Rising Markups or Changing Technology?*

Lucia Foster
U.S. Census Bureau

John Haltiwanger
University of Maryland and NBER

Cody Tuttle
University of Texas at Austin

January 2021

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 (computer investment per worker, capital intensity) versus market structure (concentration ratios) and find patterns in support of changing technology as the driver.

* Contact information: Foster: Center for Economic Studies, Bureau of the Census, Washington, DC 20233; Haltiwanger: Department of Economics, University of Maryland, College Park, MD 20742. Tuttle: Department of Economics, University of Texas at Austin, Austin, TX 78712 . Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release (DRB Approval Number: CBDRB-FY20-CED006-0022). We thank Jan De Loecker, Jan Eeckhout, Devesh Raval, John Eltinge and Cheryl Grim for their helpful comments on an earlier draft.

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 is clever and simple. The methodology builds on Hall (1988) and De Loecker and Warzynski (2012). 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 of the information in the annual series and create estimates in rolling five-year intervals which we refer to as "rolling annual" estimates. This is in contrast to 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. For example, using a Cobb-Douglas specification at the 2-digit level with "rolling annual" estimates we find the sales-weighted markup increases by more than 40 log points from 1980 to 2005. The analogous change using a 4-digit specification with "rolling annual" estimates yields only a 24 log point increase from 1980 to 2005. In both cases, we find estimated markups fall from the mid-2000s to 2014, returning to early 1990s levels. The 2-digit Cobb-Douglas specification with "rolling annual" estimates yields an increase in the sales-weighted markup from 1980 to 2014 of only 15 log points. Using the 4-digit specification, the increase is only 2 log points.

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 42 log points from 1980 to 2005 and by 28 log points from 1980 to 2014. The analogous changes using a translog specification with "rolling annual" estimates are 2 and -5 log points, 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 up 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 explore this question, we take advantage of industry-level differences in the change in markups using more versus less detailed output elasticity estimates. To investigate the potential link to changes in the way establishments do business, we use observed variation in indicators of changing technology over time at a detailed (4-digit) level. The measures include the long differences in measures of capital per worker, computer investment per worker, and a measure of how much establishments in manufacturing have become part of firms with non-manufacturing activity. We 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. This pattern holds especially for the translog specifications. To explore whether the gap between the DEU type estimates and our estimates are related to changing market power, we consider long differences in concentration ratios. Concentration ratios have limitations as measures of market power but as we discuss exploring this issue also has implications for measurement error explanations of our findings. We find that the difference between the change in the markup between the less and more detailed specifications is not related to change in concentration ratios at the industry level.

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,** θ_{it}^{V} is the output elasticity for input **v** for establishment **i** in year **t**, and α_{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.[1]

The input's share of revenue, α_{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 and the output elasticity. 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.

[1] 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.

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., 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.[2]

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.[3] 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

[2] 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.

[3] 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.

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 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 understand 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. However, 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. In short, since the gap between the more and less detailed estimates grows and shrinks over time, a more complicated measurement error explanation requires that the more detailed estimates be especially biased when markups are rising. To test this, we examine how the gap evolves in industries with larger versus smaller changes in industry sales concentration. As discussed below, this is instructive for this question since shifts in sales towards larger firms within industries is an important contributor to rising measured markups. 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 that 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 changing industry concentration.

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 of 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 is 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 is 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 is 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 of these 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 (but show results for labor in the appendix).[4] 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 aforementioned 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**

[4] The adjustment cost literature finds that even at an annual frequency the patterns of employment dynamics are consistent with the presence of adjustment costs (see, e.g., Decker et. al. (2020) and Cooper et. al. (2020)).

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. 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

[5] All of 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.

(black is more restrictive, red is less restrictive) 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, it appears that 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 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 actually a decline using the translog specification (TL).

[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.

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 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

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

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 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 there is a growing gap between the sales-weighted markup from the less 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 more and less 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. In Section V.C, we test this possibility that the more detailed markup estimates are particularly biased when markups are rising and find little support for even this more nuanced explanation.

V. **Factors Driving Differences in Results**

What drives differences in markups between the less detailed and more detailed specifications? We explore this with several exercises. We examine potential factors driving differences in results. We start by looking at some measurement issues, then look at decompositions, and finally look at patterns in technology.

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. We analyze these in two figures.

[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.

Figure 5 shows the long difference in output elasticities for materials.[9] Figure 6 shows the sales-weighted revenue cost shares for all inputs 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 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. While potentially interesting, equation (3) and Figure 4 highlights that not much can be learned about the changing pattern of sales weighted markups by looking at the sales-weighted output elasticities and cost shares of revenue independently. Partly this reflects the covariance patterns between the sales weights and these components. We examine these covariance patterns further in a decomposition analysis below.

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

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

variable input). Broadly consistent with these papers, we find smaller increases in total-cost-share weighted markups even using the less detailed specifications (and actually 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 and contrast 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:

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

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 together reflect net entry as the penultimate term captures entry and the final term captures exit. Bars over terms denote weighted means.

[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.

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 90^{th}-75^{th} 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 is mitigated by the more detailed specifications (with the exception of the detailed cost share approach for skewness). This pattern is intuitive 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 and 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. 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 due to a substantial decline in all of the components (except for the cost share component where the reallocation actually increases). 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?

Taken at face value, 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 market structure.

We conduct this analysis using industry-level indicators of changing technology and market structure. We construct four measures: computer intensity, capital intensity, diversification, and concentration. We measure computer intensity as computer investment per worker at the 4-digit NAICS level which is the sum of plant-level computer investment in the industry-year divided by sum of plant-level employment in the industry-year. Capital intensity is measured as capital per worker at the 4-digit NAICS level which is the sum of the plant-level capital stock in the industry-year divided by the sum of plant-level employment in the industry-year. Both the computer investment per worker and capital measure per worker use ASM sample weights in their construction.

The diversification measure is motivated by the work of Fort et. al. (2018). U.S. firms with activity in manufacturing often have activity in non-manufacturing. There has been a positive trend in this direction as documented in Fort et. al. (2018) 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 at the 4-digit NAICS level for each year. We construct this measure taking all establishments in each manufacturing industry and computing the activity of each parent firm of such establishments in non-manufacturing. The industry-level measure is the ratio of non-manufacturing activity to manufacturing activity based on these calculations. For this measure, we use the absolute change at the industry-level motivated by the argument that firms in an industry exhibiting large absolute changes are changing their way of doing business.

Finally, as an alternative to changing technology accounting for the differences in markup patterns between using less and more detailed output elasticities, we also compute long-difference measures of changes in industry-level concentration ratios. We use the 20-firm concentration ratio at the 4-digit level for this purpose (but have found in unreported results that patterns are similar using the 4-firm concentration ratio).

