Rising Markups or Changing Technology?*

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Recent evidence suggests the U.S. business environment is changing with rising market concentration and markups. Accompanying these changes is rising dispersion of markups across firms. From the perspective of misallocation models, these changes are a drag on welfare and productivity. The most prominent and extensive evidence backs out firm-level markups from the first-order conditions for variable factors. The markup is identified as the ratio of the output elasticity to the cost share of revenue of the variable factor. Output elasticities are estimated at an industry level allowing for relatively little variation either over time or across firms within the same industry. Our analysis starts from this indirect approach, but we exploit a long panel of manufacturing establishments to permit output elasticities to vary to a much greater extent across establishments within the same industry over time. With our more detailed estimates of output elasticities, the measured increase in markups is substantially dampened. As supporting evidence, we relate differences in the markups' patterns to observable changes in technology (e.g., computer investment per worker, capital intensity, diversification to non-manufacturing) and find patterns in support of changing technology as the driver.

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I. Introduction

Increasing evidence suggests that markups of prices relative to marginal costs have been rising in the U.S. as well as other countries. The most definitive evidence for the U.S. is the recent research of De Loecker, Eeckhout and Unger (2020) (hereafter DEU). DEU present evidence from U.S. public firms for the entire private sector as well as supporting evidence from U.S. manufacturing, retail trade and wholesale trade establishments. They find that on a sales-weighted basis the average markup has increased substantially in the entire U.S. private sector for publicly traded firms and in manufacturing, retail trade and wholesale trade for all firms. An important component of the rising average markup is the reallocation of activity from low-markup to high-markup firms. In addition, they present related evidence that the dispersion in markups across firms and establishments is increasing over time. This implies that the shift in activity towards high-markup firms yields a larger increase in the sales-weighted markups.

The methodology for detecting the rise in the average and dispersion of markups builds on Hall (1988) and De Loecker and Warzynski (2012) and is clever and simple in principle. Using the first-order condition for a variable factor, the markup at the firm level is the ratio of the output elasticity of the variable factor to the cost share of revenue of that factor. This "production approach" (or "ratio approach" as recently denoted by Bond et. al. (2020)) requires an estimate of the output elasticity of the variable factor. The simplest implementation assumes a constant output elasticity at the industry level so rising markups and dispersion relate to changes in the empirical cost share of revenue of the variable factor. DEU recognized that this simple approach is potentially misleading since there might be variation over time and across firms in output elasticities. They show that their results are robust to considering output elasticities that vary across time and firms. They permit elasticities to vary at the 4-digit level by year when using cost shares of total costs to estimate output elasticities. When estimating a Cobb-Douglas specification, they permit estimates to vary at the 2-digit level by five-year interval and when using a translog (in their 2018 draft) they allow estimates to vary at the 2-digit industry level. For their estimation, they use the control function methodology but innovate on the standard approach in the literature as they recognize they are estimating revenue functions that depend on both markups and output elasticities.

We explore specifications that push the potential for changing technology to a much greater extent. For this purpose, we use annual establishment-level data from the Annual Survey of Manufactures for 1972-2014. This yields a data infrastructure with approximately 2.2 million establishment-year observations at the annual frequency. For our estimates, we use all the information in the annual series and create estimates in rolling five-year intervals which we refer to as "rolling annual" estimates. This contrasts with estimates that use Economic Census data that exists at a five-year frequency (data in years ending in "2" or "7"). While we are restricted to the manufacturing sector, this data infrastructure permits us to explore greater potential variation in output elasticities across time and establishments. Specifically, we estimate a translog specification at the 4-digit level with parameters that are "rolling annual" estimates, a Cobb-Douglas specification at the 4-digit level with parameters that are "rolling annual" estimates and also consider cost share of total costs estimates that vary at the establishment level every year.

Importantly, the large annual panel of establishment-level data permits us to use the control function approach to estimate Cobb-Douglas and translog specifications of the revenue function at a more disaggregated level with time-varying coefficients. When using Census data, DEU restrict themselves to using the cost share of total costs method for output elasticities. This reflects their use of Economic Census data (that, as noted above, is available at a five-year frequency). The control function approach relies on the innovation to unobserved revenue shocks being uncorrelated with predetermined variables (e.g., lagged inputs) and thus this approach is not well suited to Economic Census data. Their control function estimation described above only applies to their use of the COMPUSTAT data at the firm level.

We find that the increase in the average sales-weighted markup declines systematically when allowing for output elasticities that vary more by detailed industry, by establishment and by time. From their Economic Census based estimates, DEU report that the sales-weighted markup in manufacturing increases by 18% from 1977 to 2007 and by 12% from 1977 to 2012. For our cost-share specification at the 4-digit level with annual data, we find the sales-weighted markup increases by 47% from 1977 to 2007 and 29% from 1977 to 2012. The analogous changes at the plant level with annual data shows that the sales-weighted markup increases by 24% from 1977 to 2007 and 16% from 1977 to 2012.

For our Cobb-Douglas specification at the 2-digit level with "rolling annual" estimates we find the sales-weighted markup increases by 24% from 1977 to 2007 and 7% from 1977 to 2012. The analogous changes using a 4-digit specification with "rolling annual" estimates yield only an 8% increase from 1977 to 2007 and a decline of -5% from 1977 to 2012.

Even more dramatic differences occur when using the translog specification. Using the translog specification at the 2-digit level, we find that the average sales-weighted markup increases by 41% from 1977 to 2007 and by 32% from 1977 to 2012. The analogous changes using a translog specification at the 4-digit level with "rolling annual" estimates are -3% and -6%, respectively. Throughout, we refer to those output elasticities estimated with more granular measures of industry and time as "more detailed" estimates.

Our analysis does not just explore the robustness of the "production" approach to estimating markups, it also opens a more extended investigation into differences in production technologies across establishments and firms. It has long been known there are large differences in revenue productivity measures across establishments within the same measured industry (see, e.g., Baily, Hulten and Campbell (1992), Foster, Haltiwanger and Krizan (2001), and Syverson (2004)). Such differences are present in revenue per composite input taking into account multiple inputs (a TFPR type measure) or in revenue per unit input such as labor.

Hsieh and Klenow (2009) (HK) highlight that such dispersion potentially reflects wedges relative to a frictionless and distortionless allocation of activity. Such wedges include markups. The production method advocated by DEU is closely related theoretically and empirically to the HK approach as the production method uses the dispersion in the cost shares of revenue of variable inputs (e.g., materials and/or labor). Since firm and plant-level deflators are not typically available, the measured cost share of revenue is closely related to revenue per unit of nominal expenditures of the inputs. It may be that markups are the primary factor driving such measured dispersion.

Alternatively, differences in production technologies (as well as differences in input prices) may be driving the observed dispersion. We regard this as the natural flip side of the production identification approach. The "production" approach to estimating markups identifies dispersion in cost shares of revenue across firms and establishments as stemming from differences on the demand side without imposing much structure on the demand side. We investigate the alternative hypothesis that the variation is mostly coming from the supply (cost/production) side.

Differences in our results using more detailed output elasticities raise a variety of questions. Specifically, if the differences are consistent with greater variation in the production technologies over time, then presumably, we should be able to find some direct evidence of such changes. To investigate the potential link to changes in the way establishments do business, we use observed variation in indicators of changing technology at the establishment and detailed (4-digit) industry level. At the establishment-level, we explore measures of capital per worker, computer investment per worker, a diversification measure of how much establishments in manufacturing have become part of firms with non-manufacturing activity, and a relative size measure based on the share of sales accounted for by the parent firm in the industry. We find that all four of these indicators of how establishments change business exhibit increases in the mean and dispersion across establishments over time.

Moreover, all four are positively associated with the difference in the markup at the establishment-level using the "less detailed" and "more detailed" estimation of the production function. For each of the three techniques, we compare estimations at "less detailed" and "more detailed" levels where these differ in terms of variation over time (constant, rolling annual, five-year) and firms (plant-level, 6-digit, 4-digit, and 2-digit). Similarly, all four are positively associated with this difference in the output elasticity at the establishment-level using the "less detailed" and "more detailed" estimation of the production function. We also find that the industries with above median changes in these indicators of technology have greater differences in the change in the markup between the "less detailed" and "more detailed" specifications.

Our findings that output elasticities of variable factors and in turn markups are increasingly upward biased are consistent with recent findings of Hubmer and Restrepo (2021) and Demirer (2020). Hubmer and Restropo (2021) use COMPUSTAT data to estimate a

Cobb-Douglas specification with output elasticities of the variable factor of production are permitted to vary across time, industry and firm size classes. Demirer (2020) also uses COMPUSTAT data for the U.S. (and establishment-level data) with other countries and develops novel methodology for estimating production functions. Both of these papers present evidence that output elasticities of the variable factor of production are lower and falling for larger firms. Moreover, both present evidence this translates into smaller increases in variable markups.

We interpret our results as complementary with this recent literature finding that output elasticities for variable factors are lower and declining for larger firms. Our contribution is to use a large, representative panel of manufacturing establishments that permits flexible specification of technologies (e.g., translog) with fewer restrictions than the existing literature. We do not impose any structure that inherently yields differences in elasticities across firm size but with our more flexible specifications we find that output elasticities for materials and markups are smaller for larger firms. In turn, this implies the shift towards larger firms yields less of an increase in measured markups taking into account the more flexible specifications.

An important differentiating feature of our analysis is that our rich data permits us to focus on materials input as the variable factor while the analysis with COMPUSTAT requires using a composite measure of the variable input or constructing a decomposition of the components indirectly. As we argue below, the firm adjustment costs literature suggests that labor should not be treated as a variable factor even at an annual frequency.[1]

[1] Raval (2020) presents insightful analysis that markup patterns estimated from using materials and labor inputs as alternative variable factors yield inconsistent patterns. Our findings also yield inconsistent patterns across markups estimated from materials and labor. Raval (2020) investigates the hypothesis that this inconsistency can be reconciled by considering labor-augmenting technical change. From our perspective, we think the adjustment costs for labor imply that labor is not a variable factor even at an annual frequency. It may be that the appropriate frequency for labor adjustment costs is at a monthly or quarterly frequency. However, as shown in Cooper, Haltiwanger and Willis (2020) adjustment costs for labor at this higher frequency has important implications for annual moments of firm-level employment adjustment (that differ from the frictionless model where labor is a variable factor).

Another differentiating feature of our results is that we show that this pattern of differences in output elasticities extends to indicators of adopting more advanced and capital-intensive technologies. As with firm size, we find that these indicators are associated with smaller estimated output elasticities and smaller estimated markups. We also find that establishments with greater non-manufacturing activity of parent firms (diversification) have smaller estimated output elasticities and smaller estimated markups. This finding is consistent with the arguments in Fort et al. (2018) that some firms are shifting away from the production of physical goods and more towards the design and marketing of goods. Critical here is that these firms retain some manufacturing activity, but it is leaner in terms of variable inputs.

The paper proceeds as follows. Section II sets out the conceptual framework and estimation methodology. Data and measurement are discussed in section III. Output elasticity estimates and implied markups are presented in section IV. Section V presents analysis of the factors driving the differences in markups across less and more detailed output elasticity estimation. Concluding remarks are provided in section VI.

II. **Conceptual Framework and Estimation**

The DEU approach (along with earlier and subsequent literature) to estimating markups relies on the following equation derived from a cost-minimizing establishment's objective function.

$$\mu_{it} = \frac{{\theta_{it}}^V}{{\alpha_{it}}^V} \qquad (1)$$

where μ_{it} is the markup for establishment **i** in year **t,** ${\theta_{it}}^V$ is the output elasticity for input **v** for establishment **i** in year **t**, and ${\alpha_{it}}^V$ is input **v's** share of total revenue for establishment **i** in year **t**.

In other words, the markup is the 'wedge' between the establishment's output elasticity for any variable input **v** and that input's share of the establishment's revenue.[2]

The input's share of revenue, ${\alpha_{it}}^{V}$, can be measured directly in firm or establishment-level data. It is the establishment's total expenditure on the input divided by the total revenue in the establishment (the cost share of revenue). This leaves equation (1) with two unknown quantities, the markup (μ) and the output elasticity (θ). To recover the markup, the output elasticity must be estimated, and typically, it is estimated at relatively coarse levels of industry and time.

Our primary question is whether the relatively coarse variation in estimated output elasticities attributes to markups cross-sectional differences in technology and/or time-series changes in technology occurring at more disaggregated levels. We use a large, annual dataset on U.S. manufacturing establishments to estimate production technologies more flexibly and demonstrate how estimated markups change when using this more flexible approach. We do this in two ways. First, we estimate output elasticities using a cost-share approach, which, under certain assumptions, allows technology to be estimated at the establishment-by-year level. Second, we estimate the production function using proxy methods at finer levels of industry and time.

