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RISING MARKUPS OR CHANGING TECHNOLOGY?

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ABSTRACT

Recent evidence suggests the U.S. business environment is changing, with rising market concentration and markups. 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 variable factor's output elasticity to its cost share of revenue. 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 - relative to the existing literature - across establishments within the same industry over time. With our more detailed estimates of output elasticities, the measured increase in markups is substantially dampened, if not eliminated, for U.S. manufacturing. 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 of those differences.

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I. Introduction

Understanding firm market power and the degree of competition in the economy has long been a central concern of economists. The first welfare theorem relies on the assumption that firms take prices as given, and in turn, market failures have wide-ranging implications for consumer welfare and government policy. One potential measure of market power is the price markup over marginal cost. For decades economists relied on highly detailed product-specific data on prices and quantities to estimate markups. De Loecker and Warzynski (2012), however, introduce a method for identifying markups directly from plant-level production data. Their methodology builds on Hall (1988) and is clever and simple in principle. Using the first-order condition for a variable factor, the markup at the plant level is the ratio of the output elasticity of the variable factor to the cost share of revenue of that factor. This important work sparked an enormous follow-on literature that investigates trends in markups across industries and over time, and treats markup estimates as outcomes in a wide range of economic analyses (e.g., Autor et al. 2020; Baqaee and Farhi 2020; Blonigen and Pierce 2016; De Loecker, Eeckhout, and Unger 2020; De Loecker, Eeckhout, and Mongey 2022; Liu and Mao 2019).

Despite the straightforward theoretical model underlying this method, the estimation is complicated in practice. In particular, the method has been subject to criticism given challenges of estimating output elasticities (e.g., Bond et al. 2021; Doraszelski and Jaumandreu 2023) given both measurement and identification issues. These challenges are directly related to data limitations. We overcome key data limitations for the US manufacturing sector by using a longitudinal panel of establishment-level annual data from 1972-2014. Our data infrastructure enables estimating the output elasticities with a much greater granularity over time and across businesses than in the existing literature. To illustrate the importance of allowing flexibility in the estimation of output elasticities, we compare our estimates of markups to existing estimates from the leading work in this literature, De Loecker, Eeckhout and Unger (2020) (hereafter DEU).

Understanding long-run trends in markups is important in its own right—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 based on work by DEU using the production approach. DEU use this method to quantify changing markups over the last several decades in the US. Their provocative finding is that markups have risen substantially in the US over the last several decades. We find that if we use the level of detail (across industries and time) for estimating output elasticities consistent with DEU that we can largely replicate their findings. However, with more granular estimates of output elasticities that are feasible given our rich data infrastructure, the increase in markups is substantially dampened if not eliminated. Finally, we provide indirect evidence of the connection to changes in technology to our dampened increase in markups.[1]

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

[1] When we use the control function approach (our Cobb-Douglas and Translog results), we follow DEU by estimating the output elasticities from the revenue function. DEU recognize that there is likely a bias from estimating output elasticities from the revenue function. They propose an adjustment to their control function approach to address this issue, and we adopt their approach in our analysis. Specifically, following DEU, we include market share in the estimation of the revenue function. De Ridder, Grassi, Morzenti (2022) (hereafter DGM) raise a variety of questions about the estimation of output elasticities from the revenue function in their analysis comparing estimates that emerge from estimating the output function when firm-level prices are available. Their main findings are that using the revenue function rather than the output function biases the level but the correlation is high between the two approaches (mitigating concerns about the implications for changes in markups). Our analysis is distinct from DGM as we focus on allowing for more granularity (output elasticities that vary over time and detailed industries and in some cases establishments) in the estimation of output elasticities. If the DGM concerns apply to both DEU and our analysis even with the addition of the market share as a covariate in the estimation of the revenue function, we find it reassuring that they find the primary bias is in the level of markups and not in the variation. Our main finding is that using a more granular, time varying technology has a large impact on the implied change in markups.

by time. For our cost-share (CS) 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.[2] These patterns are broadly similar to those found by DEU using a cost share approach with the Economic Census data for manufacturing. The analogous changes using output elasticities that vary at the plant-by-year level yields dampened sales-weighted markup increases of 24% from 1977 to 2007 and 16% from 1977 to 2012.

For our Cobb-Douglas (CD) specification using a control function approach at the 2-digit level with annual estimates we find the sales-weighted markup increases by 24% from 1977 to 2007 and 8% from 1977 to 2012.[3] The analogous changes using a 4-digit specification with annual estimates yield only a 6% increase from 1977 to 2007 and a decline of -4% from 1977 to 2012. Even more dramatic differences occur when using a control function approach with the translog (TL) specification. Using the translog specification at the 2-digit level with time-invariant parameters, we find that the average sales-weighted markup increases by 36% from 1977 to 2007 and by 23% from 1977 to 2012.[4] The analogous changes using a translog specification at the 4-digit level with annual estimates are -10% and -12%, 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

[2] Our analysis provides estimates through 2014. We use these five-year intervals in this discussion for comparability with DEU who used the Economic Census that yields changes over these five-year intervals ending in years with 2 and 7. In their Economic Census analysis, they permitted output elasticities to vary at the 4-digit level by year.

[3] For their Cobb-Douglas estimates using COMPUSTAT, DEU permitted output elasticities to vary at the 2-digit level by year.

[4] The published version of DEU refers to translog estimates from DEU (2018, Figure 18) that has output elasticities that vary at the 2-digit level.

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 as defined by Foster, Haltiwanger and Syverson (2008)) and in revenue per unit input such as labor.

Hsieh and Klenow (2009) 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 Hsieh and Klenow (2009) approach as the production method uses the dispersion in the cost shares of revenue of variable inputs (e.g., materials and/or labor) for identification. 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.

We use observed variation in indicators of changing technology at the establishment and detailed (4-digit) industry level to investigate the connection between our findings on output elasticities and observable changes in the ways that business do business. At the establishment-level, we explore measures of capital per worker, computer investment per worker, a diversification measure based on the ratio of non-manufacturing to manufacturing activity of the parent firm, 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 the way they do business exhibit increases in the mean and dispersion across establishments over time.

For each of our three estimation approaches (CS, CD, TL), we compare markups and output elasticities estimated at "less detailed" and "more detailed" levels, where these levels differ in terms of variation over time and industry detail. The "less detailed" levels target DEU specifications. All four indicators of changing technology or business structure are positively associated with the *difference* in the "less detailed" and "more detailed" markup estimates at the establishment-level. Similarly, all four indicators are positively associated with the difference in the "less detailed" and "more detailed" output elasticity estimates. We also find that the industries with above median changes in these indicators of changing technology exhibit increasing differences over time between the "less detailed" and "more detailed" markup estimates.

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 Restrepo (2021) use COMPUSTAT data to estimate a Cobb-Douglas specification with output elasticities of the variable factor of production permitted to vary across time, industry and firm size classes. Demirer (2020) also uses COMPUSTAT data for the U.S. and develops a 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.[5]

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

[5] Raval (2023) 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 (2023) 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 (2024) adjustment costs for labor at this higher frequency have important implications for annual moments of firm-level employment adjustment (that differ from the frictionless model where labor is a variable factor).

