Online Appendix for "A Flexible Cost Share Approach to Markup Estimation"*

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A Monte Carlo Simulations

A.1 Baseline Monte Carlo

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

I simulate an economy in which markups and labor augmenting productivity differences vary across plants. In this economy, 1000 cost minimizing plants produce for 10 years. All plants have a common CES production function, as in (1), 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.[1]

*Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the Federal Trade Commission, or its Commissioners.

[1] 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

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:

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

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

First, I compare the labor markup to the materials markup using (A.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 (A.2). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table A.1, I report the average of β across 200 Monte Carlo simulations, with standard deviations across simulations in parentheses.

Table A.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
Quintile CS	0.59	0.61	0.80	0.99
	(0.44)	(0.31)	(0.27)	(0.01)
Decile CS	0.74	0.72	0.84	0.996
	(0.32)	(0.27)	(0.23)	(0.004)

Note: Estimates based on 200 Monte Carlo simulations, using (A.1) and (A.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 the flexible cost share approach, using five groups (quintiles) or ten groups (deciles). Standard deviation across 200 bootstrap estimates in parentheses.

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

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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.

In addition, both labor and materials markups have high correlations with the true markup. A 100% increase in the labor markup increases the true markup by 61% using quintiles and 72% using deciles. A 100% increase in the materials markup increases the true markup by 80% using quintiles and 84% using deciles. Thus, although imperfect, estimates using the flexible cost share estimator are highly correlated with each other and with the true markup.[2]

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

A.2 Factor Price Differences

In this section, I add differences in wages and materials prices across plants to the Monte Carlo exercise described in Section A.1. I find that the flexible cost share estimator performs similarly to the Monte Carlo without factor price differences across plants.

I simulate an economy in which markups and labor augmenting productivity differences vary across plants. In this economy, 1000 cost minimizing plants produce for 10 years. All plants have a common CES production function, as in (1), 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.[3]

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

The main difference from Section A.1 is that plants differ in their wages and materials prices. The log wage and log materials price are both distributed via a uniform distribution, with different

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

[3]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.

draws for each plant that are persistent over time.

I estimate the relationship between markup estimates using (A.1) and (A.2). First, I compare the labor markup to the materials markup using (A.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 (A.2). Here, the (logged) true markup is the dependent variable and the labor, materials, or composite markup the independent variable.

In Table A.2, I report the average of β across 200 Monte Carlo simulations, with standard deviations across simulations in parentheses.

The correlation between the labor and materials markup is positive using the flexible cost share estimator. I estimate output elasticities as cost shares within quintiles and deciles of the labor cost to materials cost ratio. A 100% increase in the materials markup increases the labor markup by 59% using quintiles and 76% using deciles.

In addition, both labor and materials markups have high correlations with the true markup. A 100% increase in the labor markup increases the true markup by 61% using quintiles and 73% using deciles. A 100% increase in the materials markup increases the true markup by 78% using quintiles and 83% using deciles. Thus, although imperfect, estimates using the flexible cost share estimator are highly correlated with each other and with the true markup.[4]

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

B Markup Stylized Facts

In this section, I show that the flexible cost estimator provides believable estimates for a set of stylized facts on markups.

I 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:

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

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.

Below, I show that the flexible cost share estimator leads to estimates for each stylized fact across both inputs and datasets that are consistent with theoretical predictions as well as internally consistent.

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

Table A.2 Relationship between Markup Estimates: Monte Carlo Estimates With Plant Specific Input Prices

Estimator	Labor on Materials	True Markup on Labor	True Markup on Materials	True Markup on Composite Input
Quintile CS	0.59	0.61	0.78	0.96
	(0.40)	(0.28)	(0.24)	(0.01)
Decile CS	0.76	0.73	0.83	0.97
	(0.29)	(0.24)	(0.21)	(0.007)

Note: Estimates based on 200 Monte Carlo simulations, using (A.1) and (A.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 the flexible cost share approach, using either five groups (quintiles), or ten groups (deciles). Standard deviation across 200 bootstrap estimates in parentheses.

B.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 (B.1) regressing markups on the logarithm of deflated sales. I report these estimates in Table B.1. I find a consistent, positive correlation between markups and size using the flexible cost share estimator. Across datasets and inputs, the markup increases, on average, between 2% and 9% with a 100% increase in sales.

B.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.[5] Table B.2 contains these estimates. The correlation of markups estimated using the flexible cost share estimator with exporting are always positive, with a 4 to 11 percentage point higher markup, on average, for exporters across inputs and datasets.