It is common to estimate output elasticities using averages of cost shares of total costs at the industry level (cost shares of total costs). The motivation for averaging to the industry level (and often over time) is that the first-order conditions for cost minimization underlying this approach are unlikely to hold for all factors at each instant of time at the micro level (see, e.g.,

[2] As noted in equation 1, the markup is defined for any variable input (v). While in theory, the markup is defined to be the same over any variable input, in practice the measured markup may differ. Below, we discuss our preference for measuring markups using materials as opposed to labor as the variable input.

discussion in Syverson (2011)). Still, this leaves open questions as to the level of industry detail that should be used and whether time averaging is needed. We push as far as we can on these dimensions by using cost shares of total costs of variable factors at the establishment-by-year level. We also compare this to a range of alternative less detailed approaches (e.g., 2-digit, 4-digit, 6-digit industry-based estimates that are constant over time or vary by year). We acknowledge using establishment-by-year estimates requires very strong assumptions but think it useful as an attempt to permit as much establishment-level variation in technology as possible.[3]

In our second approach, we follow DEU in estimating output elasticities by directly estimating the revenue function at varying levels of industry-by-time. Like DEU, we use a control function approach to estimate the output elasticities for the Cobb-Douglas and translog specifications.[4] Moreover, we take advantage of their contribution to this literature that recognized that since the dependent variable is firm or establishment-level revenue, controls for price and markup variation are potentially needed. Specifically, following DEU (2019) we include a control for each establishment's market share in their 4-digit industry, also instrumented using three lags of the establishment's market share. We adopt their approach of estimating the elasticities using a five-year rolling window to increase sample size, but we estimate at the 4-digit level. We use both Cobb-Douglas and translog specifications at the 4-digit by five-year interval window. This contrasts with DEU who use 2-digit, five-year windows for

[3] While it may seem like an extreme, using the establishment-level cost share of total costs yields a common approach for measuring markups given by R_{it} / TC_{it} where R_{it} is establishment-level revenue and TC_{it} is establishment-level total costs. Autor et. al. (2020) denote this the accounting measure of markups.

[4] In the GMM procedure, we are using three lags of materials, energy, and labor inputs to instrument for current period inputs. We also include current period capital and every three-way and two-way interaction between lagged (one-period) capital and lagged (one-period) energy as exogenous regressors. For the translog we include additional interactions of lagged instruments.

Cobb-Douglas and 2-digit, time invariant translog specifications. The latter does yield output elasticities that vary by firm and year but the underlying translog function is time invariant.

We are pushing the data hard in this analysis; the control function estimation is often used at a more aggregate industry level given that the polynomial approximations are sensitive to smaller samples. We provide analysis of why the time series patterns of the difference in the markups between the "more" and "less" detailed output elasticities is inconsistent with a simple measurement error explanation. As a further robustness check, we conduct our analysis for the 50 largest industries (in terms of number of establishments) since these are the industries where sample size restrictions are less binding. Finally, we also explore the relationship between observable indicators of changing technology and the growing gap in markups we find when using "less" and "more" detailed output elasticity estimates.

In sum, we have three different estimation methods for output elasticities: cost-share (CS), production function using Cobb-Douglas (CD), and production function using translog (TL). We estimate these over two samples (full and top 50) and with varying degrees of flexibility in industry (2-digit, 3-digit, 4-digit, 6-digit, plant-level) and time (constant, 5-year rolling, and annual). In the final section of the paper, we explore how differences in these markup estimates relate to changing technology and business structure.

Before proceeding to the analysis, it is instructive to consider how to interpret potential differences in estimated output elasticities. For this purpose, we find it useful to consider conceptually the difference between the estimated output elasticity and the true elasticity. We specify this difference as: $\hat{\theta}_{it} - \theta_{it} = \varepsilon_{it}$. Plugging this into the expression for the markup, the difference between the actual and estimated markup is equal to: $\varepsilon_{it} / \alpha_{it}$. Several inferences can be drawn from this simple expression.

First, at the establishment-level, the average bias depends on the mean of $\varepsilon_{it} / \alpha_{it}$. This is given by: $\operatorname{cov}(\varepsilon_{it}, 1/\alpha_{it}) + E(\varepsilon_{it})E(1/\alpha_{it})$. Thus, the average bias in the markup depends not only on the bias in the output elasticity but on the covariance between the error and the (inverse) of cost share of revenue Second, at the establishment-level the bias may vary systematically with the technology adopted by the establishment. Such systematic relationships can help account for the dispersion in errors in estimated markups across establishments. The error in the revenue-weighted average markup depends on the mean of $\omega_{it}\varepsilon_{it} / \alpha_{it}$ where ω_{it} is the revenue share. This expression reminds us that the average bias in the revenue-weighted markup will depend further on covariances of the error and the cost share of variable inputs of revenue with the revenue share.

This discussion highlights that, on the one hand, it is instructive to examine differences in output elasticities across estimation methods directly. Other things equal, a rising bias in the output elasticity itself will yield an increase in average (weighted or unweighted) markups. On the other hand, examining the sign or change in magnitude of the bias in output elasticities is insufficient. We build on this insight in the analysis that follows.

III. Data and Measurement

We use manufacturing data from the Annual Survey of Manufacturers (ASM) for 1972 through 2014. The ASM, conducted in both Census and non-Census years surveys roughly 50,000-70,000 establishments. The ASM is a series of five-year panels (starting in years ending in “4” and “9”) with probability of panel selection being a function of industry and size. We use ASM sample weights in all our analysis. We provide an overview of our measurement methodology in the main text but provide more details in the data appendix.

A. Nominal Measures

We require nominal measures of revenue and input expenditures to compute the two types of cost share measures (cost shares of revenue and costs shares of total costs). Nominal revenue is measured as the total value of shipments adjusted for changes in final and intermediate inventories. Nominal materials are measured as the sum of the cost of materials and parts, the cost of resales and the cost of contract work done for the establishments by others on the establishment's materials. Nominal labor costs are measured as salary and wages for all workers. Nominal energy expenditures are the sum of the cost of purchased electricity and the cost of purchased fuels consumed for heat, power, or electricity generation. Nominal expenditures for capital are the product of the user cost of capital we obtain from the Bureau of Labor Statistics (BLS) at the 3-digit industry level times the real capital stock. We have both measures separately for structures and equipment. Real capital stocks are constructed using a perpetual inventory method. Nominal expenditures are deflated with industry-level investment deflators. We use 3-digit industry-level deflators from BLS for both investment expenditures and the depreciation rate.

These nominal measures permit us to construct *cost shares of revenue* for materials and labor. We focus on the cost share of revenue for materials since materials is much more plausibly a variable input. While we show results for labor in the appendix, the firm-level adjustment costs literature provides evidence that labor is not a variable factor of production even at an annual frequency (see Cooper et al. (2020) and Decker et al. (2020)). We also use these data to construct *cost shares of total costs* in our cost-share based estimation of output elasticities at the establishment-by-year level. For our output elasticities measured from cost shares at the industry-level we use the appropriately weighted establishment-level cost shares aggregated to the industry-level measures from the NBER-CES database along with the deflators and user cost measures.

B. Real Measures

For our production/revenue function estimation we follow standard practice of converting the nominal revenue and input expenditure measures into real measures using industry-level deflators. For nominal revenue, materials, and energy we use 6-digit NAICS deflators from the NBER-CES database (extended to 2014). For the labor input measure for estimating output elasticities, we use the measure of total hours constructed as the production worker hours times the ratio of salary and wages for all workers to those for production workers. This method includes an adjustment for difference in labor quality for production and non-production workers.

IV. **Estimates of Output Elasticities and Markups**

We start by providing the results of the estimations in three sets of tables. Tables 1a and 1b show the distribution of estimated output elasticities from cost shares of materials of total costs (CS) at different levels of aggregation. Table 1a shows results for the entire manufacturing sector while Table 1b shows the results for the top 50 industries. Tables 2a and 2b show the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the Cobb-Douglas (CD) specification. Tables 3a and 3b show the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the translog specification (TL).

As we consider specifications with more industry detail and greater time variation, the estimated output elasticities for materials exhibit substantially more dispersion. For example, the standard deviation for the cost share (CS) approach rises from 0.0344 for the least detailed estimation (2-digit, constant) to 0.2051 for the most detailed estimation (plant-level, yearly). The Cobb-Douglas (CD) specification has an increase in similar magnitude (0.01838 to 0.1093), but the translog (TL) specification has a less dramatic increase (0.1765 to 0.1951). The patterns for the top 50 industries are broadly similar to the full sample of industries. We focus on the full sample for the remainder of the analysis (but show results for the top 50 industries in the appendix). Results for estimates of output elasticities for labor show similar patterns and are reported in Tables A.1-A.3.

We now turn to the estimated markups.[5] Figures 1 to 3 show the implied pattern of changing markups on a sales-weighted basis (for cost-shares, Cobb-Douglas, and translog estimations). Panel a in each figure shows long differences from 1980 to 2014 for alternative cases. The color of the bars denotes differences in time variation (black is more restrictive and is denoted by "Constant", red is less restrictive and is denoted by either "1 yr" or "5 yr") and the bars are grouped by industry level. Panel b in each figure shows annual markups for two key benchmark cases: (1) dotted black lines shows "less detailed" that corresponds closely to the level of aggregation used by DEU and (2) the red solid line shows "more detailed."

Focusing first on panel a, as we consider specifications with more industry detail and greater time variation, the increase in markups is substantially dampened. In some cases, the time variation is driving this decrease, in other cases it appears that the industry variation is driving the decrease. For example, industry differences appear to dominate for cost shares (CS) approach, but time variation appears to dominate for both proxy methods. These patterns of

[5] All the markup estimates are winsorized in each year at the 1st and 99th percentiles. Our reading of DEU is that they trim the 1% tails rather than winsorize. Given that we consider a wide range of alternative markup estimates, winsorized markups facilitate avoiding disclosure issues from trimming each of the alternative estimates. Figure A.1 shows that the long differences for our benchmark "less detailed" and "more detailed" cases are very similar for the results based on winsorized vs. trimmed markup distributions.

implied markups are robust to consideration of the top 50 industries in the appendix (see Figure A.2).[6] The robustness to the largest 50 industries in terms of establishments provides reassurance regarding our consideration of more detailed output elasticities that vary to a greater degree across firms and time.

Turning to the time series pattern of markups in panel b of the figures shows further interesting patterns. In all three cases, the "more detailed" cases (red lines) are everywhere below the "less detailed" cases (black dotted lines) but the gap between the two series widens starting in the late 1990s. For the "less detailed" specifications (black dotted line), there is still an overall increase in markups from 1980 to 2014. However, with "more detailed" specifications (red solid line), we find only a modest increase in markups using the Cobb-Douglas (CD) specification and a decline using the translog specification (TL).

Comparing our results with those of DEU, we note that for these results we start, as they do for their analysis of Economic Census data, at the establishment level. They aggregate to the firm level within manufacturing and then to the industry level and finally the aggregate (total manufacturing level). The findings in Figures 1 to 3 focus on the total manufacturing level patterns although we explore results at a more disaggregated level below. Our results at the total manufacturing level are comparable conceptually to the estimates in DEU. While appropriate caution is required in direct comparisons given their focus on the cost share approach with the Economic Census, a comparison of Figure 1 using the 4-digit by year benchmark to their results

[6] Long differences from 1980 to 2014 for implied change in markups using labor as the variable factor are in Figures A.3 (all industries) and A.4 (top 50 industries) for the less detailed and more detailed specifications. For the cost share approach to estimating elasticities, we obtain similar results to those for materials. Results are less systematic using less detailed versus more detailed for Cobb-Douglas and translog. Even so, we find markups decline overall from 1980 to 2014 using the translog specification for labor as the variable input whether using less or more detailed specifications for the top 50 industries. For all industries, the less detailed translog yields a sharp decline in markups while the more detailed yields little change.

from the Census of Manufactures also using 4-digit by year cost shares shows broadly similar patterns.

Notably, the increase in markups from 1972 to 2014 peaks in the mid-2000s, and from 2006 to 2014, markups decline substantially. This peak in markups around 2005 occurs in all three "less detailed" cases and in the "more detailed" cost share and Cobb-Douglas cases.[7] The analysis of Economic Census data in DEU offers a glimpse at this fall in markups. In their work, the average markup for manufacturing decreases from 2007 to 2012, falling below the level of markups from 1992-2002. Our analyses with annual data confirm that this decrease is not simply a one-year dip, but rather a persistent decline from 2005 through 2014. Averaging across the three less detailed specifications, markups decrease by about 20% from 2005 to 2014, returning to the levels estimated for the mid-to-late 90s. Although we find a smaller rise in the more detailed cases using cost share and Cobb-Douglas approaches, we likewise find a smaller decrease of around 14% from 2005 to 2014, with markups again returning to 1990s levels. This marked decrease in markups is robust to estimation strategy and is not present in COMPUSTAT data (see DEU 2019 draft, Appendix 12.1). This further highlights the value of using ASM/CM data and abstracting from the greater measurement issues raised in this paper, suggests that estimated markups for manufacturing have fallen dramatically in recent years.

We believe the time series patterns in Figures 1-3 provide reassurance that our findings are not being driven by a greater impact of measurement or specification error with our more detailed output elasticities. The patterns in Figures 1-3 show that the sales-weighted markup estimates from the "less detailed" and "more detailed" specifications are quite similar for about the first ten years of our sample (e.g., 1972 to the mid-1980s). In the middle part of our sample

[7] The more detailed translog case does not exhibit a rise in markups, and thus, there is no corresponding decrease.

there is a growing gap between the sales-weighted markup from the “less detailed” and “more detailed” output elasticity specifications. Finally, in the last ten years of our sample, this gap either stays about the same or even falls. Also, it is notable that markups from both “less detailed” and “more detailed” output elasticity specifications decline in the last ten years of our sample. These time series patterns would require a time series evolution of measurement/specification error that was minimal in the first part of our sample, increased substantially in the middle part of our sample and then stabilized or declined in the last part of our sample.

V. **Factors Driving Differences in Results**

What drives differences in markups between the “less detailed” and “more detailed” specifications? We explore this question with several exercises examining three potential factors driving differences in results. These are measurement issues (aggregation and weights), shifting shares as evidenced through decompositions, and fundamental changes in production technology as captured by capital intensity, computer investment per worker, diversification, and relative firm size.