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, Pierce, and Schott (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 are 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 papers by the authors) 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.[6]

[6] 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. We discuss our preference for measuring markups using materials as opposed to labor as the variable input in footnote 5 and later in the paper.

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 flexibly and demonstrate how estimated markups change when using this 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. 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.[7]

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. Moreover, we take advantage of their contribution to this literature that recognized that since the dependent variable is firm or establishment-level revenue, accounting for the wedge between unobserved output and input prices is potentially needed. Specifically, following DEU, we include as a covariate the establishment's market share in their 4-digit industry (instrumented using three lags of the establishment's market share). We discuss details in Appendix C but note that we follow the specification of DEU closely with the exception that we include lagged electricity prices that vary at the state by year level to address potential identification problems in using the control function approach. [8]

We are pushing the data hard in our analysis; the control function estimation is often used at a more aggregate industry level given that the polynomial approximations are sensitive to smaller samples. As a 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. In addition, we also explore the relationship between observable indicators of

[7] 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.

[8] In an earlier draft of this paper, we did not use these additional instruments implying that in the earlier version the specification was even closer to that used in DEU (results from earlier paper available upon request). As is clear from the results in the current or earlier version of our paper, when we use their level of aggregation in terms of time and industry, we obtain results similar to theirs both qualitatively and quantitatively.

changing technology and the growing gap in markup estimates we find when using "less detailed" 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, annual). In the penultimate 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: $\mathrm{cov}(\varepsilon_{it}, 1/\alpha_{it}) + E(\varepsilon_{it})E(1/\alpha_{it})$. 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

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. 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 analyses. We provide an overview of our measurement methodology in the main text but provide more details in Appendix B.

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 cost 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 (calculated separately for structures and equipment) 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. 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 more plausibly a variable input. While we show results for labor in Appendix A, the firm-level adjustment costs literature provides evidence that labor is not a variable factor of production even at an annual frequency (see Cooper, Haltiwanger, and Willis (2024) 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 appropriately weighted establishment-level cost shares.

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).[9] 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

[9] See https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

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 tables (corresponding to our three methodologies: CS, CD, and TL). Panel A of Table 1 shows the distribution of estimated output elasticities from cost shares of materials of total costs (CS) at different levels of aggregation. Panel B shows the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the Cobb-Douglas (CD) specification. Panel C shows the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the translog specification (TL).[10]

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 (0.0173 to 0.1103), but the translog (TL) specification has a less dramatic increase (0.1849 to 0.2042). Results for estimates of output elasticities for labor show similar patterns and are reported in Tables A.2-A.4.[11]

We now turn to the estimated markups.[12] Figures 1 to 3 show the implied pattern of changing markups on a sales-weighted basis (for cost-shares, Figure 1; Cobb-Douglas, Figure 2;

[10] We present estimates for the Top 50 industries in Table A.1. Results are robust to this restriction.
[11] The output elasticities in Tables A.2-A.4 are reported for the primary "less" and "more" detailed specifications.
[12] 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 versus trimmed markup distributions.

and translog estimations, Figure 3). 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 striped is less restrictive and is denoted by “1yr”) 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 implied markups are robust to limiting to the top 50 industries (see Figure A.2).[13]

Turning to the time series pattern of markups in panel (b) of Figures 1-3 shows further interesting patterns. In all three cases, the “more detailed” cases (red solid 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 lines), there is still an overall increase in markups from 1980 to 2014. However, with the “more detailed” specifications (red solid lines), we find only a moderate increase in markups using the cost-share approach (CS), little change using the Cobb-Douglas specification (CD), and a decline using the translog specification (TL).

[13] 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 a relatively small increase in markups.

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, then to the industry level, and finally to the 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. Also, while it is an apples-to-oranges comparison, our results using the control function approach with the manufacturing establishment data are similar to those they report using the control function approach for COMPUSTAT using manufacturing firms (see Appendix C for more discussion).

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.[14] 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

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

decrease of around 13% from 2005 to 2014, with markups again returning to 1990s levels. This 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 substantially over the 2005-2014 period.

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 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. Measurement Issues: 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:[15]

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

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.

[15] 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.

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.[16] Figure 6 shows the sales-weighted revenue cost shares for all 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 (CD) and translog (TL) 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 rises 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 BLS.

Figure 7 depicts the long differences in the sales-weighted returns to scale. For the "less detailed" and "more detailed" Cobb-Douglas (CD) specification there is some mild evidence of rising (sales-weighted) returns to scale. For the "less detailed" translog (TL) there is no change.

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

For the "more detailed" translog (TL), there is evidence of a non-trivial decline in (sales-weighted) returns to scale.

As a further cross-check on the basic patterns, we follow DEU and Edmond, Midrigan and Xu (2018) 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. Shifting Shares: 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.[17] We are interested in whether the differences we observe are driven by specific components. The decomposition is given by:

$$\Delta\mu_t = \sum_{i\epsilon c}\omega_{it-1}\Delta\mu_{it} + \sum_{i\epsilon c}(\mu_{it-1} - \overline{\mu_{t-1}})\Delta\omega_{it} + \sum_{i\epsilon c}\Delta\mu_{it}\,\Delta\omega_{it} + \sum_{i\epsilon N}(\mu_{it} - \overline{\mu_{t-1}})\omega_{it} - \sum_{i\epsilon X}(\mu_{it-1} - \overline{\mu_{t-1}})\omega_{it-1} \qquad (4)$$

[17] 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.

The first term in equation (4) is the within term. The second (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 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 Table 1).

The decomposition of the changing markups for both the "less detailed" and "more detailed" specifications is reported in Table 2. We compute the terms in Table 2 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 (CS, 4-digit industry, 1 year). For that specification, we find results broadly consistent with theirs, showing a positive contribution of the within, net entry and reallocation terms, 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 terms. 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 substantial decline in aggregate markups in manufacturing. While reallocation plays a critical role with the more detailed specifications, the magnitude of the reallocation terms is smaller than it is in 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 since dispersion in markups rises by a smaller amount in more detailed specifications, this shift yields less of an increase in the sales-weighted markup.

C. Changing Technology?

Our findings imply that permitting greater variation in the estimation of output elasticities across time and firms substantially dampens the measured increase in markups in U.S. manufacturing. 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 the "less detailed" and "more detailed" markup patterns and observable measures of changing technology and firm structure. 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 in the parent firm) 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 ASM in 2000. U.S. firms with activity in manufacturing often have activity in non-manufacturing. Fort, Pierce, and Schott (2018) document there has been a positive trend in this direction with some firms with only modest levels of 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.[18] The share of the parent firm's sales in industry sales is measurable in Economic Census years when all establishments are covered.[19]

Figure 10 shows that all four indicators exhibit an increase in mean and three of the four indicators exhibit an increase in dispersion over time.[20] 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

[18] Specifically, we measure the ratio of non-manufacturing to manufacturing employment for the parent firm.
[19] Since the computer investment per worker and the ratio of non-manufacturing to manufacturing employment can be zero, we do not use a log transformation of these variables. Instead, we use a transformation based upon a simple relative change measure developed by Tornqvist et al. (1985) that has been actively used in the literature on firm dynamics for a measure of firm growth that accommodates entry and exit (Davis et al., 1996) (DHS). Specifically, the DHS transformation is given by $(x_{it} - \overline{x}) / (0.5*(x_{it} + \overline{x}))$ which is a second order approximation of the log difference of x_{it} from its grand mean ($\overline{x}$). We note that this transformation is scale independent and avoids the pitfalls of scale dependent transformations as discussed in the recent papers by Chen and Roth (2023) and Mullahy and Norton (2022).
[20] 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.