These measures are only available consistently in Economic Census years for 1977 onward. For every industry, we calculate the long difference (using inverse hyperbolic sine) from 1977-2007 for each of the measures. 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.

For every establishment, we calculate markups using factor elasticities estimated from our three methods: cost-share (CS), proxy method with Cobb-Douglas (CD), proxy method with translog (TL). For each of these methods, we focus on our benchmark cases with less detailed and more detailed estimation of the production structure. For every establishment and markup estimation method, we calculate the sales-weighted difference between the less-detailed and more-detailed based markups for each year at the 4-digit NAICS level.

To explore the relationship between these changing technology indicators and changing market structure estimators with the change in markups, we estimate a series of panel regressions with the dependent variable equal to difference between the less and more detailed markup at the 4-digit by year level for each of the production function specifications.[11] 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 intuition for the technological change specifications is that if the less detailed estimates capture changes in markups and changes in technology while the more detailed estimates only capture changes in markups, then when we difference that out, we should see an increase in industries with greater technological change but a smaller increase in industries with lower technological change. In other words, if the rise in markups from the less detailed estimates is partly 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 technological change.

An alternative explanation for the difference in estimates is that the more detailed estimates are measured with error. In previous sections, we argue that the time series pattern of markups is inconsistent with a simple measurement error explanation. Namely, the gap in the more and less detailed estimates changes over time, and thus any measurement error explanation must account for that time series variation. One possibility is that the more detailed estimates are

[11] It may be that high markup firms are more likely to invest in advanced technology. However, it is not clear this has any systematic implications on the difference in markups emerging from the less minus the more detailed benchmark cases.

especially biased when markups are rising. Although it is not clear why that bias would arise, we provide a test of this hypothesis. Evidence from DEU and others suggest that there is a positive relationship between sectors with greater increases in concentration and markups. This is consistent with reallocation of activity towards larger firms accounting for substantial fraction of rising measured markups through the reallocation channel discussed above. If our estimates are systematically biased when markups are rising, we would expect the gap between the more and less detailed estimates to grow largest for industries with large changes in sales concentration. We use the panel specification described above, focusing on industry concentration, to conduct this test.

Table 5 presents the estimates for this panel specification. The estimated coefficients are positive for all of 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.

To provide more perspective, Figures 10-12 plot the mean difference between the less detailed and more detailed markup estimates in each year for industries with above median industry-level technology changes versus below median industry-level technology changes using the translog specifications. We find that the industries with above median changes in these technology measures exhibit an increasing larger difference between the less detailed and more detailed based markups. Figure 13 plots the analogous relation using changing concentration ratios. The results in Table 5 and Figure 13 suggests that this index of changing market structure is not associated with the smaller increases in markups we find when using more detailed output elasticity specifications. The general time series patterns in our more detailed estimates rule out a simple measurement error explanation, and these results suggest that even a more complicated explanation does not explain our main findings.

In short, we interpret the results in this section as providing support for the view that the more detailed output elasticity specifications are capturing real changes in the structure of technologies within and across industries. When using such detailed output elasticity specifications, we find much smaller increases in measured markups using the production approach.

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 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) 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. For example, DEU (2018) consider a translog specification with the publicly traded firm-level data with parameters that vary by 2-digit industry but are time invariant. The translog specification yields time varying output elasticities at the firm level but the production technology itself is stable. Using our large annual establishment-level data, we estimate a translog specification that permits parameters to vary at the 4-digit NAICS level with a five-year rolling window.

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 smaller increases in the *dispersion* of markups and smaller roles for reallocation in accounting for the changing mean. These inferences hold especially for the control function estimation approaches using Cobb-Douglas or translog specifications.

Taken at face value, our results imply that much of measured increases in markups may instead reflect changing production technology. We acknowledge that our understanding of how production technologies varies across businesses in the same industry is limited. To help provide further insights and evidence that our findings are consistent with changing production technologies, we take advantage of information on the nature of changing technology at the detailed (4-digit NAICS) level. Specifically, we classify industries into whether they have above or below median long-differences (from 1977 to 2007) in computer intensity, capital intensity, and diversification outside of manufacturing. We find that industries that have above the median long-differences in these indicators of changing technology have substantially greater differences between our benchmark less detailed and more detailed production technology cases. We also classify industries into whether they have above or below median long differences in market concentration (using the 20-firm sales concentration ratio). We find no relationship between changes in market concentration and the differences in less detailed versus more detailed changes in markups. We regard our evidence as supportive of the interpretation that our more flexible production technology estimation is capturing changes in production technologies over time.

Our findings are more suggestive than conclusive and raise important questions about the changing structure of U.S. businesses over the last few decades. First of these is whether our results extend beyond manufacturing. Unfortunately, the CMP database developed for U.S. manufacturing establishments is not easily replicated for other sectors. A second more fundamental question is how should we 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. If this is so, then we need an alternative approach to characterize how different businesses in the same industry accomplish their activities. In some 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.

References

Acemoglu, Daron, and Pascual Restrepo, (2019), "The Task Content of Production," Working Paper.

Baily, Martin Neil, Charles Hulten, and David Campbell, (1992) "Productivity Dynamics in Manufacturing Establishments" (pp. 187-249), in M. Baily and C. Winston (Eds.), *Brookings Papers on Economic Activity: Microeconomics* (Washington: Brooking's Institution).

Bond, Steve, Arshia Hashemi, Greg Kaplan, Piotr Zoch, (2020), "Some Unpleasant Markup Arithmetic: Production Function Elasticities and Their Estimation from Production Data," NBER Working Paper No. 27002.

Cooper, Russell, John Haltiwanger, Jonathan Willis. (2020), "Declining Dynamism at the Establishment Level: Sources and Productivity Implications," July, Working Paper.

Cunningham, Cindy, Lucia Foster, Cheryl Grim, John Haltiwanger, Sabrina Wulff Pabilonia, Jay Stewart, and Zoltan Wolf, 2020. "**Dispersion in Dispersion: Measuring Establishment-Level**

Differences in Productivity," Working Papers 18-25, Center for Economic Studies, U.S. Census Bureau.

De Loecker, J., J. Eeckhout, and G. Unger (2020). "The Rise of Market Power and the Macroeconomic Implications", *Quarterly Journal of Economics*, May, 135(2), 561–644

De Loecker, J., J. Eeckhout, and G. Unger (2018). "The Rise of Market Power and the Macroeconomic Implications", Working Paper, November.

De Loecker, J., and F. M. P. Warzynski (2012) "Markups and Firm-level Export Status," *American Economic Review*, 102(6), 2437–2471.