A. Output Elasticities, Revenue Shares, and Total Cost Weighting

First, we highlight some measurement issues related to aggregation. We show that the results cannot simply be interpreted through the lens of separately examining the patterns of output elasticities (θ) and cost shares of revenue (α). The sales-weighted mean of the estimated markup at any level of aggregation is:

$$\sum_i \omega_{it}\,\mu_{it} = \sum_i \omega_{it}\,\frac{\theta_{it}{}^V}{\alpha_{it}{}^V} \qquad (2)$$

Where the sales weight of plant i is given by ω_{it}. It is apparent that the sales-weighted average of markups is not equal, in general, to the ratio of the sales-weighted output elasticities to the sales-weighted cost shares of revenue. We refer to the latter as the naïve markup given by:[8]

$$Naive\ Markup = \frac{\sum_i \omega_{it}\, \theta_{it}{}^V}{\sum_i \omega_{it}\, \alpha_{it}{}^V} \qquad (3)$$

Figure 4 shows the long differences of the naïve markups for the selected benchmark cases. It is evident that the patterns in Figure 4 are distinct from those in Figures 1-3. Under the less detailed specifications, the naïve markup exhibits little change for the cost share (CS) approach, declines under Cobb-Douglas (CD) and increases under the translog (TL) but much less than implied by Figure 3. For the more detailed specification, the naïve markup declines for the Cobb-Douglas (CD) and translog (TL) specifications.

While the naïve markup is not directly informative about the actual markup, it is still interesting to consider the numerator (sales-weighted output elasticities) and denominator (sales-weighted revenue cost shares of inputs) of the naïve markup. Recall from the discussion earlier that the bias in the estimated aggregate markup will depend on revenue-weighted average output elasticity and the revenue-weighted average cost share of variable inputs. The point of our earlier discussion is that examining these moments independently is insufficient given underlying covariances, but they are still informative.

We analyze these two moments in Figures 5 and 6. Figure 5 shows the long difference in output elasticities for materials.[9] Figure 6 shows the sales-weighted revenue cost shares for all

[8] The naïve markup is not exactly what one would compute from aggregate data (see e.g., equation (11) from DEU when output elasticities are constant) since we use sales weighting for both the output elasticity and the cost share of revenue. We use this formulation to highlight that caution needs to be used in drawing inferences from the "aggregate" patterns of output elasticities and cost shares of revenue regardless of the weighting used in the aggregation.

[9] Figure A.5 shows the analogous plot for labor.

inputs (materials as well as labor, energy, and capital) as well as the ratio of sales-weighted total costs to sales-weighted revenue. In Figure 5, we find that sales-weighted output elasticities exhibit different patterns across the estimation approaches and using less versus more detailed specifications. For both Cobb-Douglas and translog the more detailed specification yields a decline in the sales-weighted output elasticity for materials. Turning now to the cost share of revenue for inputs (Figure 6), we find that the (sales-weighted) materials share rises slightly, the labor and energy shares decline, the capital share declines and the overall ratio of total costs to revenue declines. We note that the capital costs in this case are based on perpetual-inventory-based capital stocks and detailed industry-specific user-costs of capital from the Bureau of Labor Statistics (BLS).

Figure 7 depicts the long differences in the sales-weighted returns to scale. For the "less detailed" Cobb-Douglas specification and the "more detailed" translog there is some mild evidence of rising (sales-weighted) returns to scale. For the "more detailed" Cobb-Douglas and "less detailed" translog, there is, if anything, evidence of an even more modest decline in (sales-weighted) returns to scale.

As a further cross-check on the basic patterns, we follow DEU and Edmonds, Midrigan and Xu (2019) by computing total-cost-share weighted markups. We show in Figure 8 the long differences of the changes of this alternate measure of markups (again using materials as the variable input). Broadly consistent with these papers, we find smaller increases in total-cost-share weighted markups even using the "less detailed" specifications (and a decline with Cobb-Douglas). Consistent with Figures 1-3, we find that "more detailed" specifications yield a smaller increase or larger decline in markups.

B. Within vs. Reallocation Components of Changing Markups

Underlying the finding of rising sales-weighted measured markups by DEU and the related literature is a rising dispersion across businesses in markups -- especially with an increase in the upper tail of the distribution. Accompanying this change in dispersion and skewness is a shift in sales to high markup businesses. DEU use a decomposition developed by Haltiwanger (1997) to decompose aggregate changes in sales-weighted markups into within, between, cross and net entry terms. They find that the reallocation components dominate the increase in sales-weighted markups. We use this same methodology to compare these composition effects between the more and less detailed cases.[10] We are interested in whether the differences we observe are driven by specific components. The decomposition is given by:

$$\Delta\boldsymbol{\mu}_{\boldsymbol{t}} = \sum_{i\epsilon c} \boldsymbol{\omega}_{\boldsymbol{it-1}}\Delta\boldsymbol{\mu}_{\boldsymbol{it}} + \sum_{i\epsilon c}(\boldsymbol{\mu}_{\boldsymbol{it-1}} - \overline{\boldsymbol{\mu}_{\boldsymbol{t-1}}})\Delta\boldsymbol{\omega}_{\boldsymbol{it}} + \sum_{i\epsilon c}\Delta\boldsymbol{\mu}_{\boldsymbol{it}}\,\Delta\boldsymbol{\omega}_{\boldsymbol{it}} + \sum_{i\epsilon N}(\boldsymbol{\mu}_{\boldsymbol{it}} - \overline{\boldsymbol{\mu}_{\boldsymbol{t-1}}})\boldsymbol{\omega}_{\boldsymbol{it}} - \sum_{i\epsilon X}(\boldsymbol{\mu}_{\boldsymbol{it-1}} - \overline{\boldsymbol{\mu}_{\boldsymbol{t-1}}})\boldsymbol{\omega}_{\boldsymbol{it-1}} \qquad \textbf{(4)}$$

The first term in equation (4) is the within term. The second term captures (between effect) and third (cross effect) terms together capture reallocation across continuing establishments. The last two terms combined reflect net entry as the penultimate term captures entry and the final term captures exit. Bars over terms denote weighted means.

Before showing the results of the decomposition, we first examine the dispersion in our measures of markups. We focus on two measures of dispersion: an overall measure (standard deviation) and one that focuses on the right tail (the 90th-75th percentiles differential). Figure 9 illustrates that we also find rising dispersion (panel a) and a rising right tail (measured by the 90-75 differential in panel b) in markups across establishments for both "less detailed" and "more detailed" specifications. The rising dispersion and skewness are mitigated by the "more detailed" specifications (except for the detailed cost share approach for skewness). This pattern is intuitive

[10] We apply the decomposition at the establishment rather than the firm-level. Our objective is to quantify the relative contribution of the different components for less and more detailed output elasticity specifications.

since the “more detailed” specifications absorb more of rising dispersion with dispersion in output elasticities (see Tables 1-3).

The decomposition of the changing markups for both “less detailed” and “more detailed” specifications is reported in Table 4. We compute the terms in Table 4 first for the five-year intervals between Economic Census years from 1977 to 2012. We then cumulate the components over the entire time period. Recall the specification that is closest to DEU’s analysis of the Economic Census is in the first row of the table. For that specification, we find results broadly consistent with theirs showing a positive contribution of the within, net entry and reallocation with the latter component dominating. More generally, for the less detailed specifications, we find that the reallocation from continuing establishments dominates the increase in markups although net entry also contributes substantially.

For the more detailed specifications, the much smaller increase in markups is associated with a general tendency of all components to fall in magnitude. Especially noticeable is the substantial negative within contribution for all of the more detailed specifications. That is, the markup is declining substantially on a sales-weighted basis within businesses. The reallocation terms are all positive for the more detailed specifications offsetting the declining within. In that respect, reallocation continues to play a critical role. Our findings suggest that if there had not been this shift towards high markup businesses then there would have been a decline in aggregate markups in manufacturing. While reallocation plays a critical role with the more detailed specifications, the magnitude of the reallocation terms tends is smaller than the less detailed (with the exception of the cost share, plant, 1 year approach). The findings in Figure 9 help explain this declining contribution of reallocation. There is a shift in activity towards higher markup businesses but with dispersion in markups rising by a smaller amount with more detailed specifications this shift yields less of an increase in the sales-weighted markup.

C. Changing Technology?

Our findings imply that with more detailed estimation of output elasticities that permit greater variation across time and firms that the measured increase in markups in U.S. manufacturing is substantially dampened. This inference depends on the robustness of estimating output elasticities at this level of disaggregation. As discussed above, there are multiple factors that provide support for this robustness. In this section, we take an additional step by exploring the relationship between differences in markup patterns with more detailed output elasticities and observable measures of changing technology and indicators of the structure of firms. This analysis also provides insights into why the more detailed specifications yield smaller increases in estimated markups.

We exploit observable plant-level indicators of capital intensity (capital per worker), computer intensity (computer investment per worker), diversification (ratio of non-manufacturing to manufacturing activity) and relative firm size (share of the parent firm's sales in industry sales). Capital intensity is measurable for all establishments from 1972 to 2014. Computer investment is available in the Economic Census for 1977, 1982, 1987, 2002, and 2007 and in the Annual Survey of Manufactures in 2000. U.S. firms with activity in manufacturing often have activity in non-manufacturing and Fort et al. (2018) document there has been a positive trend in this direction with some firms with only modest manufacturing being described as a form of factory-less production. Based on this work, we use the Longitudinal Business Database (LBD) to construct a measure of the extent of this activity using the parent firm for each establishment.[11]

[11] Specifically, we measure the ratio of non-manufacturing to manufacturing employment for the parent firm.

The share of the parent firm's sales in industry sales is measurable in Economic Census years when all establishments are covered.

Figure 11 shows that all four indicators exhibit an increase in mean and three of the four indicators exhibit an increase in dispersion over time.[12] These findings are important indicators that establishments are changing the way they are doing business with increased differentiation across establishments. The log firm share is related to changing market structure with the shift towards superstar firms. As discussed in both DEU and Autor et al (2020), the shift towards superstar firms is connected to rising measured markups as larger firms have higher measured markups. However, it may be that this reflects differences in output elasticities between smaller and larger firms as well as differences in the covariance between output elasticities and cost shares across firm size. We investigate that question as we explore the connection between the "less detailed" and "more detailed" measured markups and estimated output elasticities and these indicators of changing technology and changing structure of the economy.

Before presenting regression results that investigate this question, we provide summary statistics for the dependent and explanatory variables in Table 5. Turning to the regression results, the top panel of Table 6 presents bivariate establishment-level regressions that relate the difference in establishment-level "less detailed" minus "more detailed" estimated markups using the translog specification to these technology/business structure measures. All specifications control for detailed industry (6-digit) by year effects. All four of the measures are positively related to the less minus more detailed estimated markups.

The bottom panel of Table 6 presents the analogous bivariate establishment-level regressions with the dependent variable the "less detailed" minus more "detailed estimate" of the

[12] It is not surprising that as the log firm share rises rapidly in the post 2000 period that dispersion falls as large firms increasingly dominate.

output elasticity. Again we find that all four of the measures are positively related to the less minus more detailed estimated output elasticities at the establishment-level.[13]

These findings are consistent with the hypothesis that establishments that have adopted different ways of doing business within industries have systematically different estimated markups and output elasticities. The results on log firm size imply that larger firms have smaller estimated output elasticities of variable factors (and smaller measured markups) when using specifications that permit greater differences in output elasticities across establishments within and across industries as well as time. These findings on firm size are consistent with those in Hubmer and Restrepo (2021) who present evidence that output elasticities of variable factors of larger firms are smaller using COMPUSTAT data.[14] There is large literature on technology adoption that provides theory and evidence that larger and growing businesses are more likely to adopt advanced technologies (see, e.g., Dunne, Haltiwanger and Troske (1997) and Dunne, Foster, Haltiwanger and Troske (2004) for evidence early in our sample; Acemoglu et al (2022) for more recent evidence).[15] The logic is that there are fixed costs associated with changing technology. The results on capital intensity, computer investment per worker and diversification combined with those on firm size are consistent with this interpretation. Within industries, establishments with higher indicators of these variables have lower estimated output elasticities of the variable factor and in turn lower estimated markups.

[13] In Appendix Table A.4, we explore whether the relationships in Table 5 have changed over time. The basic answer is no.

[14] Hubmer and Restrepo (2021) is more theoretically focused and much of the attention in their analysis is on the declining labor share. However, in an extension of their framework they consider variable markups estimated in a manner similar to DEU using COMPUSTAT data. Rather than estimate flexible functional forms (as we do with for example translog) they estimate a Cobb-Douglas specification with output elasticities of the variable factor of production are permitted to vary across time, industry and firm size classes. Their imposition of constant returns to scale implies capital output elasticities must be higher and rising for large firms.

[15] As noted, there is a large theoretical literature as well. Early papers include Cooper, Haltiwanger and Power (1998) while more recent papers include Acemoglu and Restrepo (2018).

It is instructive to compare the magnitude of the coefficients in the upper and lower panels of Table 6. The estimated coefficients are uniformly higher in the upper panel (markups) as compared to the lower panel (output elasticities of materials). The difference in these magnitudes depend on the difference in the covariance between the "less detailed" minus "more detailed" markup with the explanatory variable and the covariance of the "less detailed" minus "more detailed" output elasticity with the explanatory variable. If, for the purpose of discussion, we treat the differences between "less detailed" and "more detailed" using the notation section II , then these differences reflect the differences in $\mathrm{cov}(\varepsilon_{it} / \alpha_{it}, X_{it})$ (where X is the explanatory variable) and $\mathrm{cov}(\varepsilon_{it}, X_{it})$. The findings imply both these covariances are positive, but the former is larger than the latter. Put differently, this is a reminder that it is insufficient to only examine the impact of differences across businesses in output elasticities, but one needs to take into account covariances including the cost share of the variable input.