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 3. A highlight is the enormous variation across establishments in these variables. Turning to the regression results, the top panel of Table 4 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 4 presents the analogous bivariate establishment-level regressions with the dependent variable as the "less detailed" minus "more detailed" estimate of the 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.[21]

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

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

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.[22] 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).[23] 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.

It is instructive to compare the magnitude of the coefficients in the upper and lower panels of Table 4. 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 from

[22] 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 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.

[23] As noted, there is a large theoretical literature as well. Early papers include Cooper, Haltiwanger and Power (1999) while more recent papers include Acemoglu and Restrepo (2018).

section II, then these differences reflect the differences in $\text{cov}(\varepsilon_{it} / \alpha_{it}, X_{it})$ (where *X* is the explanatory variable) and $\text{cov}(\varepsilon_{it}, X_{it})$. 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, 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)).[24]

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/business structure changes. We

[24] Given the above and below median classification is based on industry-level measures, no DHS transformation is needed for this analysis. In unreported results, we show results where the classification is based on industry-level DHS based changes and results are very similar.

find that the industries with above median changes in capital intensity (Figure 11), computer intensity (Figure 12), and diversification (Figure 13) exhibit an increasing difference between the less detailed and more detailed based markups. Industries with larger changes in concentration ratios (Figure 14) 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 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.[25]

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 are producing output 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

[25] We provide further evidence on the industry long differences in Table A.6. These specifications are broadly similar to analogous to those reported in Tables 4 and A.5. 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 the 2006-14 subperiod for Cobb-Douglas and translog approaches. In contrast, the estimates for the concentration measure are small in magnitude and never statistically significant.

between the "less detailed" and "more detailed" estimates of markups and output elasticities.[26] 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 in ways 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 approach" on 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 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.

[26] 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.

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. We can use a more flexible approach by relying on the dataset developed by the Collaborative Micro Productivity (CMP) project at the Census Bureau that tracks large (roughly 55,000 establishments per year) representative samples of U.S. manufacturing establishments from the ASM from 1972 to 2014.[27] These data permit much greater flexibility in estimating 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 almost 30 percent from 1980-2014. Using the 4-digit translog specification with parameters that vary by year, we find the sales-weighted markups declines by about 9 percent from 1980-2014. 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

[27] The CMP data underlie the public domain DiSP data on within industry productivity dispersion (see Cunningham et al. (2023)).

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 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.[28] Unfortunately, the CMP database developed for U.S. manufacturing establishments is not easily replicated for other sectors. A second more 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

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

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) and Acemoglu et al. (2022)) 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, Alternative Approaches

Level of aggregation	Mean	SD
Panel A. Cost Share		
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. Cobb Douglas		
2-digit, constant over time	.5384	.0173
3-digit, constant over time	.5284	.07718
4-digit, constant over time	.5138	.09567
6-digit, constant over time	.4992	.1214
2-digit, yearly	.5301	.03796
3-digit, yearly	.5154	.08882
4-digit, yearly	.4875	.1103
Panel C. Translog		
2-digit, constant over time	.5699	.1849
3-digit, constant over time	.5518	.1928
4-digit, constant over time	.527	.1943
6-digit, constant over time	.5109	.2111
2-digit, yearly	.5652	.1889
3-digit, yearly	.5432	.1966
4-digit, yearly	.4959	.2042

Notes: Simple means and standard deviations reported for the pooled full sample. For the Cost Share approach, the mean statistics in the first row applies to all following rows in the panel. Results based on about 2.16 million establishment-year observations.

Table 2. Decomposition of the Change in Markups 1977-2012

	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, 1yr	0.1542	-0.1285	0.08509	0.1109	.	.	.
CD, Ind4, 1yr	0.1424	-0.231	0.04269	-0.04586	0.07536	0.6541	0.2705
TL, Ind2, Constant	0.3632	-0.1679	0.05434	0.2496	.	.	.
TL, Ind4, 1yr	0.1555	-0.2975	0.0643	-0.07764	0.6345	0.396	-0.03042

Notes: The markups in the above table are estimated using materials as the variable input. The decomposition above uses revenue weights. 1yr for CD and TL are from five year rolling windows around focal year.

Table 3: Summary Statistics for Plant-Level Regressions Relating Less minus More Detailed Markups and Less minus More Detailed Output Elasticities

Variable	***Mean***	***SD***
Less minus more detailed markup	.6403	1.009
Less minus more detailed output elasticity	.242	.2244
Capital Intensity (log (K/L))	4.908	1.325
Computer Intensity (DHS Comp Inv Per Worker)	-.7437	1.363
Diversification Index	-.9281	1.012
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 DHS 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.

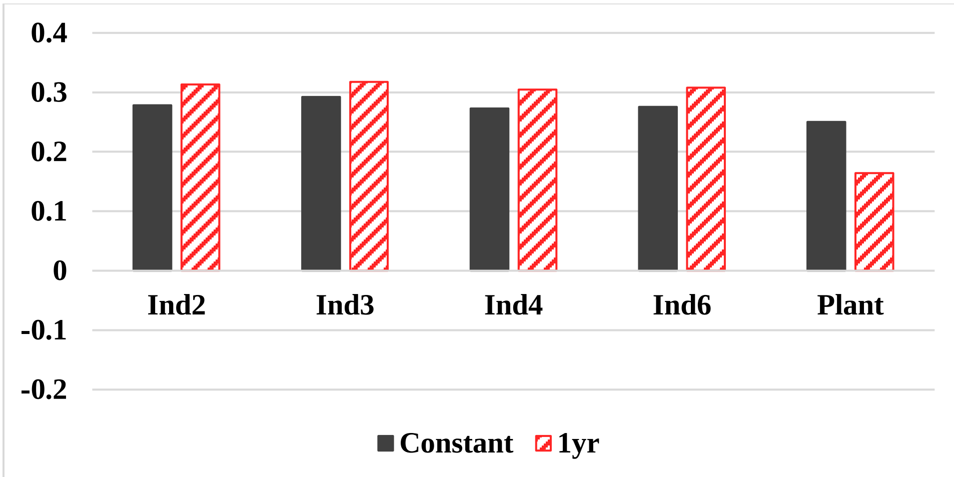
Table 4: Relationship Between Less minus More Markups and Output Elasticities and Indicators of Technology and Firm Structure

	log(Capital Intensity)	DHS(Computer Inv Per Worker)	Diversification Index	Log(Firm Share)
Less minus More Detailed Markup				
Slope Coefficient	0.1541***	0.0384***	0.0978***	0.1250***
	(0.0249)	(0.0109)	(0.0166)	(0.0154)
Constant	-0.1158	0.6722***	0.7416***	1.045***
	(0.1224)	(0.0081)	(0.0154)	(0.0538)
R-squared	0.371	0.394	0.366	0.430
Less minus More Detailed Output Elasticity, Materials				
Slope Coefficient	0.0438***	0.0109***	0.0284***	0.0418***
	(0.0055)	(0.0028)	(0.0044)	(0.0037)
Constant	0.0270	0.2569***	0.2710***	0.3844***
	(0.0270)	(0.0021)	(0.0041)	(0.0128)
R-squared	0.384	0.400	0.393	0.439
Observations	2164000	394000	1924000	472000