Decker, Ryan, John Haltiwanger, Ron Jarmin and Javier Miranda (2020) " Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," March,

Edmond, C. V. Midrigan and D. Xu (2018) "How costly are markups," NBER Working Paper No. 24800.

Fort, Teresa C. and Shawn D. Klimek, 2018. "**The Effects of Industry Classification Changes on US Employment Composition**," Working Papers 18-28, Center for Economic Studies, U.S. Census Bureau.

Fort, Teresa, Justin Pierce and Peter Schott (2018) "New Perspectives on the Decline of US Manufacturing Employment," Journal of Economic Perspectives, 32(2), 47-72.

Foster, Lucia, Haltiwanger, John, and C. J. Krizan, (2001) "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in Edward Dean, Michael Harper, and Charles Hulten (Eds.), New Developments in Productivity Analysis (Chicago: University of Chicago Press).

Hall, R. (1988) "The Relation between Price and Marginal Cost in U.S. Industry," Journal of Political Economy, 96(5), 921–947.

Haltiwanger, John (1997) "Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence," Federal Reserve Bank St. Louis Review, 79(3), 55–77.

Syverson, Chad, (2004) "Product Substitutability and Productivity Dispersion, *Review of Economics and Statistics*, 86:2 , 534-550.

Syverson, Chad. (2011). "What determines productivity." *Journal of Economic Literature*, 49(2):326-365.

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.[12]

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

We calculate real materials as $M_{jt} = \left(CP_{jt} + CR_{jt} + CW_{jt}\right)/PIMAT_t$, 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 $N_{jt} = \left(EE_{jt} + CF_{jt}\right)/PIEN_t$, 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 a 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.

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.

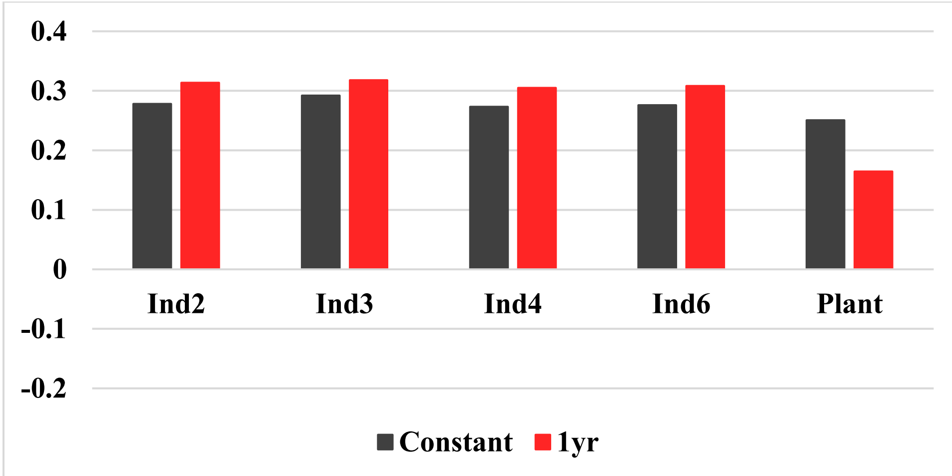
Table 5. Difference in Markups and Changes in Industry-Level Measures

	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

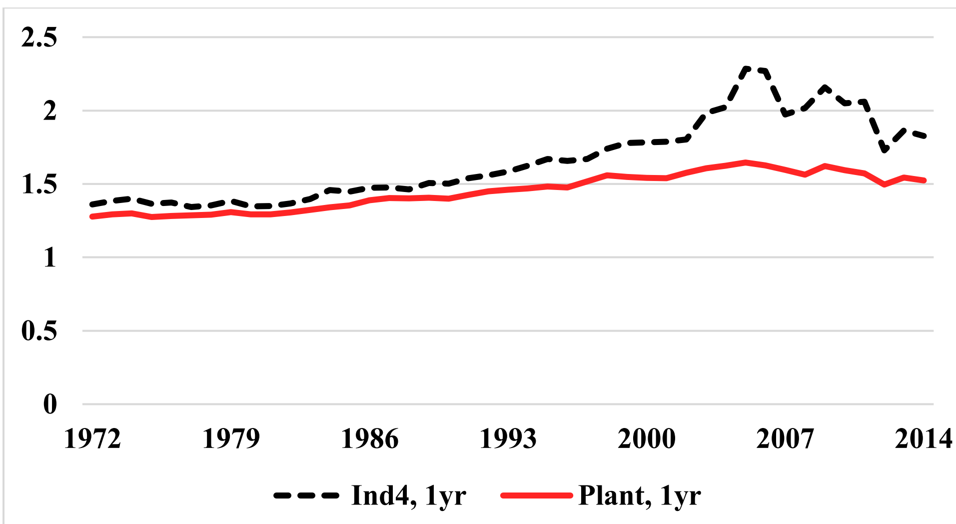
Notes: The markups above are estimated using materials as the variable input. All specifications use revenue weights. Standard errors are clustered at the 6-digit FK-NAICS industry. "Above med." is a dummy variable equal to one if the change in the industry from 1977-2007 is above the revenue-weighted 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 1. Markups Estimated Using Cost Shares (CS)

(a) Long difference in markups 1980-2014



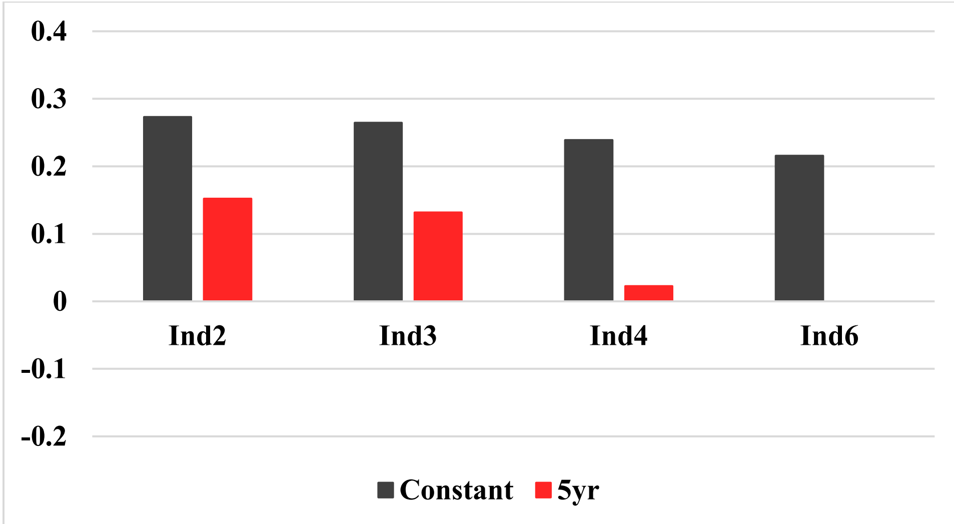
(b) Markups from 1972-2014, benchmark cases



