The seventh dataset is store-level data from a major US nation-wide retailer for three years, comprising thousands of stores across the United States.

G.2 Capital

Capital costs are the most involved variable to construct. For each dataset, a capital stock is constructed for each type of capital available. 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.

For all datasets except the US, 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

[8]Unlike the balanced panel, the unbalanced panel comprises a much lower share of turnover and employment at the beginning of the sample compared to the end of the sample. In 2011, the balanced panel comprises 65% of turnover and 51% of employment for Spain, 61% of turnover and 54% of employment for Italy, and 75% of turnover and 58% of employment for Portugal. The unbalanced panel is 93% of turnover and 89% of employment for Spain, 95% of turnover and 94% of employment for Italy, and 101% of turnover and 89% of employment for Portugal in 2019, and 78% of turnover and 69% of employment for Spain, 70% of turnover and 62% of employment for Italy, and 91% of turnover and 75% of employment for Portugal in 2011.

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.[9]

For depreciation rates, I match the depreciation rates calculated for US industries to the equivalent industries in each country for structures and equipment. For transportation, I set the depreciation rate to 0.19.[10]

For the US, I use rental rates developed in Oberfield and Raval (2021) at the 3 digit NAICS level based on an external real rate of 3.5%, which account for the tax treatment of investment. Because these rental rates are separate for structures and equipment, I aggregate them using an average of the current and lag share of equipment in total capital for the industry from the NBER Productivity Database.

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 Colombia, India, and Indonesia, 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.[11]

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.[12] I drop observations with zero or negative capital services for equipment or for total capital.

For the US, I have data on the aggregate net book value of plant, property, and equipment and

[9] For Chile and Colombia, the real interest rate series starts in 1985 and 1986, respectively, so I use interest rates starting from these dates. For Southern Europe, the World Development Indicators only include the real interest rate for Italy, so I use the averaged Italian rate for Spain and Portugal as well.

[10] 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%. For the US and Southern Europe, I construct an average depreciation rate at the 3 digit NAICS level aggregating depreciation rates of structures and equipment using an average of the current and lag share of equipment in total capital from the NBER Productivity Database. I match by year for the US and use the 2010 depreciation rates for Southern Europe.

[11] 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.

[12] 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.

yearly capital expenditures, but neither capital nor investment measures are broken out by type of asset. I first convert historical cost tangible fixed assets to current cost fixed assets using BEA historical cost to current cost deflators at the 3 digit NAICS level. I then construct a perpetual inventory measure of capital starting with the first year reporting a positive value of the book value of capital.

For Southern Europe, only the book value of tangible fixed assets is available, so I use the book value as the measure of 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, Indonesia, the US, and Southern Europe, I use a general capital deflator: at the 4 digit ISIC level for Indonesia, at the aggregate level for India, at the 3 digit NAICS level for the US (aggregated via a Tornqvist index with investment weights from 4 digit NAICS deflators available from the NBER productivity database), and at the 2 digit NACE level for Southern Europe.[13]

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

Nominal capital services are then the sum of the real capital stock of each asset type multiplied by the appropriate deflator and capital rental rate, plus rent. Real capital services are the sum of the real capital stock of each asset type multiplied by the appropriate capital rental rate, plus deflated rent.[14]

G.3 Labor

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

For labor costs, I use the sum of total salaries and benefits for all of the datasets except the US. For the US, data on wages are only available for about 10% of the sample. I thus follow Keller and Yeaple (2009) and Demirer (2020) and set labor costs as the number of employees multiplied by an average wage for the 3 digit NAICS industry. I measure the average wage from the NBER productivity database as payroll divided by employment aggregated to the 3 digit NAICS

[13]For Southern Europe, I obtain capital deflators from Eurostat. These deflators are at the country level with separate deflators for Spain, Portugal, and Italy. For Spain, these deflators are at the manufacturing level only, while for Italy, some NACE industries are combined. In particular, industries 16 through 18, 22 through 23, 24 through 25, 29 through 30, and 31 through 33 are combined for Italy.

[14]For Chile, rent is not differentiated by capital type, so I deflate using the structures deflator. Colombia differentiates between structures rent and machinery rent, India between land rent, building rent, and machinery rent (I use net rents for all three), and Indonesia between land rent and structures/machinery rent. For the US, rent is not differentiated by capital type, so I deflate using the overall investment deflator. For Southern Europe, data on rental payments are not available. For the retailer, I deflate rent using the structures deflator, as most capital is structures.

level, based upon a Tornqvist index with payroll based weights across 6 digit NAICS industries. Because the payroll data in the NBER Productivity database does not include benefits, I multiply this average wage by the ratio of compensation to wages and salaries at the 3 digit NAICS level available from the BEA.[15]

G.4 Energy and Materials

I can separate energy costs from raw materials for the four manufacturing censuses. 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.

Unlike all other datasets, for the US I do not have materials costs as a separate data field. Thus, I follow Keller and Yeaple (2009) and Demirer (2020) and define materials costs as cost of goods sold plus selling, general, and administrative expenses minus depreciation and minus labor costs as defined above. I deflate these materials costs using 3 digit NAICS level materials deflators aggregated via a Tornqvist index with materials cost weights from the NBER Productivity database.

[15] For earlier years when only SIC data is available, I match SIC 2 digit industries to the equivalent NAICS 3 digit industries, and adjust for the industry difference using the average difference in ratio for 1998-2000 when both SIC and NAICS level data are available.

For Southern Europe, I use materials costs for materials. I deflate materials by creating materials deflators at the NACE 2 digit level; these are a harmonic index of output deflators from Eurostat for the Euro 19 area at the NACE 2 digit level, with weights as shares from the 2015 product by product input-output table.

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

G.5 Sales

For the manufacturing censuses, 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 US, I use total sales and deflate using 3 digit NAICS level output deflators from the NBER Productivity database, aggregated via a Tornqvist index with sales weights. For Southern Europe, I use total sales and deflate using output deflators at the 4 digit NACE level (3 digit or 2 digit NACE if 4 digit deflator not available) for the Euro 19 area from Eurostat. For the retailer, I deflate total sales using PPI deflators for the relevant goods.

G.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.

For the US, I only include firms incorporated in the US. Because firms vary in the end of their fiscal year, I set the year to be the current year for statements ending after May 31st and to the previous year otherwise. I remove firms with missing or non-positive values of sales, employment, cost of goods sold, selling, general, and administrative expenses, and depreciation. I also remove firms with missing capital expenditures and with less than 10 employees.

For Southern Europe, I only include firms incorporated in the relevant country (i.e. Italy for Italy, etc.). Because firms vary in the end of their fiscal year, I set the year to be the current year for statements ending after May 31st and to the previous year otherwise. I remove observations missing a BVD ID or year, as well as duplicate observations with the same BVD ID and year. I remove firms with missing or non-positive values of sales, employment, fixed assets, operating expenses, materials costs, and wages, or employment above 2 million employees. Finally, I only use the balanced panel, i.e. firms present for all 10 years of the sample.

G.7 Products

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

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

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

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

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

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

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

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

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

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

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

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

Table G.1 below contains the total number of observations, and number of distinct manufacturing plants, for each product.

Table G.1 Homogeneous Products

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

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