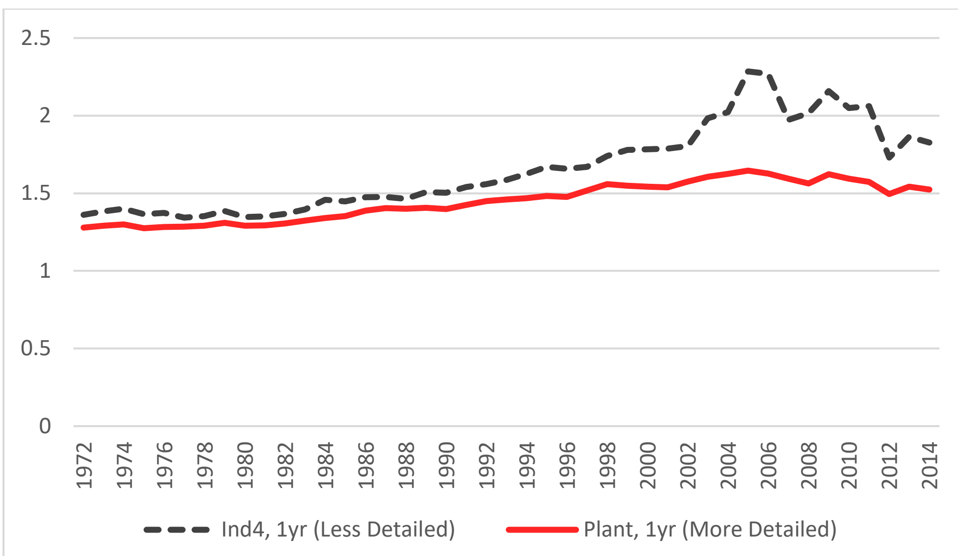
Notes: All specifications control for 6-digit industry by year effects using establishment-level observations. Less minus more detailed markup and output elasticity from translog specification. See notes to Table 5.

Figure 1. Markups Estimated Using Cost Shares (CS)

(a) Long difference in markups 1980-2014



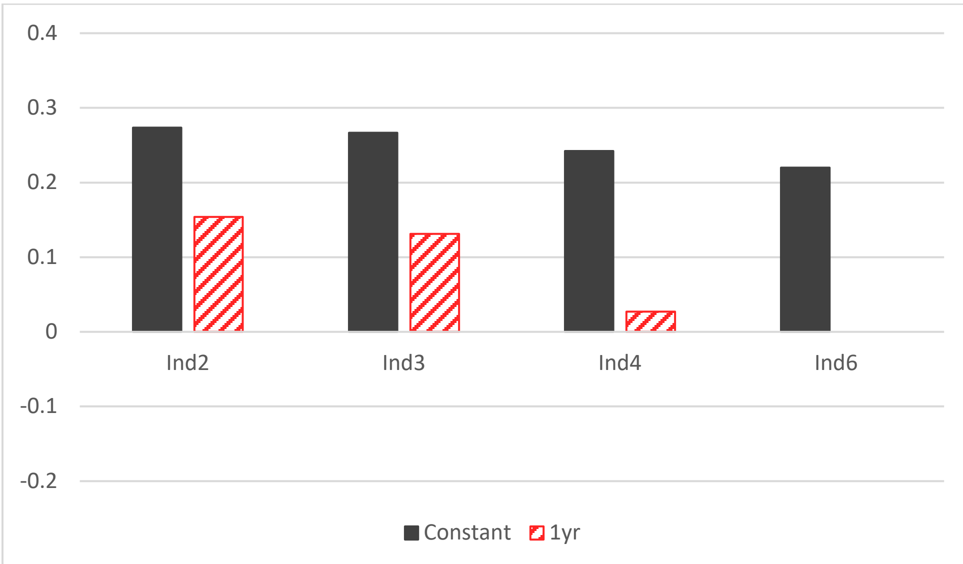
(b) Markups from 1972-2014, benchmark cases



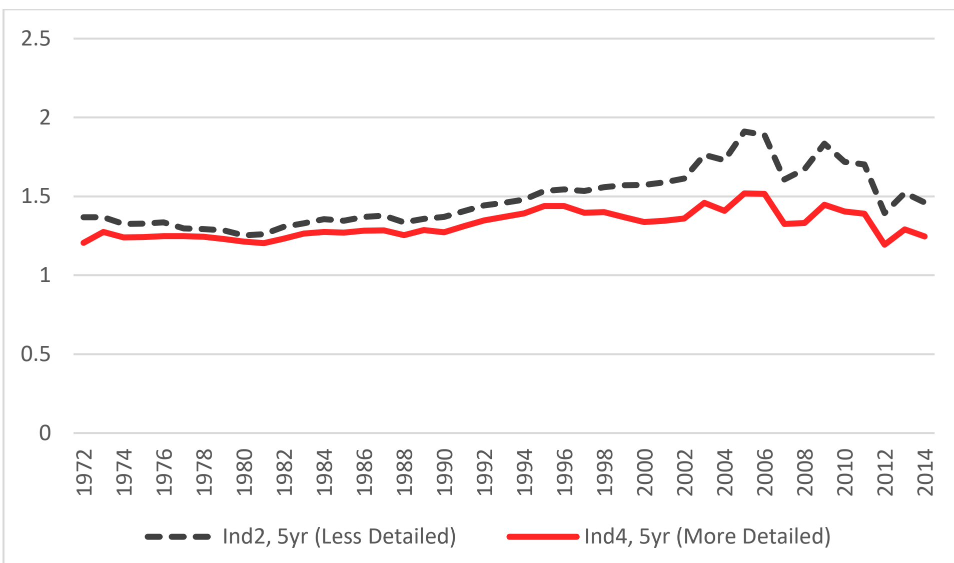
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

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

(a) Long difference in markups 1980-2014



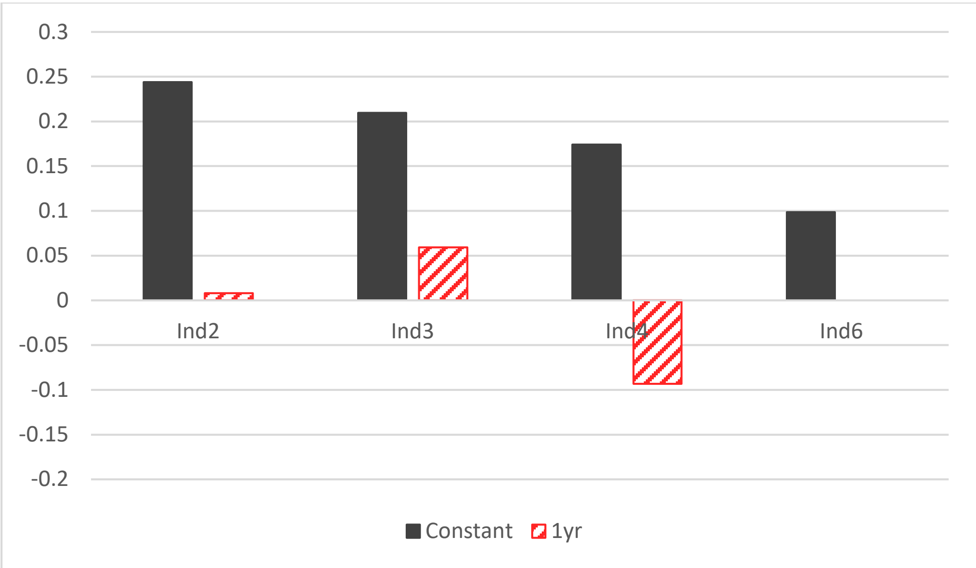
(b) Markups from 1972-2014, benchmark cases