To provide additional perspective, we exploit industry-level variation in the "less detailed" minus "more detailed" markups and related industry-level changes in indicators of technology and business structure. For the latter, we classify industries based upon the long difference from 1977-2007 for capital intensity, computer intensity, diversification and a measure of concentration. We use this window of time since this corresponds to the time interval (using Census years) of the largest increases in markups using the "less detailed" specifications in Figures 1-3. As discussed above, markups decline from the mid-2000s to 2014. For computer intensity and capital intensity, we use the value of each industry's change and classify industries as above/below the median change for each variable (using the revenue-weighted median for the industry). For the diversification measure, we use the absolute value of the change since industries with either increases or decreases are changing business structure. For concentration, we use the 20-firm concentration ratio at the 4-digit level for this purpose (this is closely related to the superstar firm measures used by Autor et al. (2020)).

Figures 11-14 plot the mean difference between the "less detailed" and "more detailed" markup estimates in each year for industries with above median industry-level technology/business structure changes versus below median industry-level technology changes. We find that the industries with above median changes in capital intensity, computer intensity, and diversification exhibit an increasing larger difference between the less detailed and more detailed based markups. Industries with larger changes in concentration ratios have about the same increase in the difference between industry differences in "less detailed" minus "more detailed" markups.

The industry-level findings provide further support for the interpretation that the differences the increase in "less detailed" minus "more detailed" markups reflects changes in technology (and business structure). In other words, if the rise in markups from the "less detailed" estimates is attributable to a change in technology, then markups under the "less detailed" estimates should increase particularly so (beyond the "more detailed" estimates) in industries with greater indicators of technological change and change in business structure.[16]

Putting the pieces together, we interpret the findings of this section along with those in the earlier sections as consistent with the following narrative. The way that manufacturing businesses

[16] We provide further evidence on the industry long differences in Table A.5. These specifications are broadly similar to analogous to those reported in Tables 5 and 6. The RHS variable is a dummy variable equal to one if the industry has a long difference change from 1977-2007 above the sales-weighted median for the technology change (or concentration ratio) interacted with sub-period dummy variables. The omitted subperiod is 1972-80 with subperiod dummies for 1981-89, 1990-2005 and 2006-14. The estimated coefficients are positive for all the technology change measures under all output elasticity estimation approaches for all periods after 1990 and for virtually all approaches after 1980. They are statistically significant for computer intensity for the 1990-2005 subperiod for all output elasticity estimation approaches and for selected other subperiods for specific estimation approaches. For capital intensity, the estimates are statistically significant for translog for both the 1990-2005 and 2006-14 subperiods. For the absolute change in diversification, the estimates are statistically significant for both the 1990-05 and 2006-14 subperiods for Cobb-Douglas and translog approaches (and for the cost share approach in the 2006-14 subperiod). In contrast, the estimates for the concentration measure are small in magnitude and never statistically significant

are producing has changed substantially over time (the mean increases in Figure 10) with an uneven pattern across establishments (the standard deviation increases in Figure 10). These indicators of uneven changing patterns of production are significantly related to the differences between the "less detailed" and "more detailed" estimates of markups and output elasticities.[17] The main finding from the "more detailed" estimates of production technologies is that they yield less of an increase in markup. The findings in this section provide supporting evidence that these "more detailed" estimates of production technologies are related to observable changes in technology at the establishment and industry-level.

Our findings do not provide causal evidence about why some establishments, their parent firms, and industries are changing their technology and ways of doing business that differ from others. Instead, we show that indicators of such within and between industry heterogeneity are closely related to estimates of differences in the estimates of the output elasticities of the production technology. Our findings highlight that exploring the causes and consequences of such heterogeneity should be a high priority for future research.

VI. Conclusions and Future Research

Measuring markups from firm or establishment-level data using the "production (ratio) approach" using U.S. data yields a striking pattern of rising (sales-weighted) first and second moments of markups. The rising first and second moments are related since a substantial fraction of the rising sales-weighted mean is accounted for by the reallocation of sales activity away from low to high measured markup businesses. The "production (ratio) approach" depends critically on accurate estimates of the output elasticities of the variable factors of production. There is a

[17] The uneven nature of technology adoption is a core feature of the empirical evidence (see, e.g., Acemoglu et al. (2022)) with accompanying evidence that large firms are more likely to adopt capital intensive, advanced technologies.

large literature estimating output elasticities either from cost shares of total costs or from estimates of the production/revenue function. Much of this literature imposes the same time-invariant output elasticities across businesses within the same industry.

In the recent pathbreaking work of DEU, output elasticities are permitted to vary across businesses within industries and over time. They find that permitting output elasticities to exhibit variation across time and businesses mitigates the measured increase in sales weighted markups but the residual increase in markups is still substantial. DEU use annual firm-level data for publicly traded firms and the quinquennial Economic Census data for manufacturing, retail, and wholesale trade establishments. This limits the degree to which output elasticities can be permitted to vary across businesses and time. This paper takes advantage of a dataset that has been created in the Collaborative Micro Productivity (CMP) project at Census that tracks large (roughly 55,000 establishments per year) representative samples of U.S. manufacturing establishments from the Annual Survey of Manufactures (ASM) from 1972 to 2014. These data permit much greater flexibility in output elasticities across establishments.

Using either cost share or estimation methods, we find greater flexibility in output elasticities (over time and industry) substantially mitigates the measured increase in sales-weighted markups. Using the 2-digit translog specification with time-invariant parameters as in DEU, we find the sales-weighted markup in U.S. manufacturing increases by about 30 log points from 1980-2014. Using the 4-digit translog specification with parameters that vary over time using a five-year rolling window, we find the sales-weighted markups declines by about 5 log points from 1980 to 2014. Similar substantial differences are evident using either cost share or Cobb-Douglas revenue estimation approaches.

We find that the substantially mitigated increases in markups with more flexible and changing production technologies are associated with declines in the sales-weighted markups within businesses, smaller increases in the *dispersion* of markups, and smaller roles for reallocation in accounting for the changing mean. A key finding in the literature is that there has been a shift towards businesses with higher markups within industries. We also find this pattern but the differences in markups across business within industries are less pronounced. Moreover, the reallocation component is offsetting a substantial within business decline in markups when using the more flexible production function specifications.

Our results are consistent with the hypothesis that much of measured increases in markups instead reflect changing production technology. We present supporting evidence for this hypothesis using observable indicators of changing technology and business structure. We find that the mean and dispersion across establishments of capital intensity, computer intensity, diversification into non-manufacturing and the relative industry size are increasing over time. Moreover, all of these indicators are positively related with establishment-level differences in the "less detailed" minus "more detailed" markups and "less detailed" minus "more detailed" output elasticity estimates. We also show there is an important between industry component of these relationships. Our findings are consistent with related findings in the recent literature that part of the explanation for estimated rising markups is lower and declining output elasticities of variable factors at larger firms.

More research is needed on several dimensions. First of these is whether our results extend beyond manufacturing.[18] Unfortunately, the CMP database developed for U.S. manufacturing establishments is not easily replicated for other sectors. A second more

[18] Hubmer and Restrepo (2021) is an important step in this direction for publicly traded firms.

fundamental question is how we should characterize the production technology at the establishment and firm level. Our findings suggest that the common practice of imposing the same technology across all establishments in the same (even detailed) industry is likely problematic. This practice has had a large influence on the literature on misallocation and now this more recent related literature on markups. Our results suggest we need to open the black box of different production technologies across businesses in the same industry. In many respects, we regard this inference as more important than the inference that markups may not be rising as much as recent work suggests. We think the task approach developed in a series of recent papers (e.g., Acemoglu and Restrepo (2019)) may be helpful for this important research agenda of characterizing differences across businesses in how they conduct business.

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Table 1. Output Elasticities for Materials Cost Share (CS) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.5856	0.0344
3-digit, constant over time		0.07435
4-digit, constant over time		0.1026
6-digit, constant over time		0.1199
Plant-level, constant over time		0.1813
2-digit, yearly		0.03707
3-digit, yearly		0.0797
4-digit, yearly		0.107
6-digit, yearly		0.1259
Plant-level, yearly		0.2051
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.5761	0.0631
3-digit, constant over time		0.09867
4-digit, constant over time		0.1253
6-digit, constant over time		0.1325
Plant-level, constant over time		0.1911
2-digit, yearly		0.06506
3-digit, yearly		0.1024
4-digit, yearly		0.1286
6-digit, yearly		0.1359
Plant-level, yearly		0.2122

Notes: Simple means and standard deviations reported for the pooled full sample. The mean statistics in the first row of each panel applies to all following rows in the panel. Panel A has about 2.16 million establishment-year observations. Panel B has about 750 thousand establishment-year observations.

Table 2. Output Elasticities for Materials Cobb-Douglas Proxy Method (CD) approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.5381	0.01838
3-digit, constant over time	0.5314	0.07713
4-digit, constant over time	0.5193	0.09744
6-digit, constant over time	0.5058	0.1249
2-digit, 5-year rolling window	0.5295	0.03857
3-digit, 5-year rolling window	0.5185	0.08687
4-digit, 5-year rolling window	0.4953	0.1093
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.4802	0.02689
3-digit, constant over time	0.4993	0.06252
4-digit, constant over time	0.4814	0.09022
6-digit, constant over time	0.4801	0.1057
2-digit, 5-year rolling window	0.4695	0.04653
3-digit, 5-year rolling window	0.4797	0.0912
4-digit, 5-year rolling window	0.4579	0.1323
6-digit, 5-year rolling window	0.4577	0.1416
2-digit, yearly	0.475	0.04992
3-digit, yearly	0.4853	0.09785
4-digit, yearly	0.4636	0.1405
6-digit, yearly	0.4627	0.1531

Notes: Simple means and standard deviations reported. See notes to Table 1.

Table 3. Output Elasticities for Materials Translog Proxy Method (TL) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.5653	0.1765
3-digit, constant over time	0.5498	0.1857
4-digit, constant over time	0.527	0.1887
6-digit, constant over time	0.5138	0.206
2-digit, 5-year rolling window	0.5617	0.1813
3-digit, 5-year rolling window	0.5424	0.1897
4-digit, 5-year rolling window	0.5019	0.1951
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.5344	0.1965
3-digit, constant over time	0.5237	0.2019
4-digit, constant over time	0.5074	0.1977
6-digit, constant over time	0.503	0.2019
2-digit, 5-year rolling window	0.5268	0.1963
3-digit, 5-year rolling window	0.5018	0.2031
4-digit, 5-year rolling window	0.4713	0.2049
6-digit, 5-year rolling window	0.468	0.214
2-digit, yearly	0.532	0.1968
3-digit, yearly	0.5023	0.2192
4-digit, yearly	0.4718	0.2303
6-digit, yearly	0.4661	0.2503

Notes: Simple means and standard deviations reported. See notes to Table 1.

Table 4. Decomposition of the Change in Markups 1982-2012

	Reallocation	Within	Net Entry	Total Change	% of Diff., Realloc.	% of Diff., Within	% of Diff., Net Entry
CS, Ind4, 1yr	0.1855	0.04112	0.08917	0.3158			
CS, Plant, 1yr	0.4041	-0.2469	0.02755	0.1847	-1.667	2.197	0.47
CD, Ind2, 5yr	0.1537	-0.1307	0.08452	0.1075			
CD, Ind4, 5yr	0.1393	-0.2341	0.04467	-0.05014	0.09163	0.6556	0.2528
TL, Ind2, Constant	0.3485	-0.09166	0.05682	0.3137			
TL, Ind4, 5yr	0.1401	-0.2544	0.06164	-0.05268	0.5688	0.4443	-0.01314

Notes: The markups in the above table are estimated using materials as the variable input. The decomposition above uses revenue weights.

Table 5: Summary Statistics for Plant-Level Regressions Relating Less minus More Detailed Markups and Less minus More Detailed Output Elasticities

Variable	*Mean*	*Standard Deviation*
Less minus more detailed markup	.6097	1.003
Less minus more detailed output elasticity	.2238	.2005
Capital Intensity (log (K/L))	4.908	1.325
Computer Intensity (IHS Comp Inv Per Worker)	.3706	.6534
Diversification Index	.5746	.7485
Log(firm share)	-3.494	1.954

Notes: Summary statistics for the dependent and explanatory variables in Tables 6. All variables are measured at the establishment level. The less minus detailed markups and output elasticities are from the translog specification. The diversification index is the IHS of the ratio of nonmanufacturing to manufacturing employment for the parent firm. The firm share is the share of sales of the parent firm in the industry of the establishment.