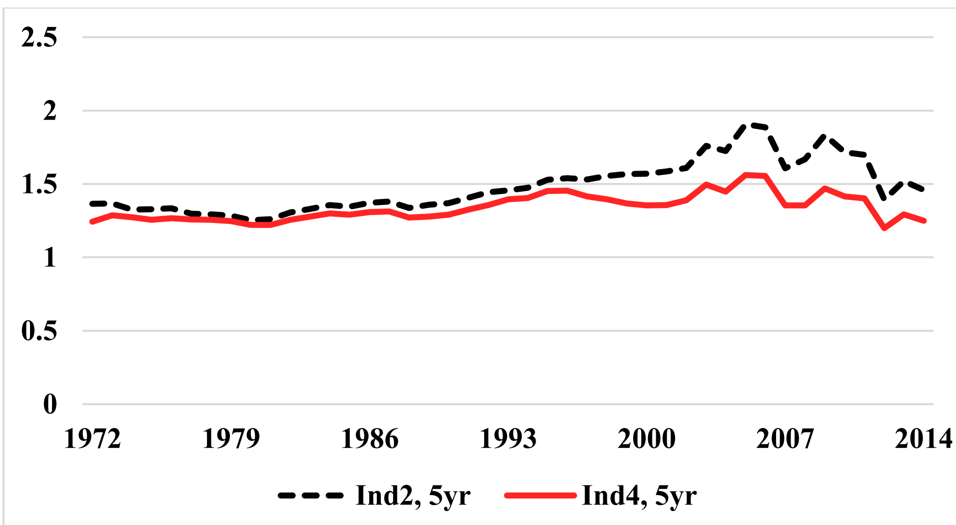
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

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

(a) Long difference in markups 1980-2014



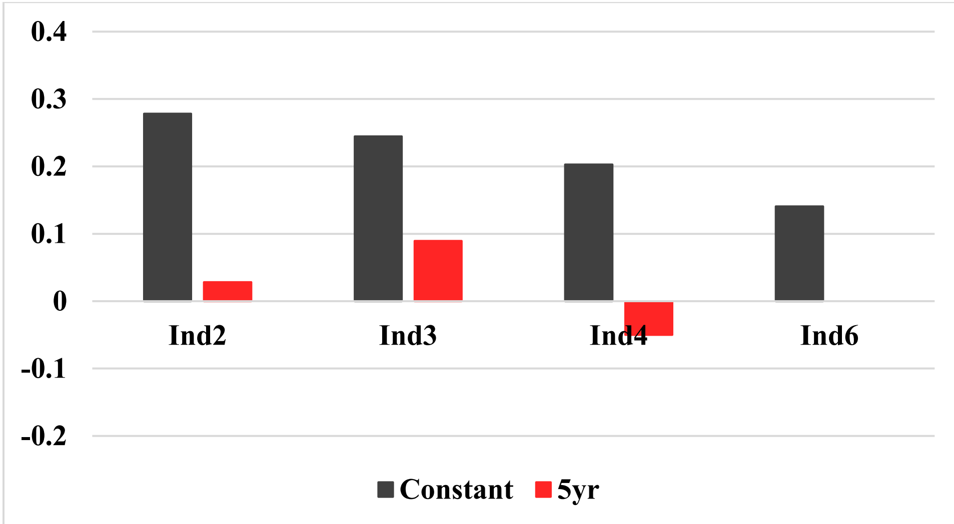
(b) Markups from 1972-2014, benchmark cases



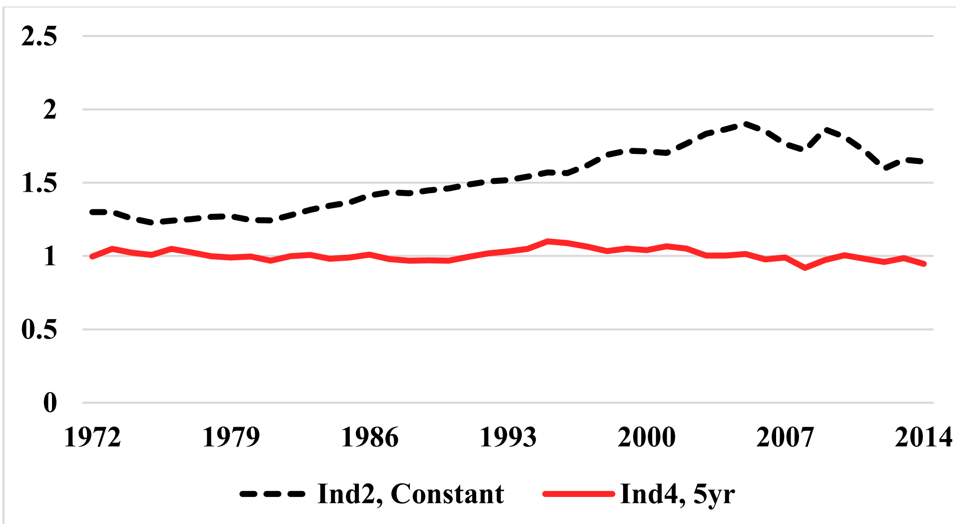
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 3. Markups Estimated Using Translog (TL)