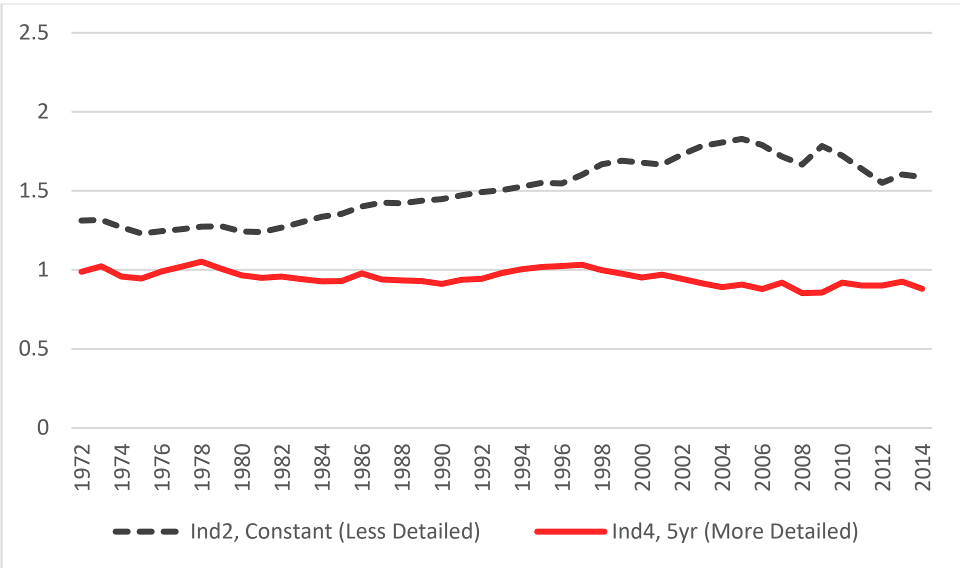
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 3. Markups Estimated Using Translog (TL)

(a) Long difference in markups 1980-2014

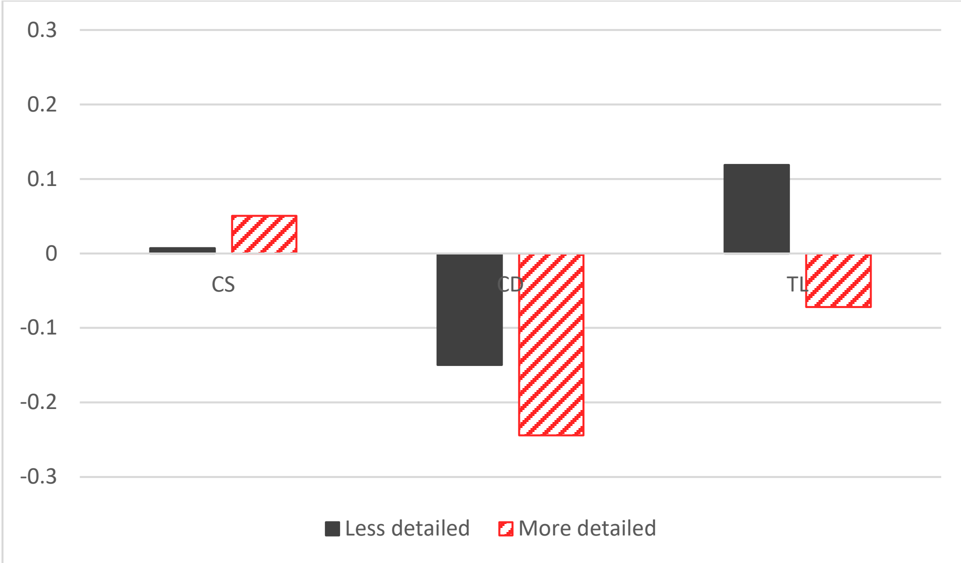


(b) Markups from 1972-2014, benchmark cases



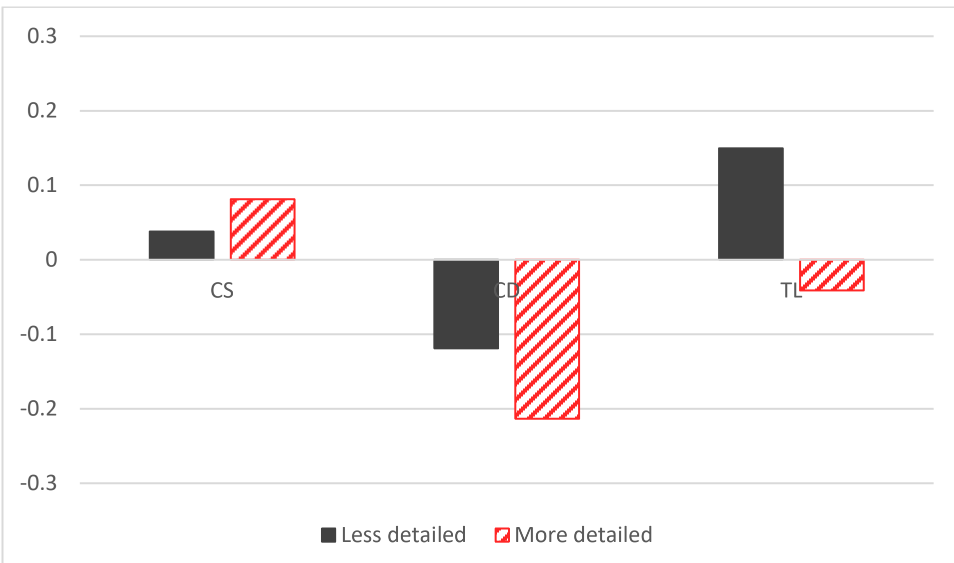
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 4. Long Difference in Naïve Markups 1980-2014



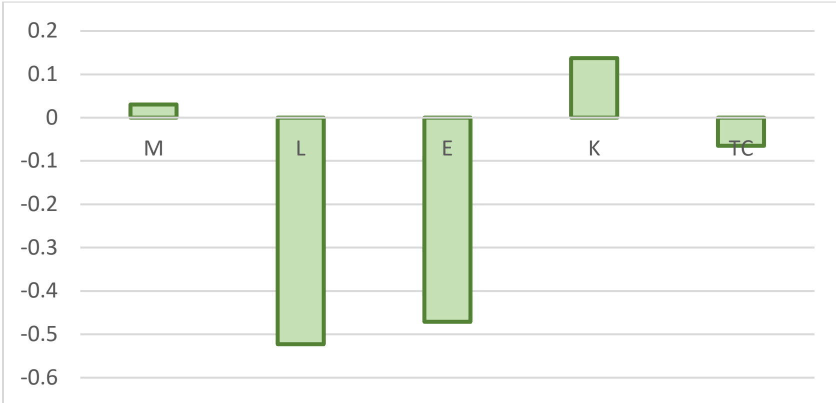
Notes: The markups above are estimated using materials as the variable input. See equation (3) for definition of naïve markup. Long differences are log differences.