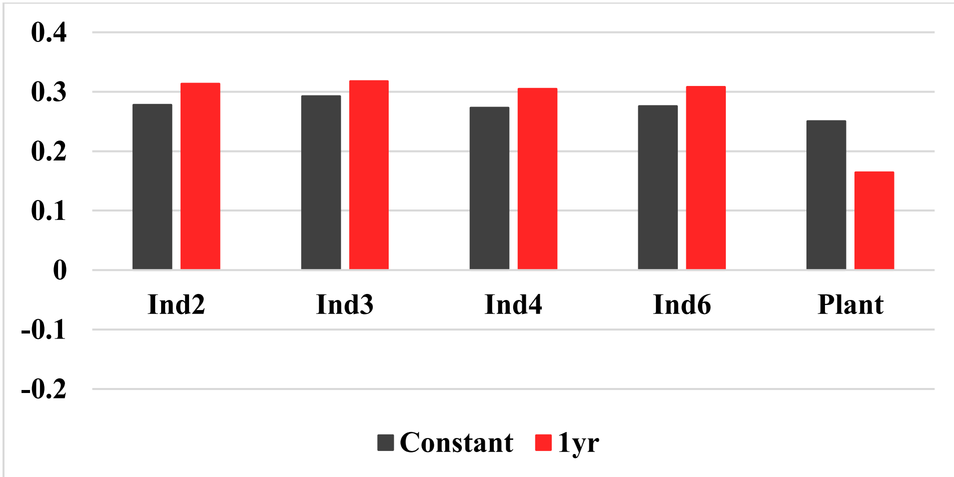
Table 6: Relationship Between Less minus More Markups and Output Elasticities and Indicators of Technology and Firm Structure

Less minus More Detailed Markup	log(Capital Intensity)	IHS(Computer Inv Per Worker)	Diversification Index	Log(Firm Share)
Slope Coefficient	0.1441***	0.0853***	0.0799***	0.1139***
	(0.0279)	(0.0281)	(0.0200)	(0.0150)
Less minus More Detailed Output Elasticity Materials				
Slope Coefficient	0.0377***	0.0175***	0.0239***	0.0371***
	(0.0056)	(0.0063)	(0.0059)	(0.0033)

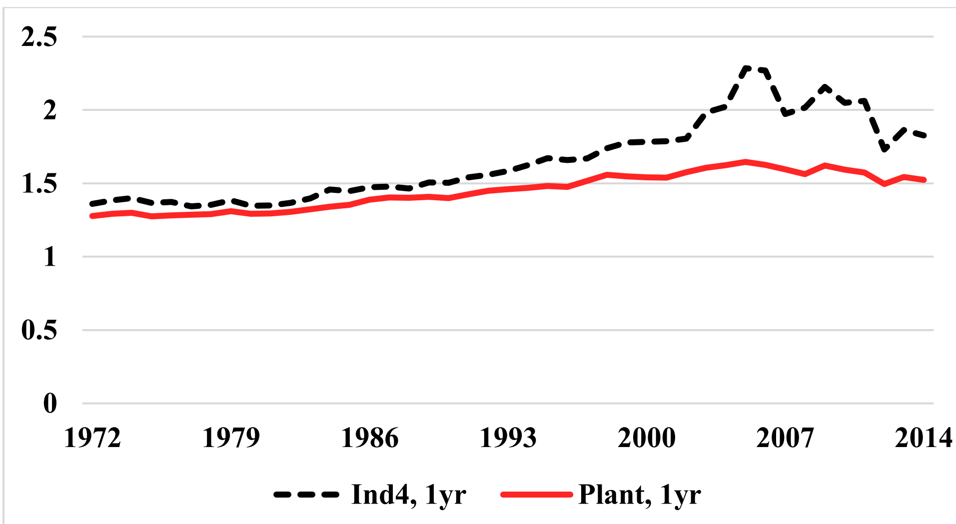
Notes: All specifications control for 6-digit industry by year effects using establishment-level observations. Less minus more detailed markup and output elasticity from translog specification. See notes to Table 5.

Figure 1. Markups Estimated Using Cost Shares (CS)

(a) Long difference in markups 1980-2014



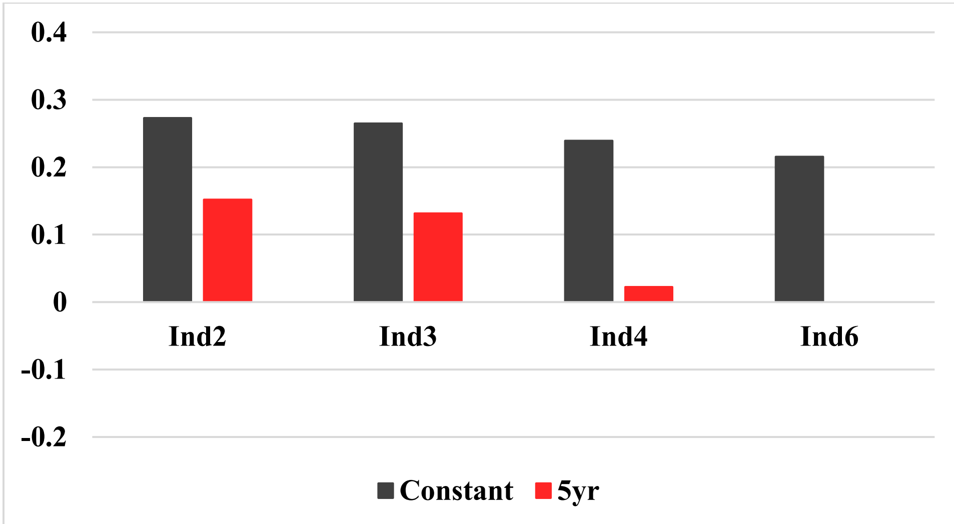
(b) Markups from 1972-2014, benchmark cases



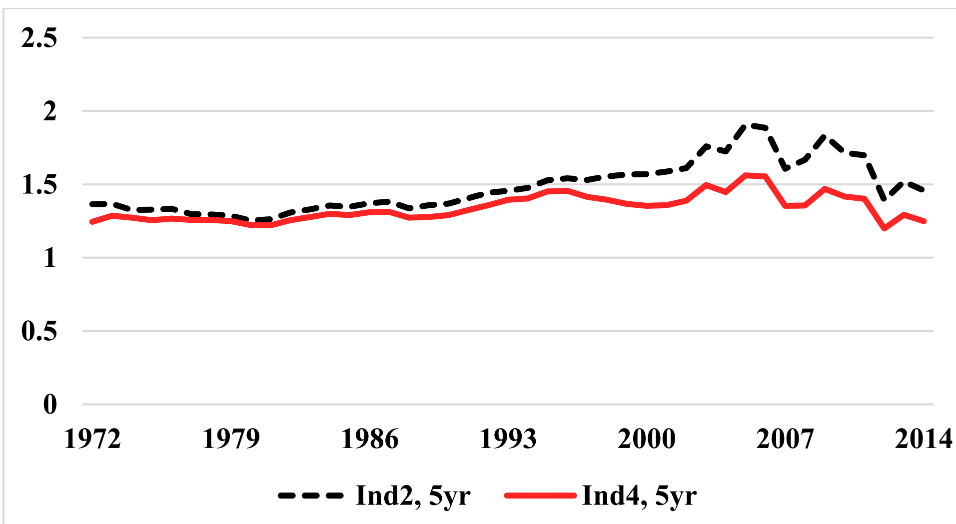
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 2. Markups Estimated Using Cobb-Douglas (CD)

(a) Long difference in markups 1980-2014



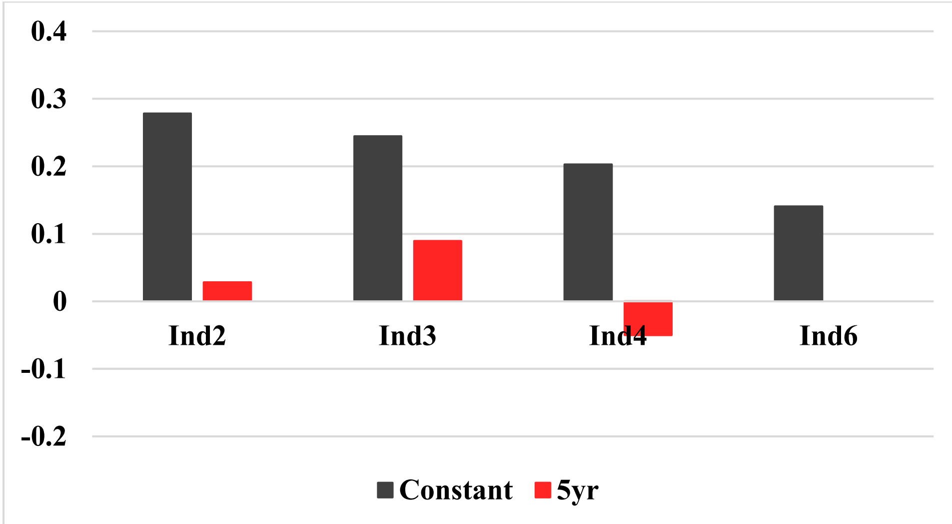
(b) Markups from 1972-2014, benchmark cases



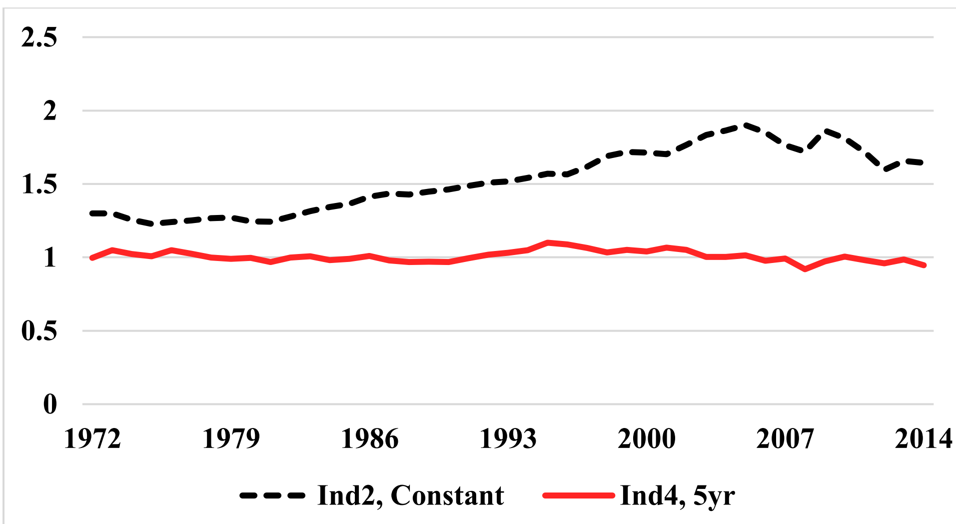
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 3. Markups Estimated Using Translog (TL)

(a) Long difference in markups 1980-2014

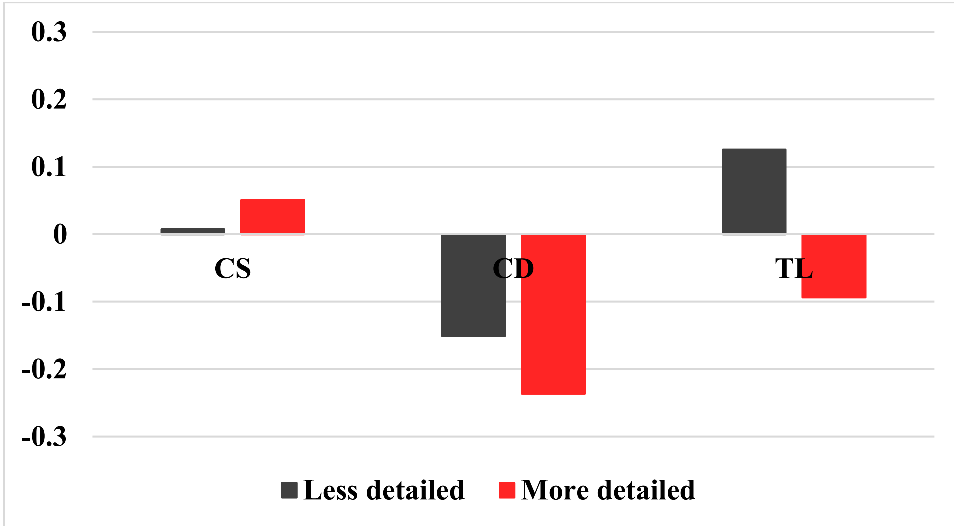


(b) Markups from 1972-2014, benchmark cases



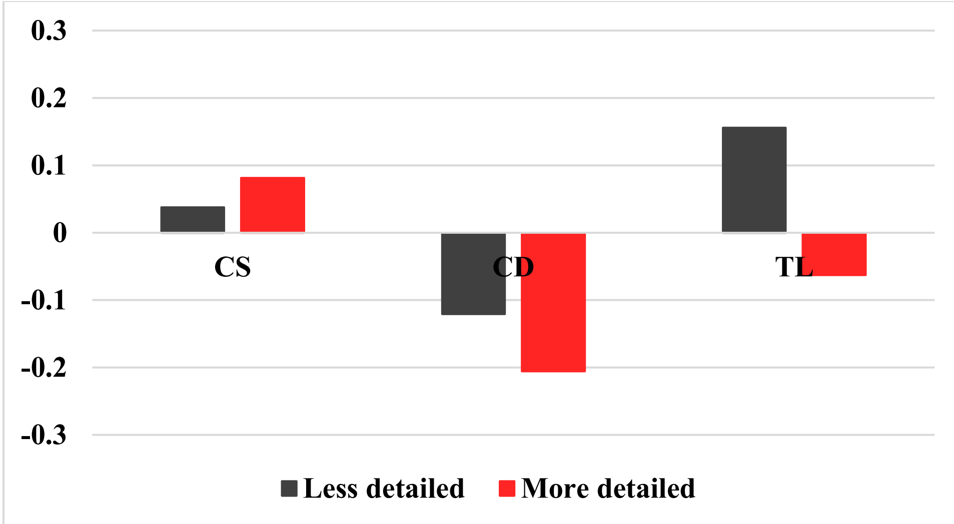
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 4. Long Difference in Naïve Markups 1980-2014



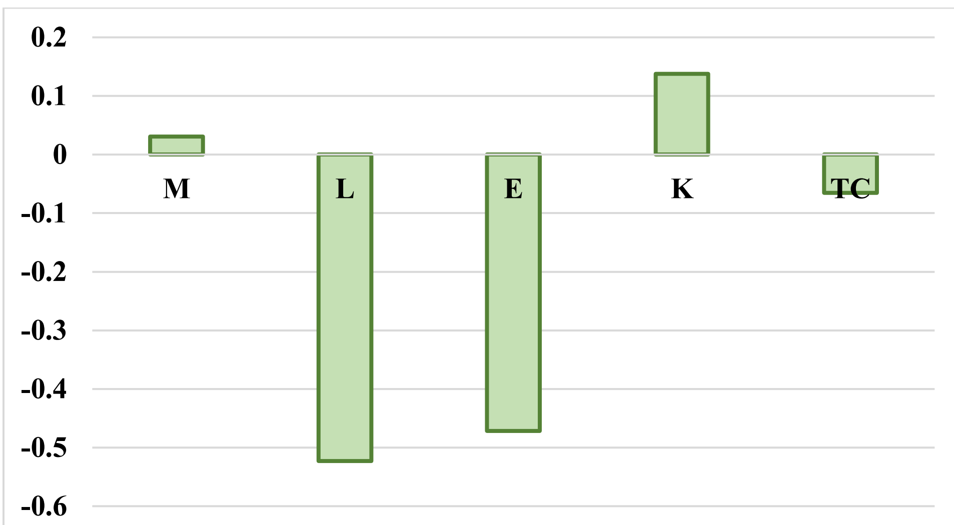
Notes: The markups above are estimated using materials as the variable input. See equation (3) for definition of naïve markup. Long differences are log differences.