(a) Long difference in markups 1980-2014

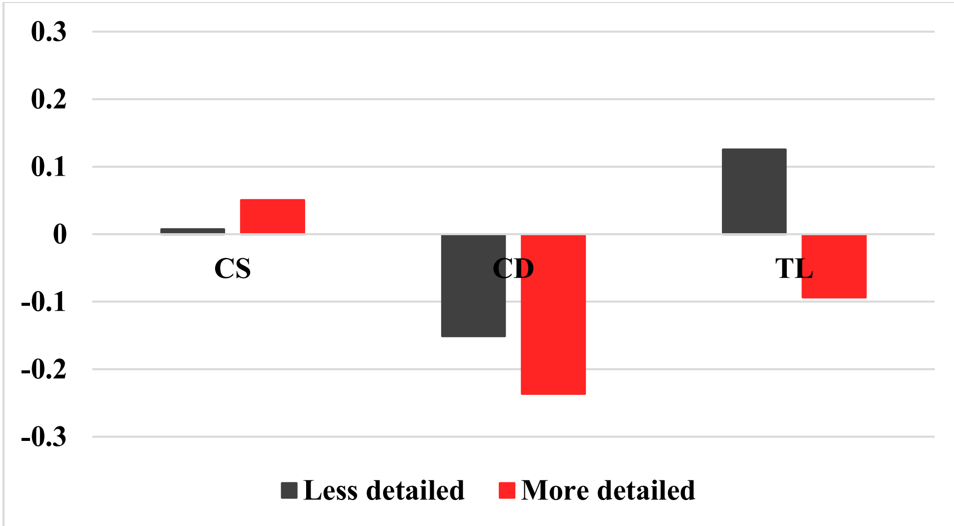


(b) Markups from 1972-2014, benchmark cases



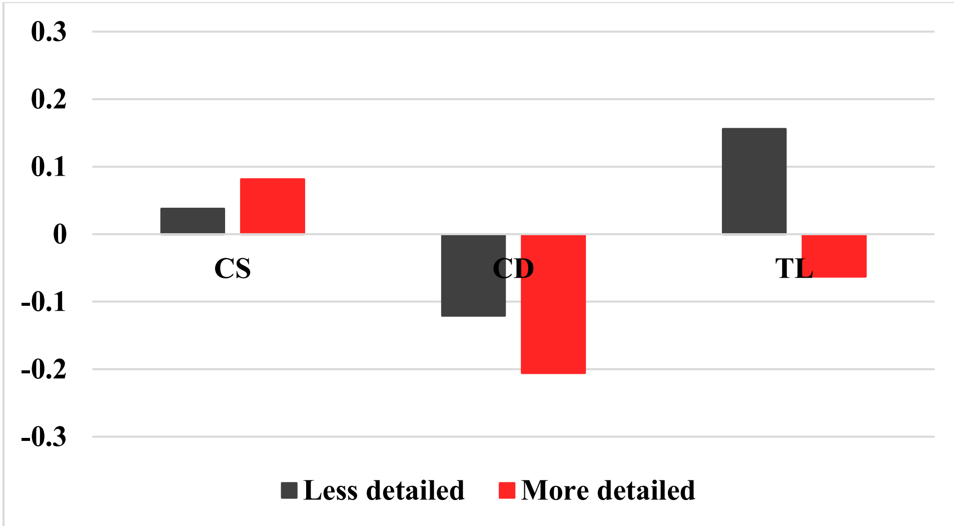
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 4. Long Difference in Naïve Markups 1980-2014



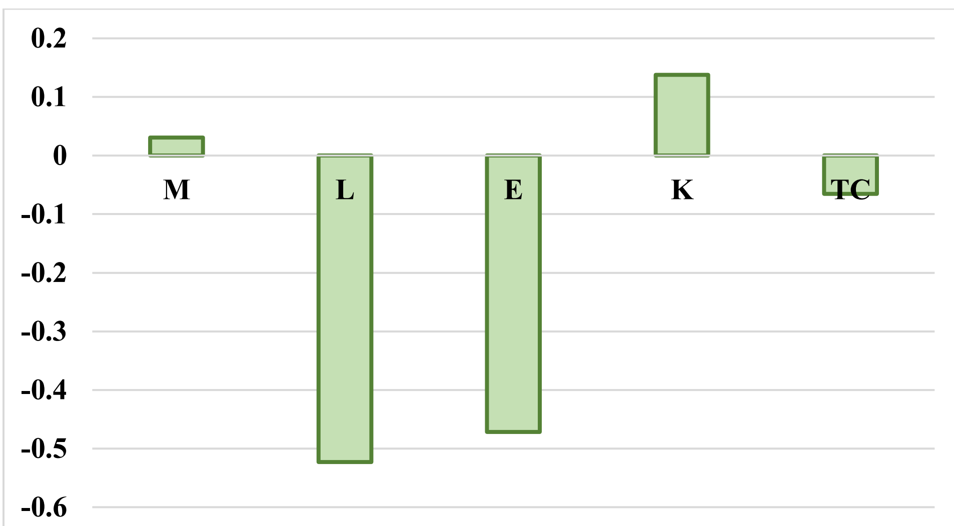
Notes: The markups above are estimated using materials as the variable input. See equation (3) for definition of naïve markup. Long differences are log differences.

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



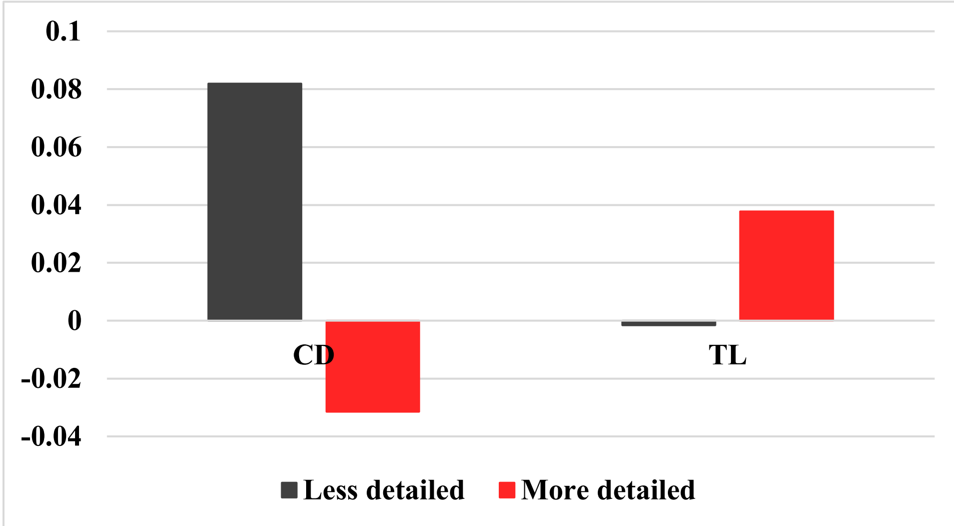
Notes: The output elasticities above are estimated for materials. Output elasticities are revenue-weighted means. Long differences are log differences.