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

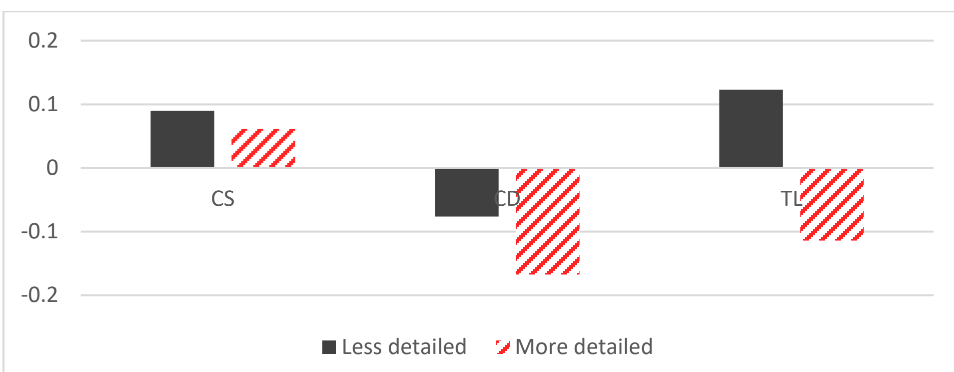


Notes: Input shares of revenue are revenue-weighted means. Long differences are log differences.

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.

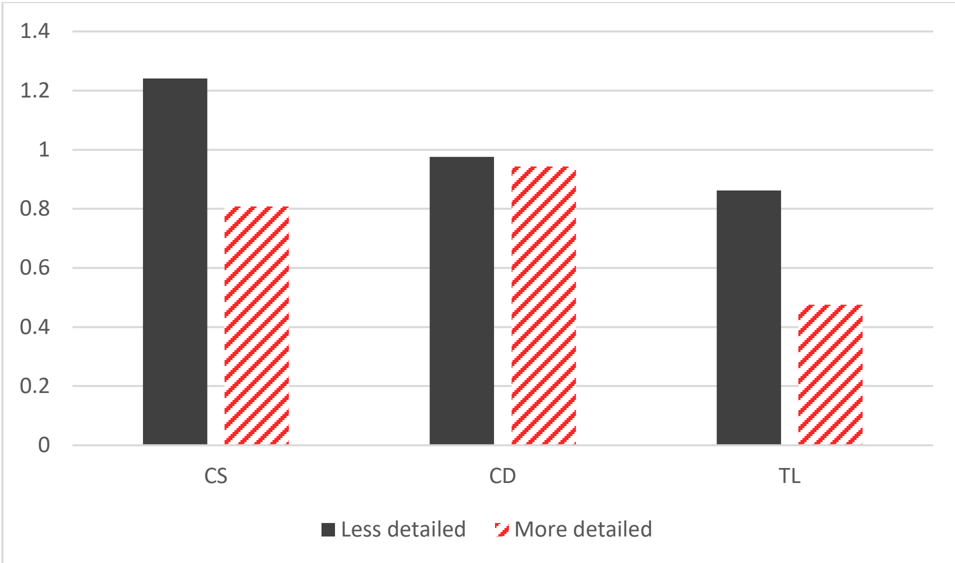
Figure 8. Long Difference of Markups from 1980-2014. Robustness to Total Cost Weighting



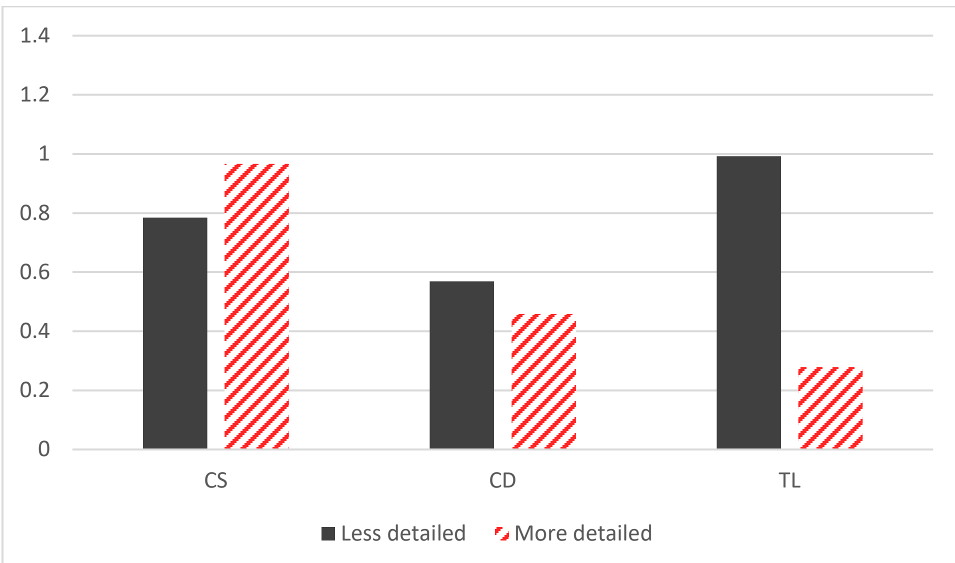
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are total cost-weighted means. Long differences are log differences.

Figure 9. Dispersion in Markups over Time

(a) Long difference in standard deviation 1980-2014



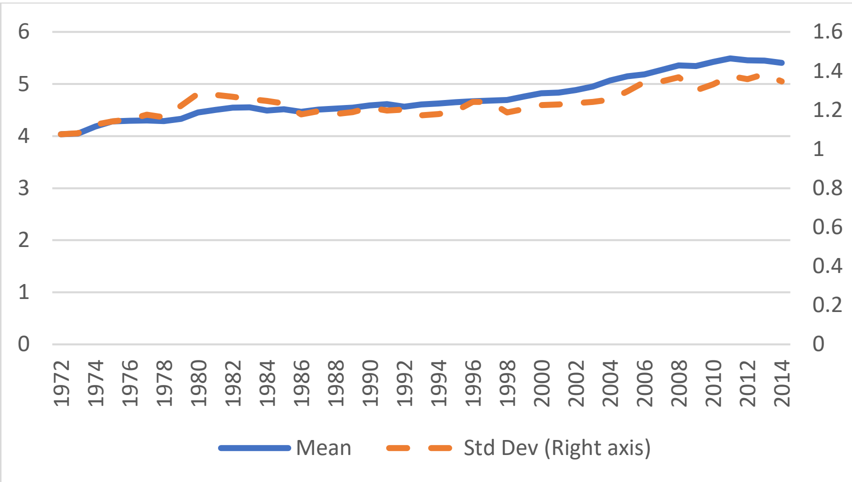
(b) Long difference in p90-p75 1980-2014