Figure 5. Long Difference in Materials Output Elasticities 1980-2014



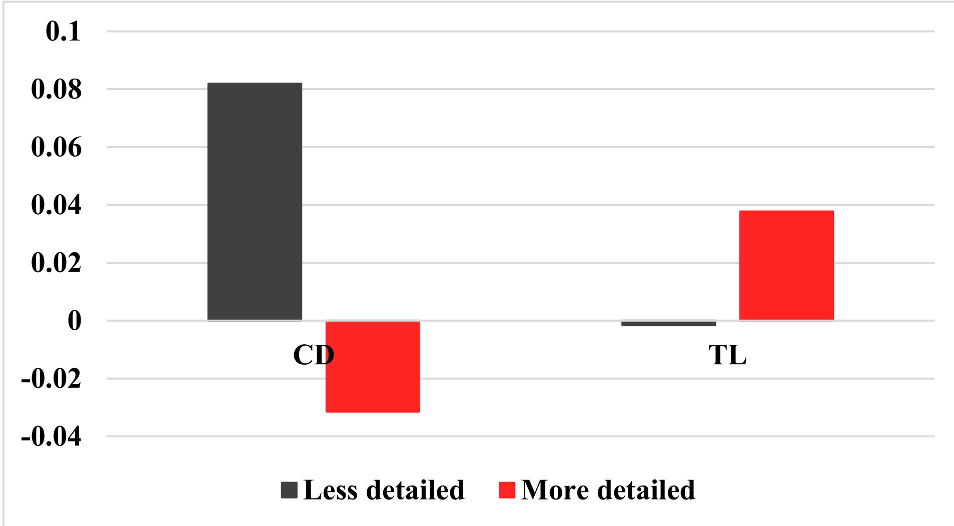
Notes: The output elasticities above are estimated for materials. Output elasticities are revenue-weighted means. Long differences are log differences.

Figure 6. Long Difference in Input Shares of Revenue 1980-2014



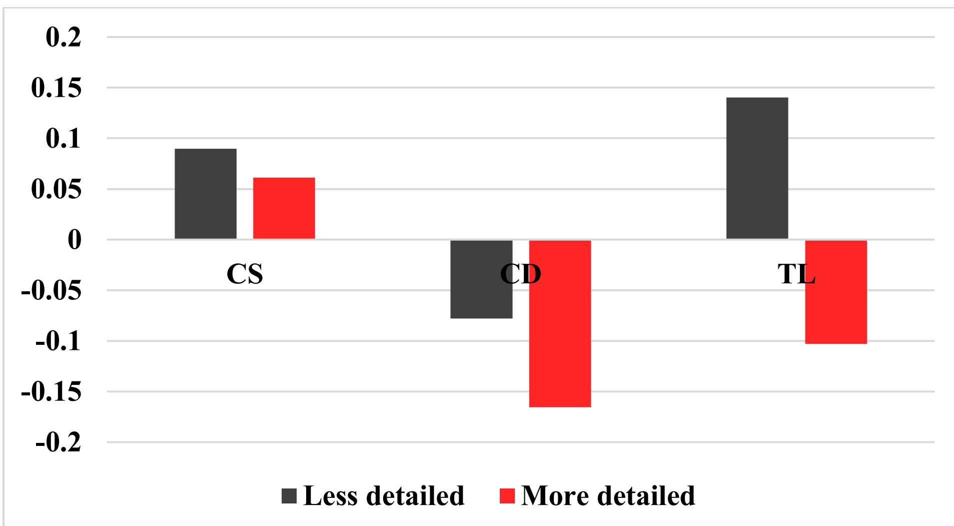
Notes: Input shares of revenue are revenue-weighted means. Long differences are log differences.

Figure 7. Long Differences of Returns to Scale 1980-2014



Notes: Returns to scale measured as the sum of estimated output elasticities. Aggregate returns to scale are revenue-weighted means. Long differences are log differences.

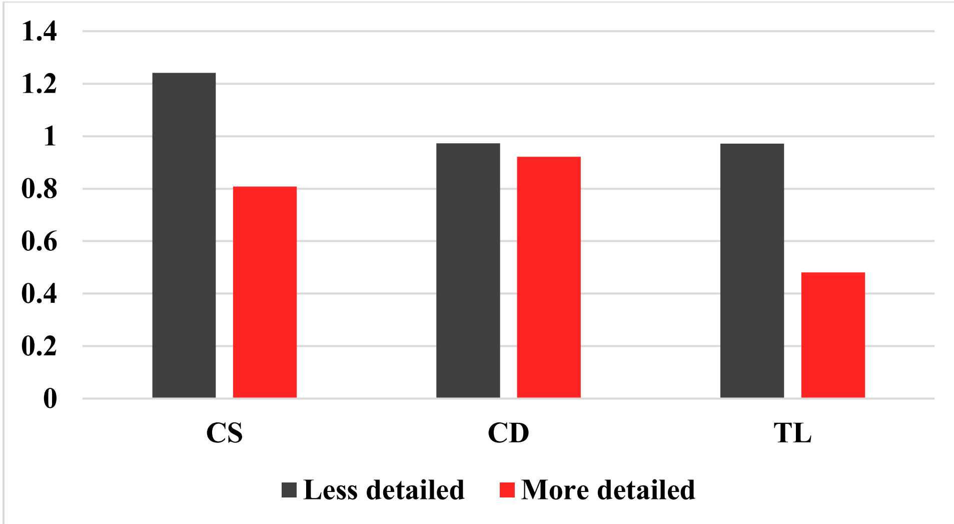
Figure 8. Long Difference of Markups from 1980-2014. Robustness to Total Cost Weighting



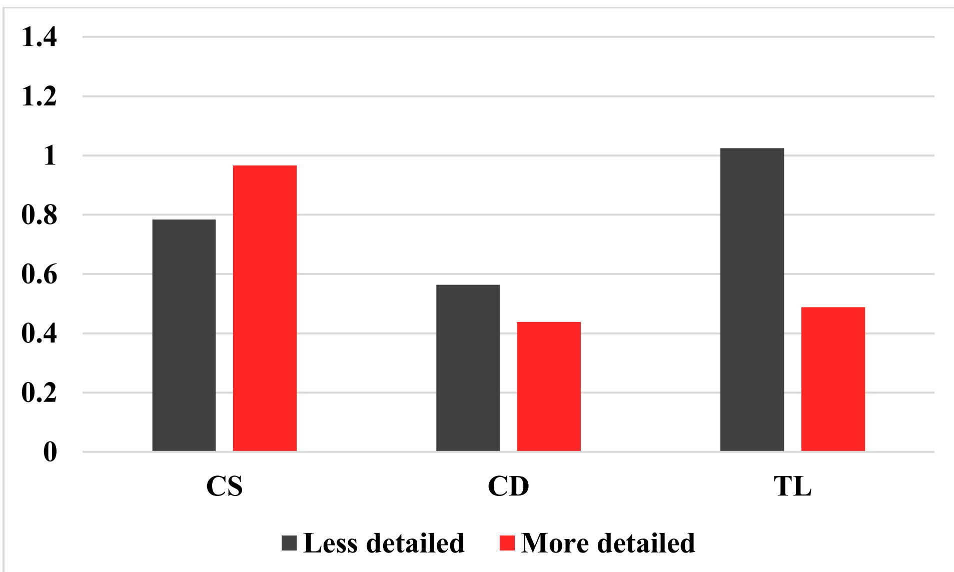
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are total cost-weighted means. Long differences are log differences.

Figure 9. Dispersion in Markups over Time

(a) Long difference in standard deviation 1980-2014



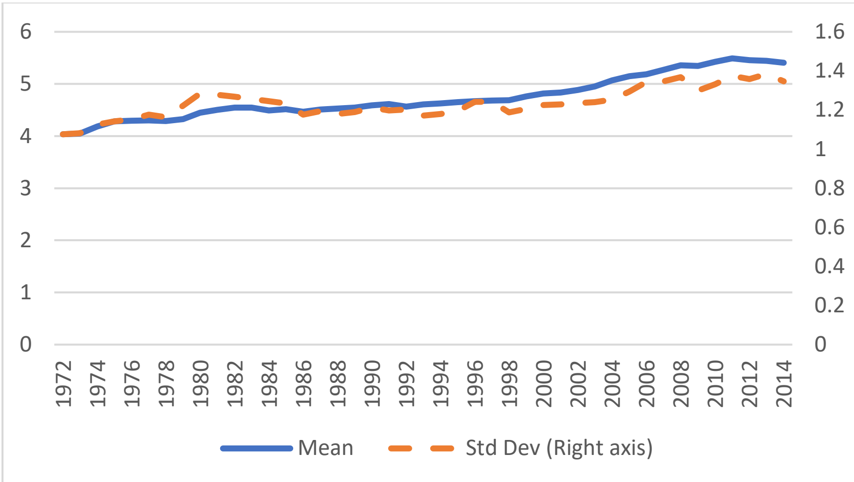
(b) Long difference in p90-p75 1980-2014



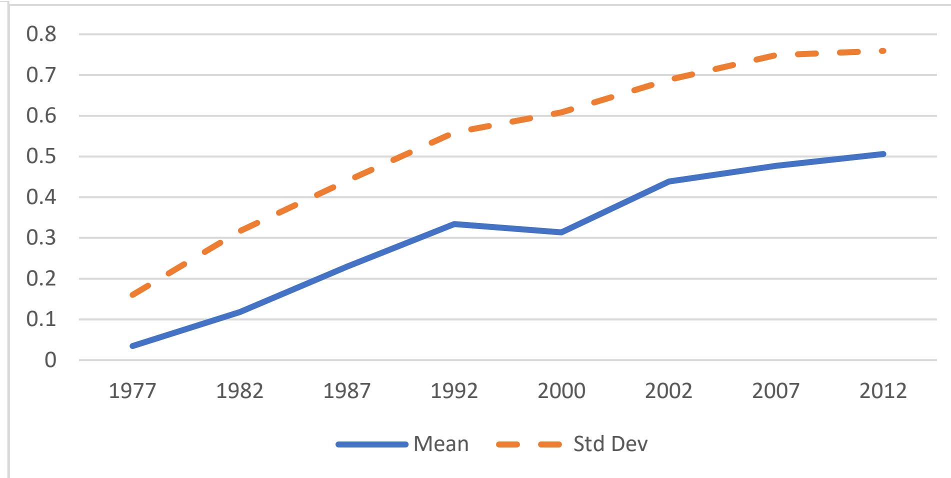
Notes: The markups above are estimated using materials as the variable input. The markup moments are computed from revenue-weighted distribution. Long differences are log differences.

Figure 10 Changes in Indicators of Plant-Level Technology

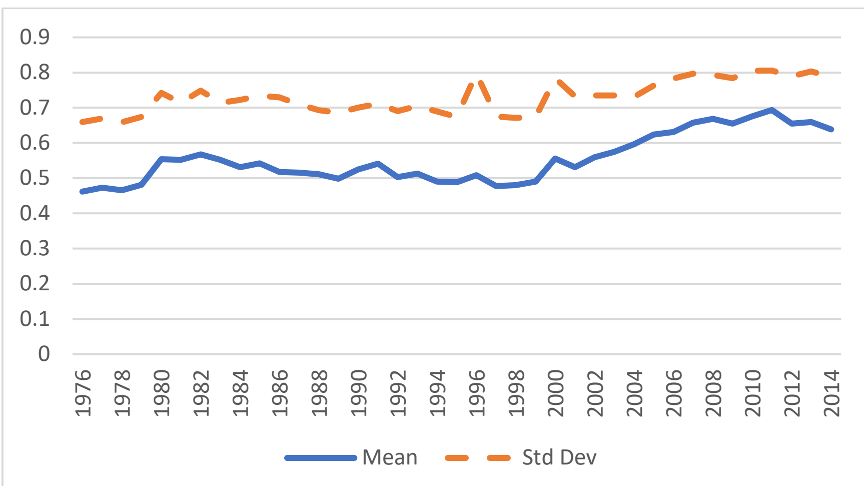
a. Capital Intensity (log(K/L))