B.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

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

Table B.1 Markups and Sales

Chile	0.06	0.04	0.05
	(0.002)	(0.002)	(0.002)
Colombia	0.04	0.02	0.03
	(0.001)	(0.001)	(0.001)
India	0.05	0.02	0.03
	(0.000)	(0.000)	(0.000)
Indonesia	0.07	0.05	0.06
	(0.001)	(0.001)	(0.001)
US	0.07	0.06	0.07
	(0.004)	(0.004)	(0.004)
S Europe	0.03	-0.00	0.01
	(0.000)	(0.001)	(0.000)
Retailer	0.09	0.06	0.07
	(0.002)	(0.001)	(0.001)

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

Table B.2 Markups and Exporting

Flexible Cost Share			
Chile	0.04	0.05	0.05
	(0.008)	(0.007)	(0.007)
Colombia	0.11	0.08	0.09
	(0.006)	(0.006)	(0.005)
India	0.06	0.05	0.06
	(0.004)	(0.003)	(0.002)
Indonesia	0.09	0.08	0.09
	(0.004)	(0.004)	(0.004)

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

the markup. We would expect this profit share based markup to be highly correlated with the production approach based markup.

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

Table B.3 Production Markup Estimates and Profit Based Markup

	Flexible Cost Share		
Chile	0.92	0.96	0.96
	(0.010)	(0.010)	(0.009)
Colombia	0.82	0.84	0.83
	(0.011)	(0.013)	(0.011)
India	0.88	0.84	0.86
	(0.005)	(0.004)	(0.004)
Indonesia	0.44	0.42	0.44
	(0.017)	(0.016)	(0.017)
Retailer	0.80	0.56	0.60
	(0.012)	(0.007)	(0.006)
Retailer (EBIT)	0.82	0.58	0.62
	(0.012)	(0.007)	(0.007)

Note: Estimates are based on (B.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.

I then regress the log production based markup on the log profit share based markup using (B.1). I report these estimates in Table B.3. Markups estimated using the flexible cost share estimator are always strongly positively correlated with the profit share based markup, with, on average, a 40% to 96% increase in the production markup with a 100% increase in the profit share based markup.

B.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 B.4.

I find a consistent, statistically insignificant increase in the markup of 0.1% from moving from Low to High competition using the flexible cost share estimator across all three inputs. Thus, using the flexible cost share estimator, the retailer does not appear to have substantially different markups across stores facing different levels of competition.

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

Table B.4 Markups and Competition

	Flexible Cost Share		
Medium Competition	-0.003	-0.002	-0.002
	(0.002)	(0.001)	(0.001)
High Competition	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)

Note: Estimates are based on (B.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.

C Data Notes

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

C.1 Country Datasets

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

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

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

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

The fifth dataset is retail store-level data from an anonymous major US nationwide retailer for three years. This retailer has thousands of stores across the United States.

C.2 Capital

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

The capital rental rate is the sum of the real interest rate R and depreciation rate δ for that type of capital. I base the real interest rate on private sector lending rates reported in the World Bank World Development Indicators, which come from the IMF Financial Statistics, for each country. This real interest rate is constructed as the private sector lending rate adjusted for inflation using the change in the GDP deflator. Thus, real interest rate R is defined as $R = \frac{i_t - \pi_t}{1+\pi_t}$ for lending rate i_t and inflation rate π_t.

I average this real interest rate over the sample period, so that, since capital rental rates are constant over time, no variation in the capital stock over time is due to changing rental rates.[6]

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.[7]

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

For the other datasets, I construct asset-specific capital stocks using a perpetual inventory method for each type of capital. For Colombia, there are four types of capital: land, structures, equipment (combining office equipment and machinery), and transportation. For India, there are six types of capital: land, structures, equipment, transportation, computers, and other (including pollution equipment). For Indonesia, there are five types of capital: land, structures, equipment, other capital (for which I use the equipment deflator), and transportation.[8] For each asset type, I construct a perpetual inventory measure of capital starting with the first year reporting a positive

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

[7]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%.

[8]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.

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

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

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

Nominal capital services are then the sum of the real capital stock of each asset type multiplied by the appropriate deflator and capital rental rate, plus rent. Real capital services are the sum of the real capital stock of each asset type multiplied by the appropriate capital rental rate, plus deflated rent.[10]

C.3 Labor

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

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

C.4 Energy and Materials

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

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

For Colombia, I calculate the average electricity price as the median ratio of value to quantity across all plants for a given year and province and deflate electricity using this electricity price.

[9] 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.

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

For fuels, I only have aggregate fuel value, which I deflate using the output deflator for the 3 digit petroleum and coal industry.

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

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

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

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

For 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.

C.5 Sales

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

C.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.

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