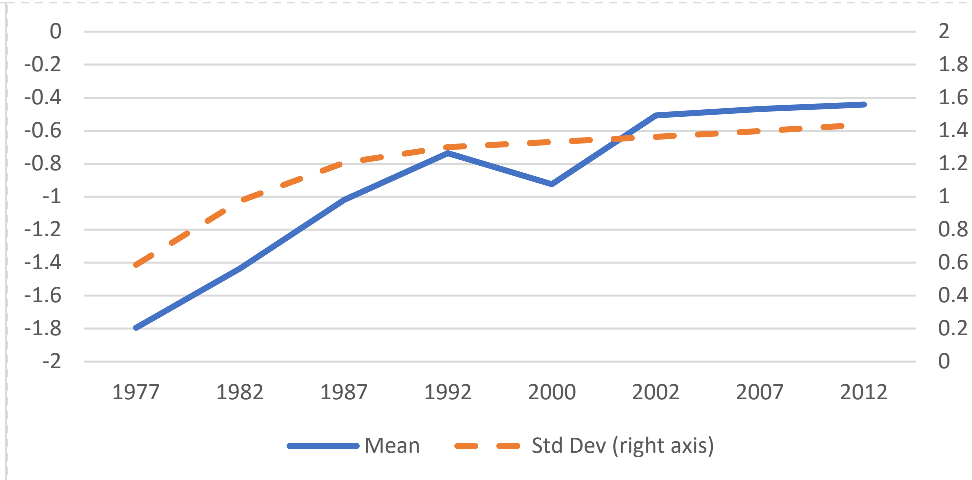
Notes: The markups above are estimated using materials as the variable input. The markup moments are computed from revenue-weighted distribution. Long differences are log differences.

Figure 10. Changes in Indicators of Plant-Level Technology

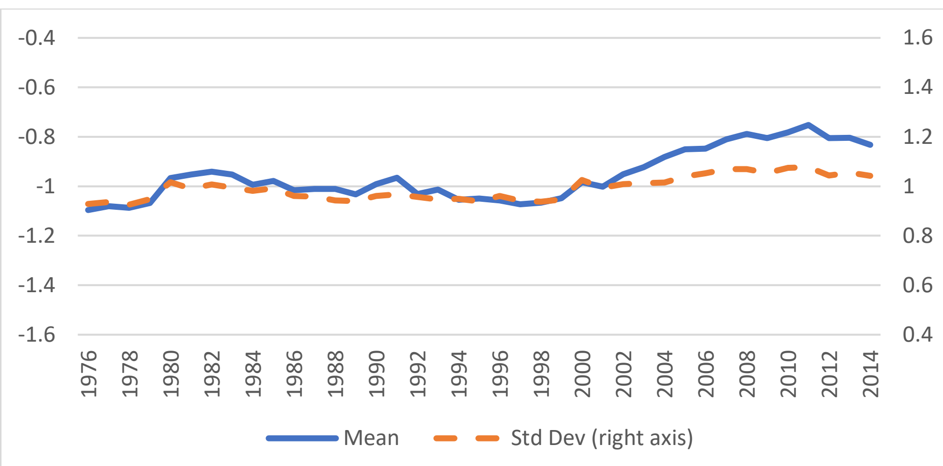
(a) Capital Intensity (log(K/L))



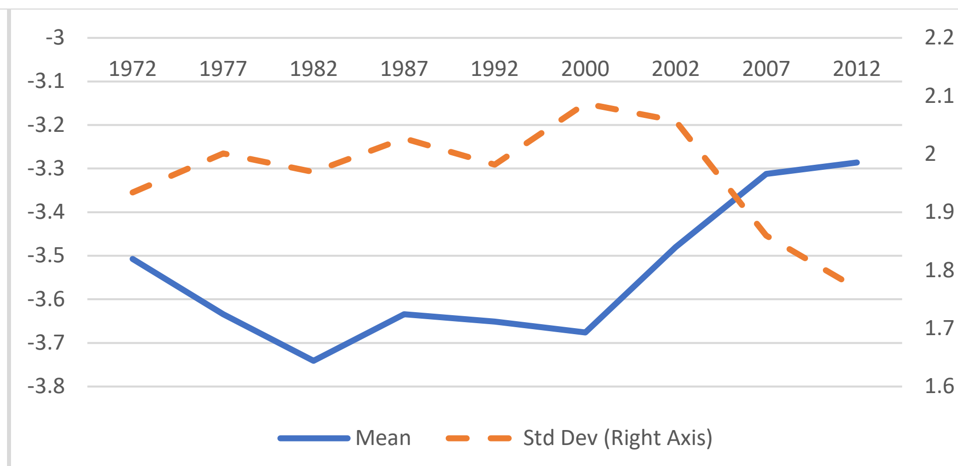
(b) Computer Investment Per Worker



(c) Diversification Index (IHS Ratio of Non-Mfg/Mfg Emp for Parent Firm)