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



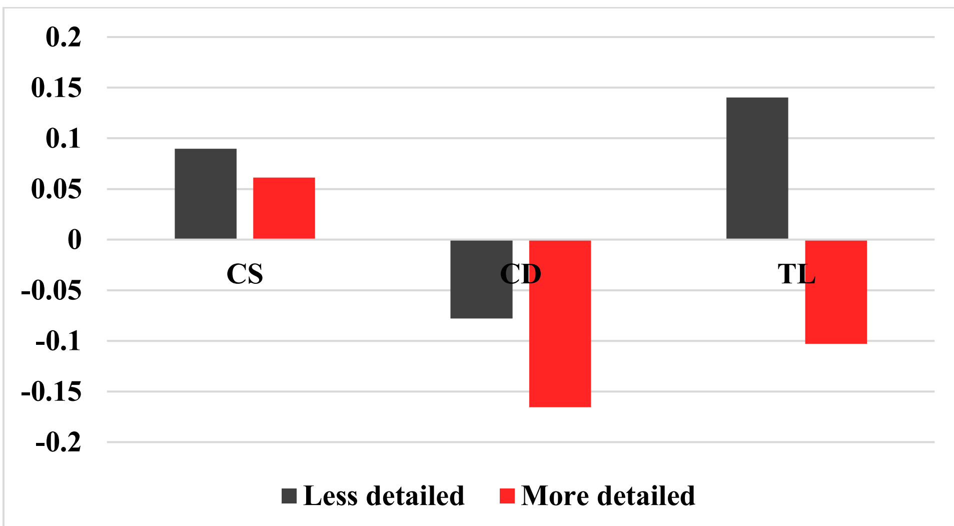
Notes: Input shares of revenue are revenue-weighted means. Long differences are log differences.

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.

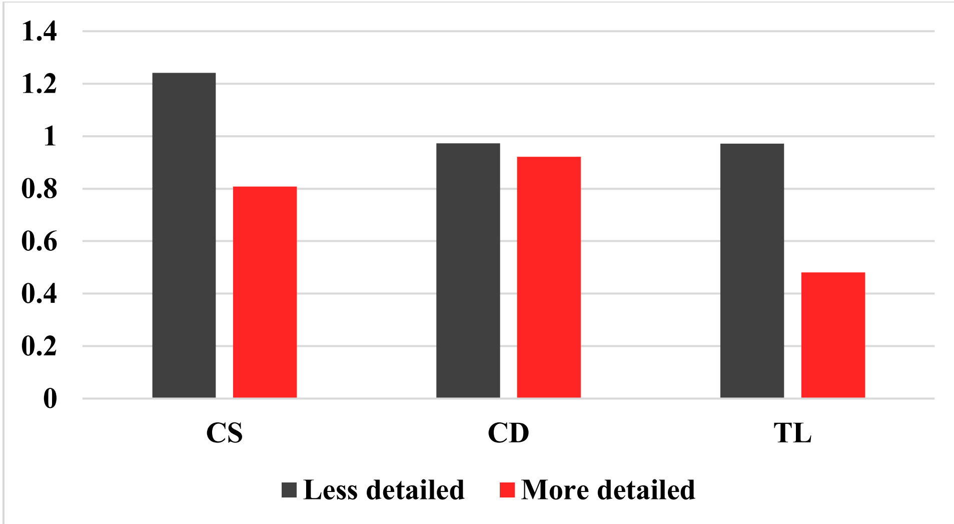
Figure 8. Long Difference of Markups from 1980-2014. Robustness to Total Cost Weighting



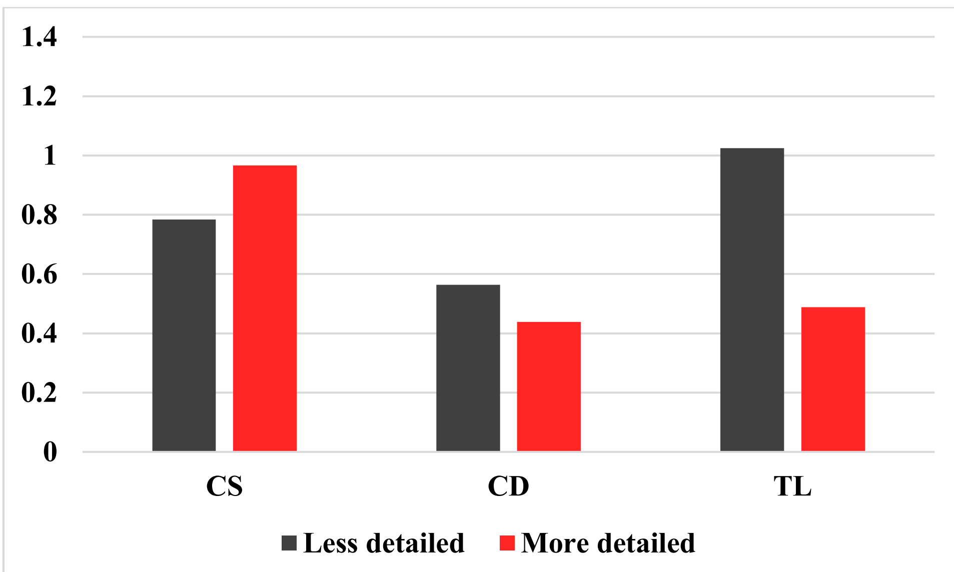
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are total cost-weighted means. Long differences are log differences.