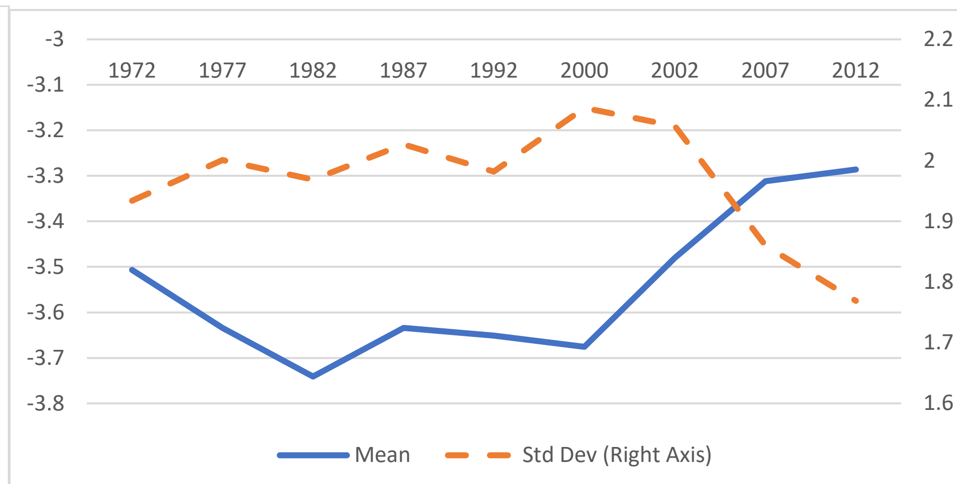
b. Computer Investment Per Worker



d. Diversification Index (IHS Ratio of Non-Mfg to Mfg Emp for Parent Firm)

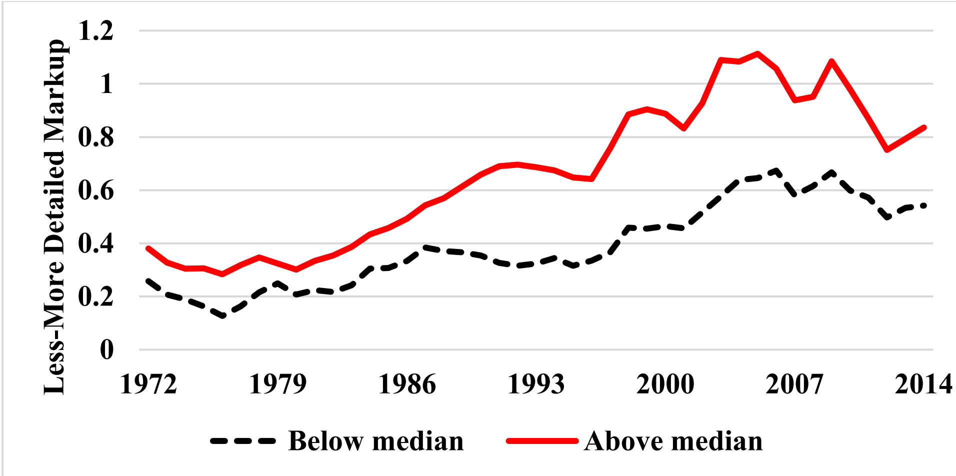


e. Log firm share



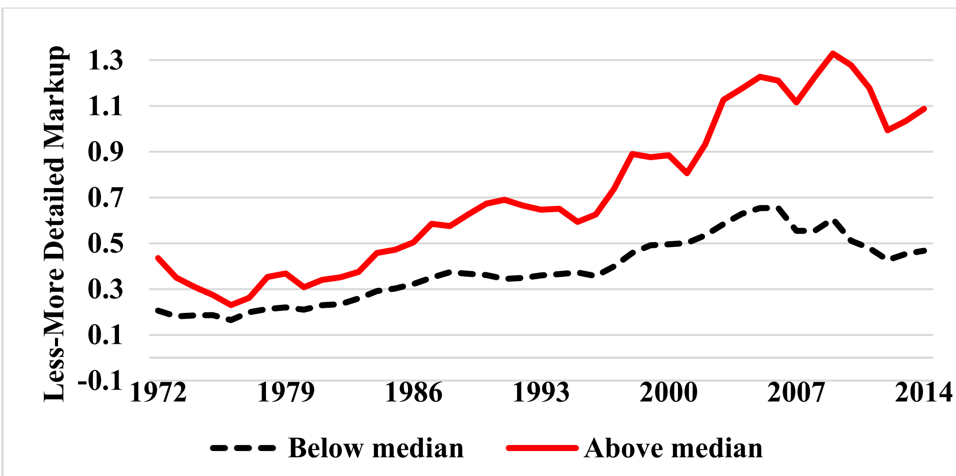
Notes: Tabulations from the ASM, CM and LBD. Computer Investment Per Worker uses the inverse hyperbolic sine (IHS). The log firm share is the share of sales of the parent firm in total industry sales. These are moments not weighted by activity.

Figure 11. Markups and Changes in Computer Intensity



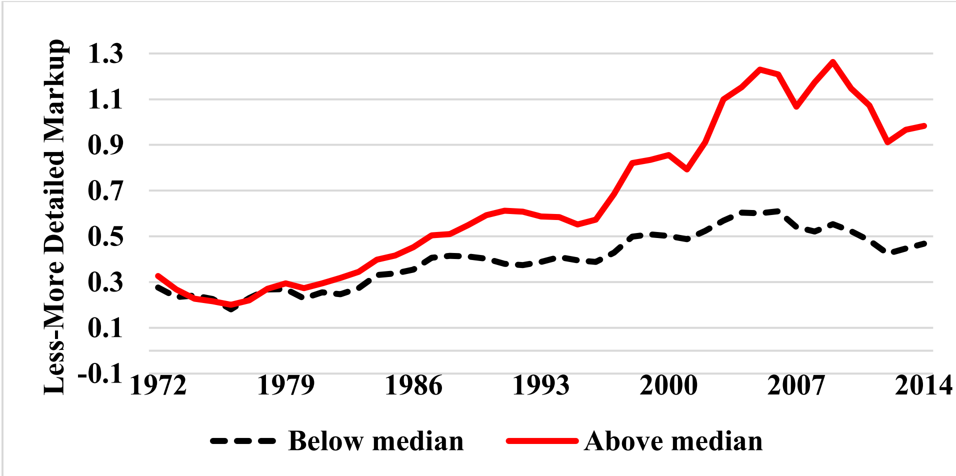
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported are differences between the less detailed and more detailed markups by year for the two groups defined by whether establishment is an industry with above or below median long differences in computer intensity (from 1977 to 2007). Aggregate markups are revenue-weighted means.

Figure 12. Markups and Changes in Capital per Worker



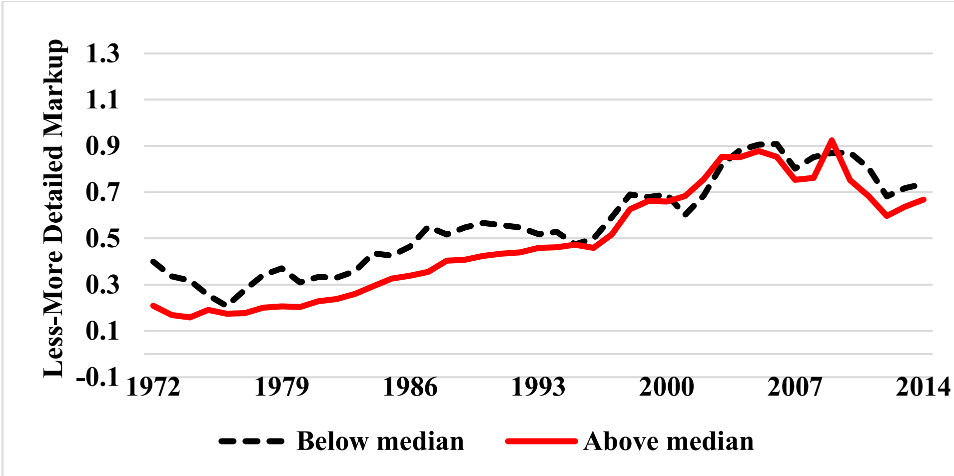
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported are differences between the less detailed and more detailed markups by year for the two groups defined by whether establishment is an industry with above or below median long differences in computer intensity (from 1977 to 2007). Aggregate markups are revenue-weighted means.

Figure 13. Markups and Absolute Changes in Diversification



Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported are differences between the less detailed and more detailed markups by year for the two groups defined by whether establishment is an industry with above or below median long differences in diversification (from 1977 to 2007). Aggregate markups are revenue-weighted means.

Figure 14. Markups and Changes in Concentration



Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported are differences between the less detailed and more detailed markups by year for the two groups defined by whether establishment is an industry with above or below median long differences in concentration (from 1977 to 2007). Aggregate markups are revenue-weighted means.

Appendix: Additional Tables and Figures

Table A1. Output Elasticities for Labor from Cost Share (CS) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
4-digit, yearly	0.2926	0.1015
Plant-level, yearly		0.1706
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
4-digit, yearly	0.2968	0.1183
Plant-level, yearly		0.1773

Notes: Simple means and standard deviations for the full sample are reported. The mean statistics in the first row of each panel applies to all following rows in the panel.

Table A2. Output Elasticities for Labor from Cobb-Douglas Proxy Method (CD) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, 5-year rolling window	0.2382	0.05379
4-digit, 5-year rolling window	0.2362	0.08864
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, 5-year rolling window	0.2345	0.06633
4-digit, 5-year rolling window	0.22	0.1031

Notes: Simple means and standard deviations for the full sample are reported.

Table A3. Output Elasticities for Labor from Translog Proxy Method (TL) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.2533	0.1175
4-digit, 5-year rolling window	0.2575	0.1807
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	0.2682	0.1446
4-digit, 5-year rolling window	0.2439	0.1888

Notes: Simple means and standard deviations for the full sample are reported.

Table A.4: Relationship Between Less minus More Markups and Output Elasticities and Indicators of Technology and Firm Structure, Time Varying Coefficients

	log(Capital Intensity)	IHS(Computer Inv Per Worker)	Diversification Index	log(firm share)
Dependent Variable: Less minus More Detailed Markup				
Slope Coefficient	0.1092**	-0.2881	0.0928	0.0923***
	(0.0427)	(0.1835)	(0.0673)	(0.0097)
SlopeX81-89	0.0095	0.3124**	-0.0256	0.0228***
	(0.0212)	(0.1499)	(0.0285)	(0.0052)
SlopeX90-05	-0.0001	0.3276*	-0.0026	0.0139
	(0.0452)	(0.1818)	(0.0759)	(0.0102)
SlopeX06-14	-0.0215	0.3578*	-0.0360	0.0182
	(0.0697)	(0.1887)	(0.0989)	(0.0182)
Constant	-0.1358	0.3373***	0.2992***	0.6758***
	(0.1686)	(0.0519)	(0.0280)	(0.0451)
R-squared	0.381	0.407	0.378	0.434
P-value				
81-89 = 90-05	0.726	0.8214	0.6501	0.3434
81-89 = 06-14	0.5549	0.539	0.888	0.7812
90-05 = 06-14	0.5179	0.6056	0.3517	0.7906
Dependent Variable: Less minus More Detailed Output Elasticity Materials				
Slope Coefficient	0.0383**	-0.1170	0.0534**	0.0337***
	(0.0182)	(0.0775)	(0.0263)	(0.0032)
SlopeX81-89	0.0062	0.1267**	-0.0161	0.0096***
	(0.0108)	(0.0585)	(0.0118)	(0.0026)
SlopeX90-05	-0.0102	0.1329*	-0.0265	0.0007
	(0.0210)	(0.0776)	(0.0295)	(0.0038)
SlopeX06-14	-0.0221	0.1213	-0.0444	0.0001
	(0.0250)	(0.0781)	(0.0345)	(0.0049)
Constant	-0.0249	0.1517***	0.1212***	0.2681***
	(0.0679)	(0.0259)	(0.0104)	(0.0216)
R-squared	0.481	0.484	0.482	0.543
P-value				
81-89 = 90-05	0.1363	0.8232	0.5931	0.0267
81-89 = 06-14	0.0581	0.8508	0.2452	0.0078
90-05 = 06-14	0.0531	0.1276	0.0047	0.9275
Observations	2164000	394000	1924000	472000

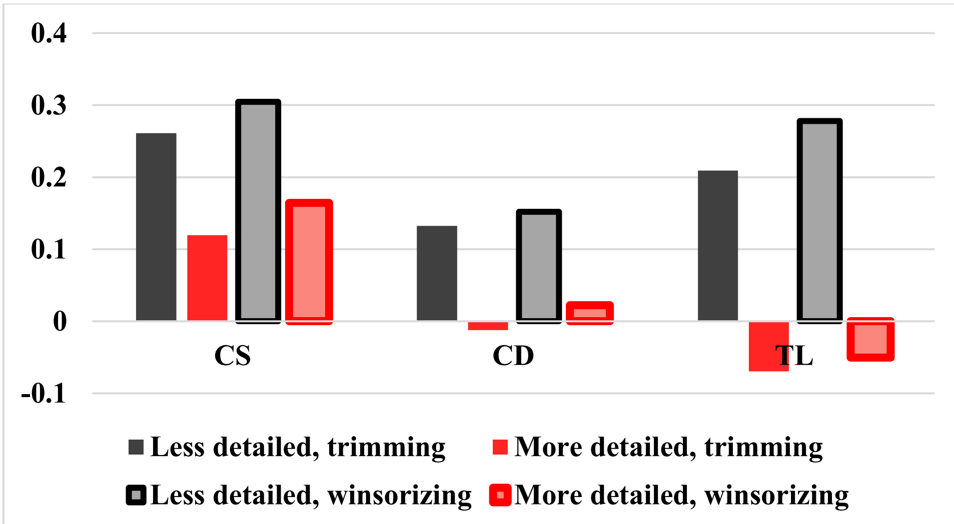
Notes: All specifications control for 6-digit industry by year effects using establishment-level observations. Less minus more detailed markup and output elasticity from translog specification.

Table A.5. Difference in Markups and Changes in Industry-Level Measures

	Dependent Variable: Less detailed markup – more detailed markup			
Change in…	Computer intensity	Capital intensity	Diversification	Concentration
	(1)	(2)	(3)	(4)
Panel A. Cost share				
Above med. X 1981-1989	0.0546***	0.0019	0.0013	-0.0251
	(0.0160)	(0.0181)	(0.0169)	(0.0167)
Above med. X 1990-2005	0.2684*	0.1026	0.1488	-0.0569
	(0.1423)	(0.1548)	(0.1427)	(0.1421)
Above med. X 2006-2014	0.1507	0.2654	0.3777*	-0.0952
	(0.1876)	(0.2235)	(0.1953)	(0.2012)
Above med.	-0.0454	0.0691	0.0746*	0.0203
	(0.0515)	(0.0439)	(0.0449)	(0.0483)
Constant	0.0936***	0.0467	0.0387	0.0643***
	(0.0220)	(0.0332)	(0.0340)	(0.0229)
Panel B. Cobb-Douglas				
Above med. X 1981-1989	-0.0075	0.0269	0.0783***	0.0072
	(0.0207)	(0.0242)	(0.0195)	(0.0215)
Above med. X 1990-2005	0.1609*	0.0783	0.2321***	0.1025
	(0.0887)	(0.0961)	(0.0881)	(0.0882)
Above med. X 2006-2014	0.1433	0.2167	0.4034***	0.1185
	(0.1354)	(0.1642)	(0.1399)	(0.1483)
Above med.	-0.0201	0.0926	-0.0370	-0.1355***
	(0.0616)	(0.0569)	(0.0592)	(0.0504)
Constant	0.0607*	0.0146	0.0704	0.1239***
	(0.0321)	(0.0362)	(0.0456)	(0.0327)
Panel C. Translog				
Above med. X 1981-1989	0.0428	0.0624	0.0722*	-0.0092
	(0.0473)	(0.0418)	(0.0416)	(0.0441)
Above med. X 1990-2005	0.2888**	0.2577**	0.3092***	0.0939
	(0.1282)	(0.1287)	(0.1187)	(0.1345)
Above med. X 2006-2014	0.2073	0.5193**	0.5624***	0.0518
	(0.2334)	(0.2237)	(0.2014)	(0.2381)
Above med.	0.1195**	0.1196**	0.0165	-0.1224**
	(0.0495)	(0.0573)	(0.0517)	(0.0526)
Constant	0.1987***	0.1989***	0.2398***	0.3123***
	(0.0318)	(0.0241)	(0.0236)	(0.0358)
Observations	2,123,000	2,123,000	2,123,000	2,123,000

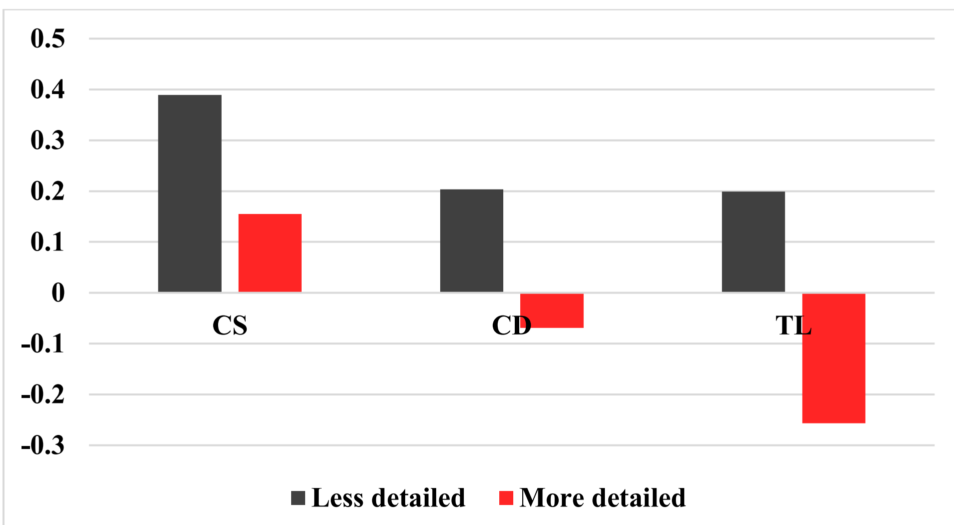
Notes: The markups above are estimated using materials as the variable input. All specifications use revenue weights. Standard errors are clustered at the 6-digit FK-NAICS industry. "Above med." is a dummy variable equal to one if the change in the industry from 1977-2007 is above the revenue-weighted median change for all industries. The "change in…" row indicates the relevant measure for calculating "above med." in each column. "1981-1989", "1990-2005", and "2006-2014" are dummy variables equal to one when the year is in that year range. The reference years for these specifications are 1972-1980.

Figure A1. Long Differences in Markups 1980-2014 Comparing Trimming versus Winsorizing



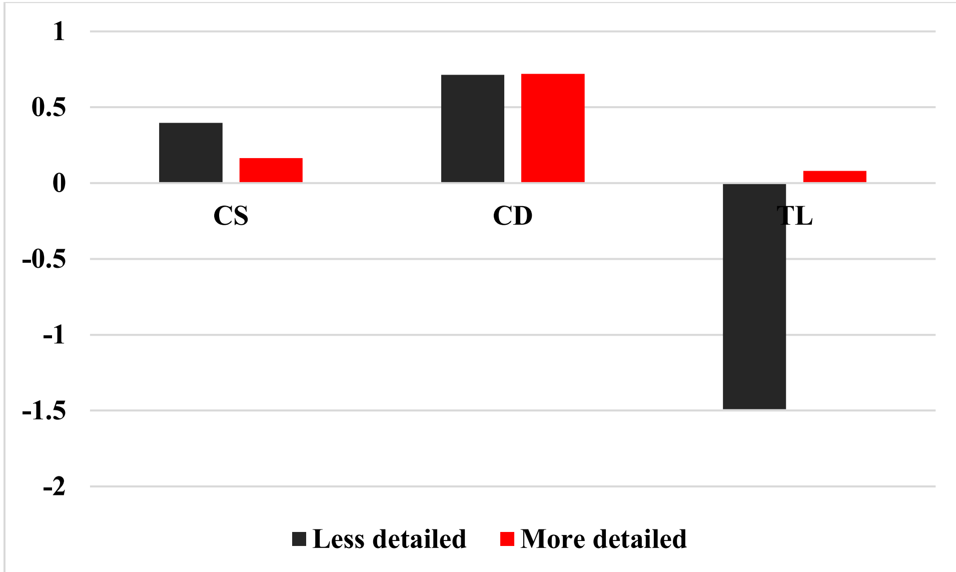
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A2. Long Difference in Markups 1980-2014, Top 50 Industries



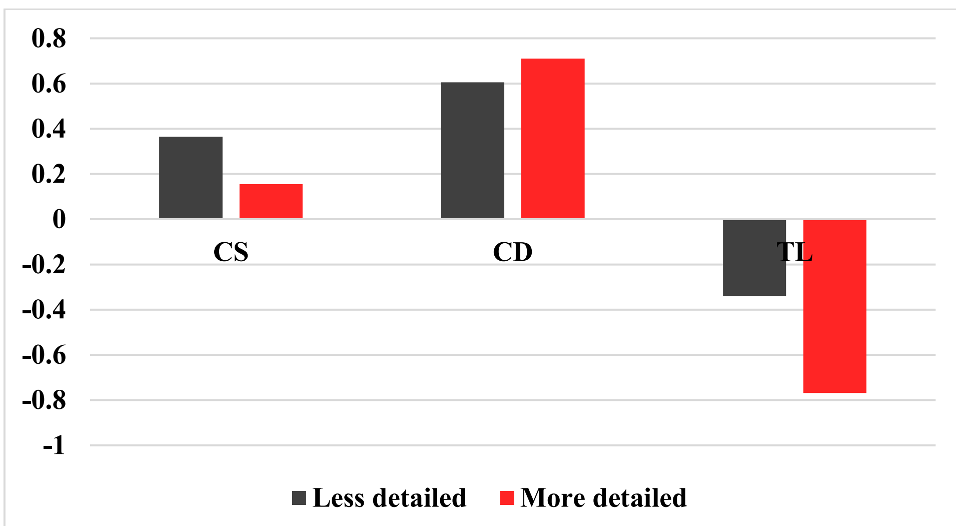
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A3. Long Difference in Markups 1980-2014



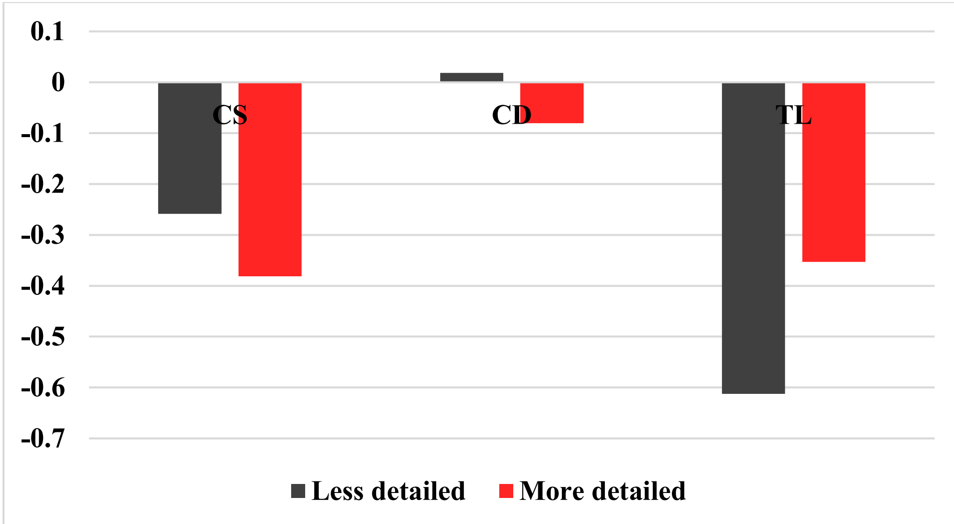
Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A4. Long Difference in Markups 1980-2014, Top 50 Industries



Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A5. Long Difference in Labor Output Elasticities 1980-2014



Notes: The output elasticities above are for labor. Output elasticities are revenue-weighted means. Long differences are log differences.

Appendix B. Data Appendix

Our analysis uses the Annual Survey of Manufacturers (ASM) from 1972 to 2014. The ASM surveys roughly 50,000-70,000 establishments. The ASM is a series of five-year panels (starting in years ending in "4" and "9") with probability of panel selection being a function of industry and size. We use the ASM sample weights to adjust for the probability of selection.

A. Output and production factors

We calculate real establishment-level revenue (or, under TFPR assumptions, output) as $Q_{jt} = \left(TVS_{jt} + DF_{jt} + DW_{jt}\right)/PISHIP_t$, where TVS_{jt} is total value of shipments, DF_{jt} is the change in (the value of) finished goods inventories, DW_{jt} is the change in (the value of) work-in-progress inventories, and $PISHIP_t$ is the *industry-level* shipments deflator, which varies by detailed industry (4-digit SIC prior to 1997 and 6-digit NAICS thereafter) and is taken from the NBER-CES Manufacturing Productivity Database and updated as part of the Collaborative Micro Productivity Project (CMP) (see Cunningham et. al. (2020). If the resulting Q_{jt} is not greater than zero, then we simply set $Q_{jt} = TVS_{jt}/PISHIP_t$. Nominal revenue just uses the numerators of these measures.

We construct labor from the ASM in terms of total hours (TH_{jt}) as follows:

$$TH_{jt} = \begin{cases} PH_{jt}\dfrac{SW_{jt}}{WW_{jt}} & \text{if } SW_{jt} > 0 \text{ and } WW_{jt} > 0 \\ PH_{jt} & \text{otherwise} \end{cases} \tag{B1}$$

where PH_{jt} is production worker hours, SW_{jt} is total payroll, and WW_{jt} is the payroll of production workers. Nominal labor costs are measured as SW_{jt}

We measure capital separately for structures and equipment using the perpetual inventory method: $K_{jt+1} = (1 - \delta_{t+1})K_{jt} + I_{jt+1}$ where K is the capital stock, δ is a year- (and industry-) specific depreciation rate, and I is investment. At the earliest year possible for a given establishment, we initialize the capital stock by multiplying the establishment's reported book value by a ratio of real capital to book value of capital derived from BEA data (where the ratio varies by 2-digit SIC or 3-digit NAICS). Thereafter, we observe annual capital expenditures and update the capital stock accordingly, where we deflate capital expenditures using BLS deflators.[1]

[1] See Cunningham et. al (2020) for more detail.

We calculate real materials as $M_{jt} = (CP_{jt} + CR_{jt} + CW_{jt})/PIMAT_t$, where CP is the cost of materials and parts, CR is the cost of resales, CW is the cost of work done for the establishment (by others) on the establishment's materials, and $PIMAT$ is the industry materials deflator. We calculate energy costs as $N_{jt} = (EE_{jt} + CF_{jt})/PIEN_t$, where EE is the cost of purchased electricity, CF is the cost of purchased fuels consumed for heat, power, or electricity generation, and $PIEN$ is the industry energy deflator. The nominal materials and energy just use the numerators for these measures.

We use the production factor and output measures described above for our estimation of the control function approach for estimation of output elasticities. For this estimation, we combine structures and equipment into a total capital stock. We use the nominal values for cost shares of revenue and cost shares of total costs. For the latter we use user cost of capital measures from BLS following Cunningham et. al. (2020).

We use the Fort and Klimek (2018) (FK) NAICS consistent industry codes back to 1976. In turn, we build on that methodology to assign NAICS consistent codes to establishments in the ASM from 1972 to 1975. The first step of that methodology is that any establishment in the 1972-75 ASM that has an FK NAICS code from the 1976 on period is assigned that code. The second step is to use SIC-NAICS concordances to assign codes with probabilistic assignment based on revenue shares when there is a one to many or many to many concordance.