Figure 9. Dispersion in Markups over Time

(a) Long difference in standard deviation 1980-2014

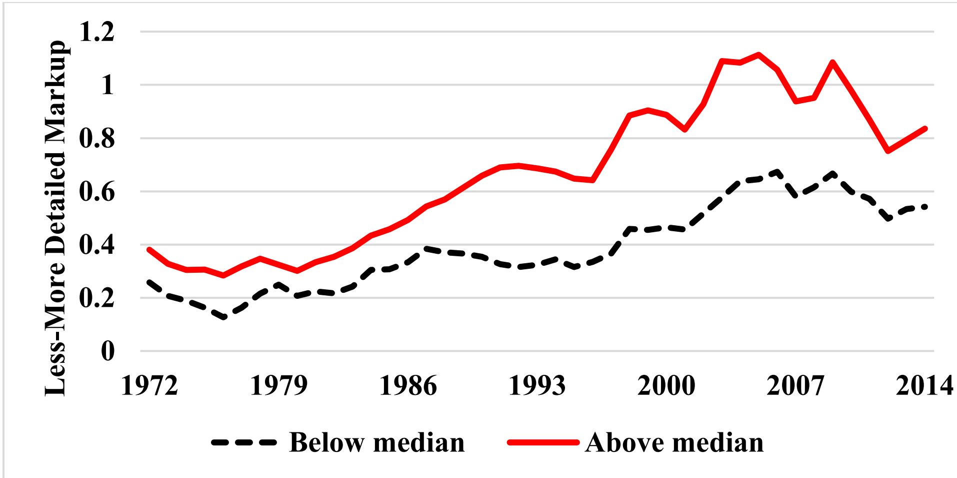


(b) Long difference in p90-p75 1980-2014



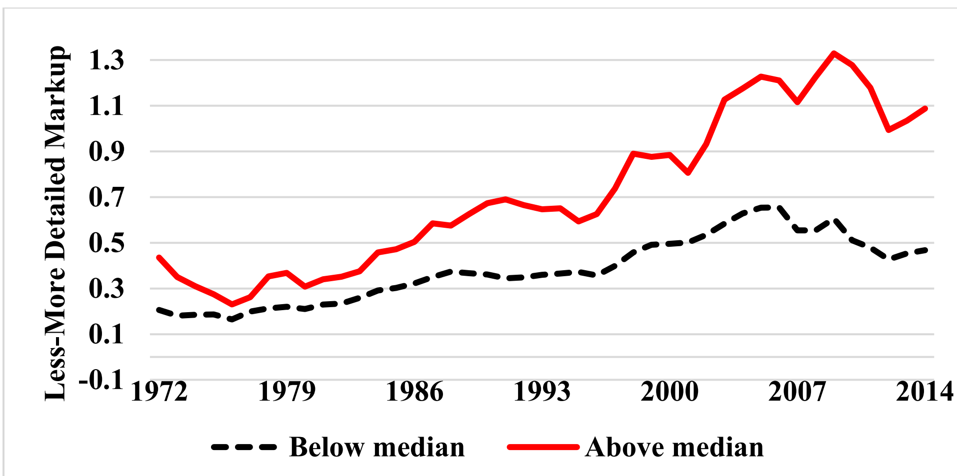
Notes: The markups above are estimated using materials as the variable input. The markup moments are computed from revenue-weighted distribution. Long differences are log differences.

Figure 10. Markups and Changes in Computer Intensity



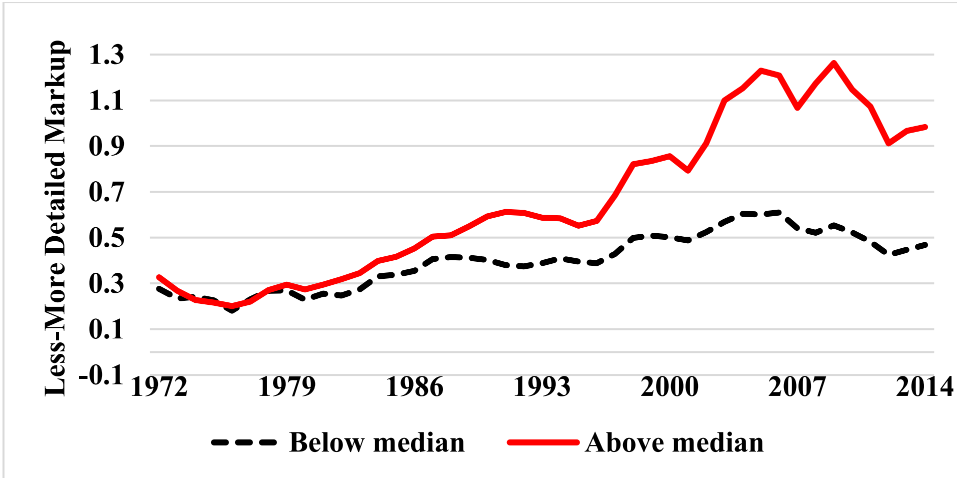
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported 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 11. Markups and Changes in Capital per Worker



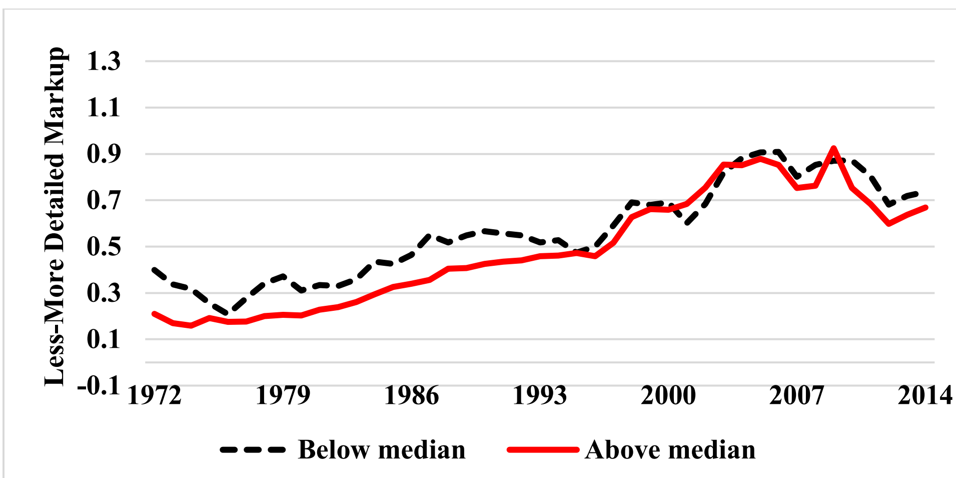
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in five year rolling intervals. Reported 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 12. 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 13. 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

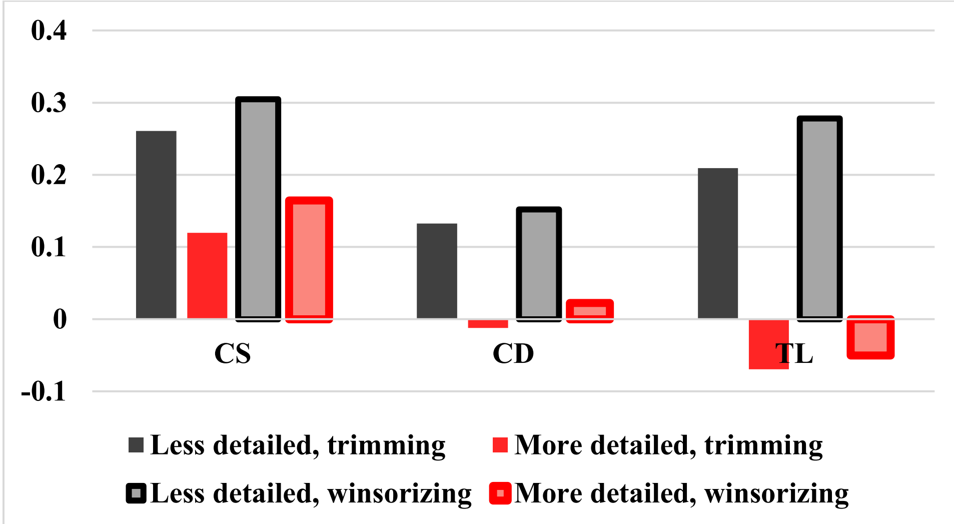
Notes: Simple means and standard deviations for the full sample are reported.

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

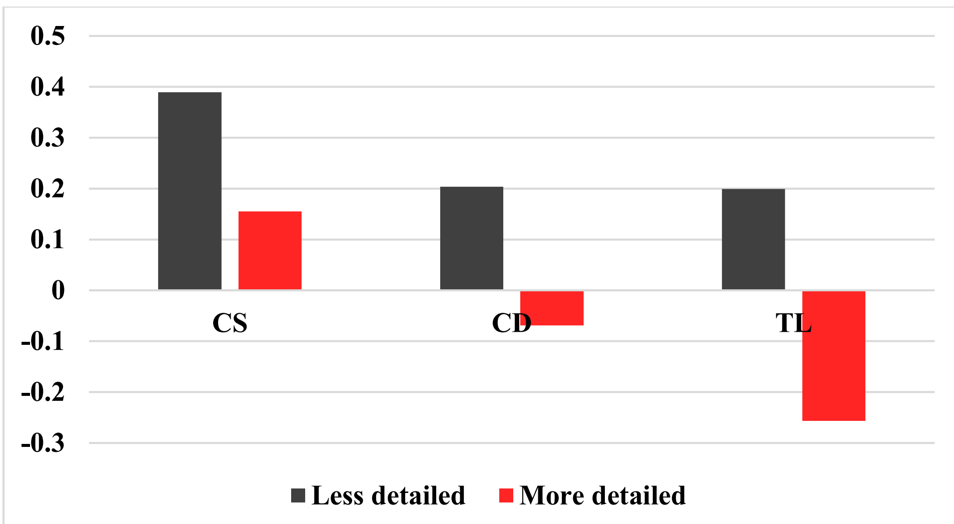
Notes: Simple means and standard deviations for the full sample are reported.

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



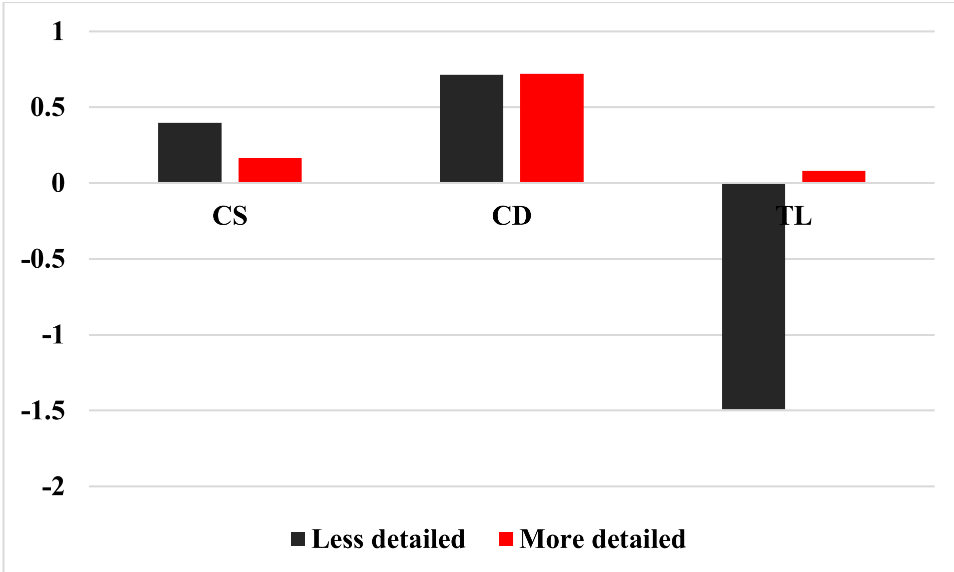
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

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



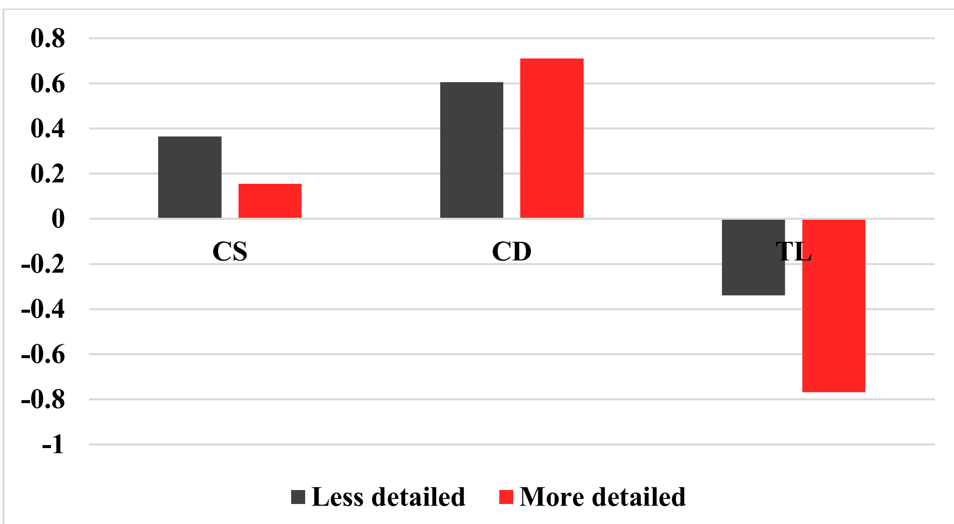
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A3. Long Difference in Markups 1980-2014



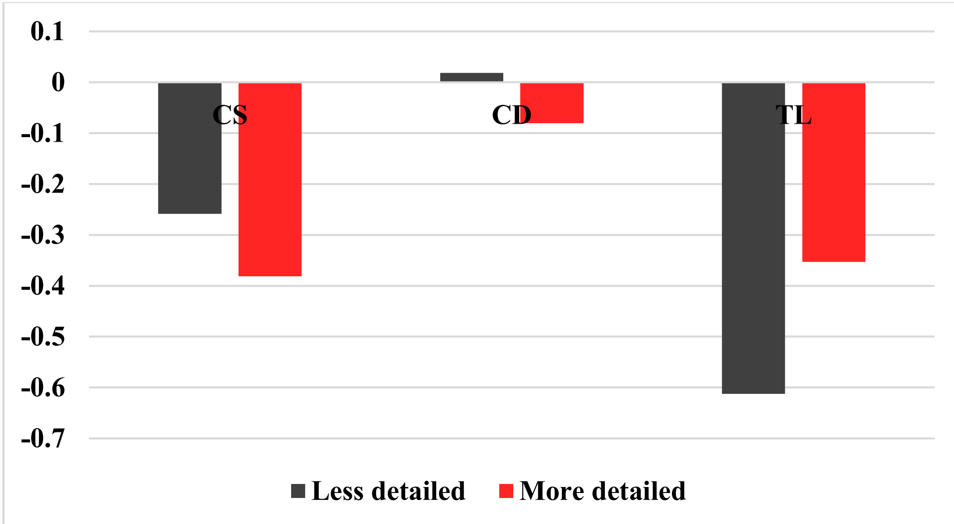
Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

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.