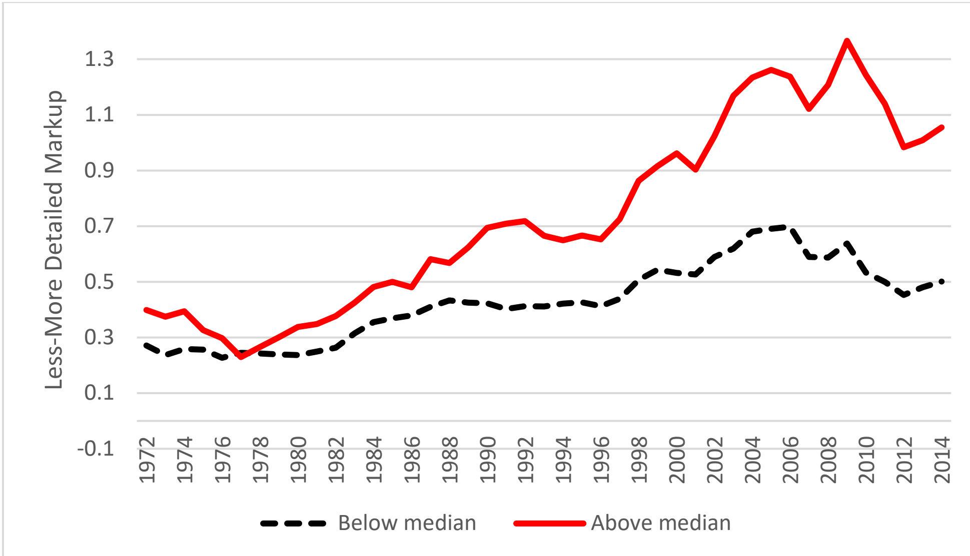


(d) Log firm share



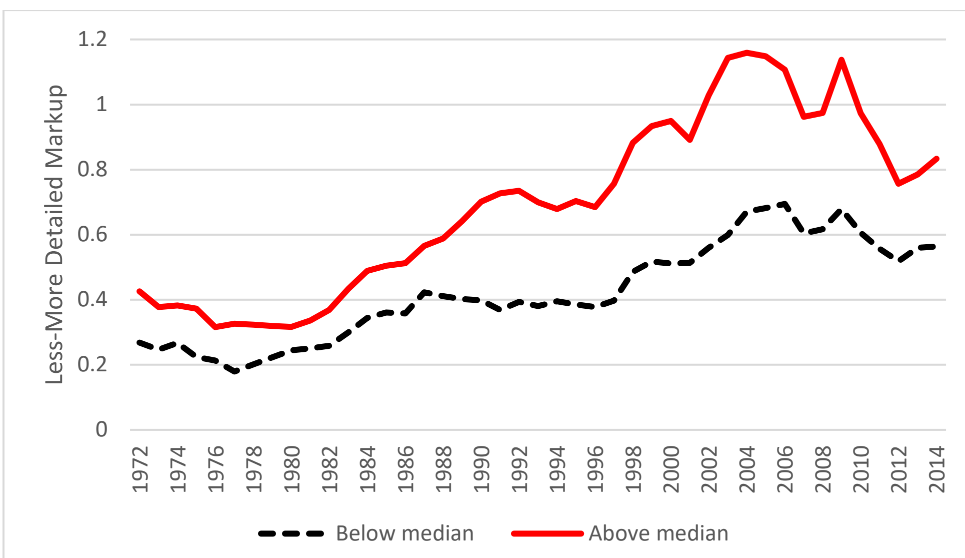
Notes: Tabulations from the ASM, CM and LBD. Computer Investment Per Worker uses the inverse hyperbolic sine (IHS). The log firm share is the share of sales of the parent firm in total industry sales. These are moments not weighted by activity.

Figure 11. Markups and Changes in Capital per Worker



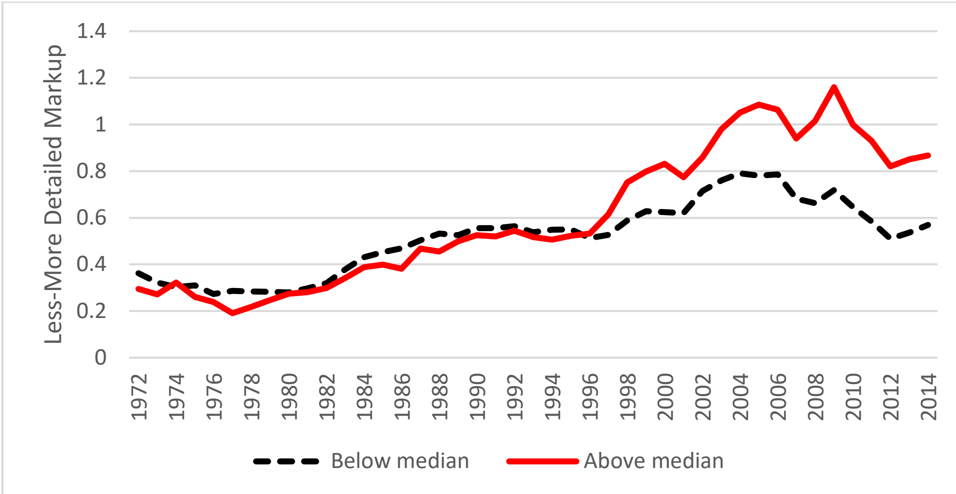
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in rolling annual intervals. Reported are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



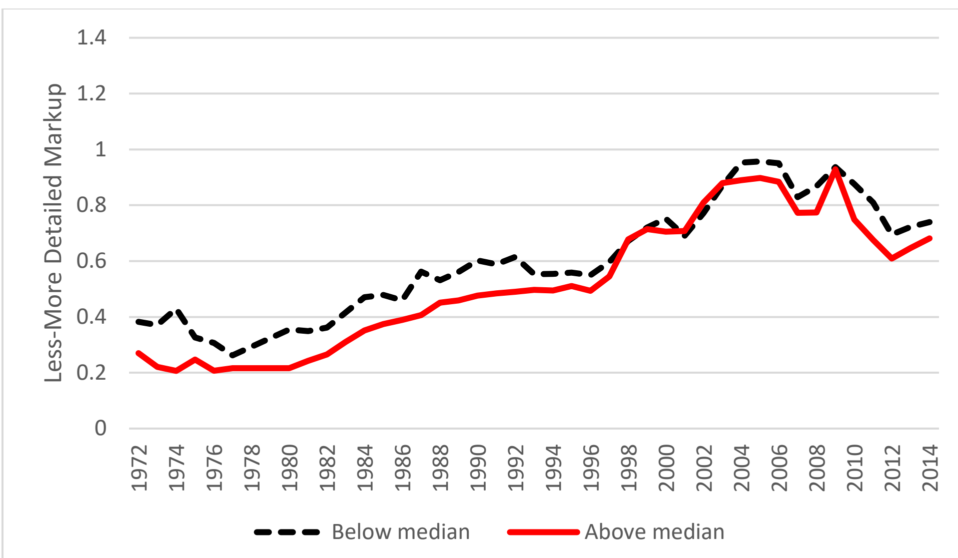
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in rolling year intervals. Reported are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

Appendices

Table A.1 Output Elasticities for Materials, Top 50 Industries

Level of aggregation	Mean	SD
Panel A. Cost Share		
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
Panel B. Cobb Douglas		
2-digit, constant over time	.4817	.02614
3-digit, constant over time	.4938	.06064
4-digit, constant over time	.4766	.08892
6-digit, constant over time	.4746	.1034
2-digit, yearly	.4712	.04587
3-digit, yearly	.4734	.09125
4-digit, yearly	.449	.133
6-digit, yearly	.4476	.1418
Panel C. Translog		
2-digit, constant over time	.5406	.2079
3-digit, constant over time	.5254	.2084
4-digit, constant over time	.5056	.2007
6-digit, constant over time	.5007	.2041
2-digit, yearly	.5323	.2051
3-digit, yearly	.4992	.2103
4-digit, yearly	.4616	.2094
6-digit, yearly	.4569	.2198

Notes: Simple means and standard deviations reported for the pooled full sample. For the Cost Share approach, the mean statistics in the first row applies to all following rows in the panel. Results based on about 2.16 million establishment-year observations.

Table A.2 Output Elasticities for Labor, 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 A.3 Output Elasticities for Labor, Cobb-Douglas Proxy Method (CD) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, yearly	.2382	.05458
4-digit, yearly	.2307	.08609
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, yearly	.2313	.0678
4-digit, yearly	.2154	.1004

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

Table A.4 Output Elasticities for Labor, Translog Proxy Method (TL) Approach

Panel A. All industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	.2476	.1085
4-digit, yearly	.2438	.1741
Panel B. Top 50 industries		
Level of aggregation	**Mean**	**SD**
2-digit, constant over time	.2599	.1287
4-digit, yearly	.234	.1826

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

Table A.5: Relationship Between Less minus More Markups and Output Elasticities and Indicators of Technology and Firm Structure, Time Varying Coefficients

Dependent Variable: Less minus More Detailed Markup				
	log(Capital Intensity)	DHS(Computer Inv Per Worker)	Diversification Index	log(firm share)
Slope Coefficient	0.1163***	-0.0575	0.0814*	0.0842***
	(0.0377)	(0.0530)	(0.0468)	(0.0154)
Slope X 81-89	0.0126	0.0848**	-0.0048	0.0368***
	(0.0207)	(0.0426)	(0.0216)	(0.0120)
Slope X 90-05	0.0130	0.0686	0.0323	0.0395***
	(0.0417)	(0.0509)	(0.0566)	(0.0125)
Slope X 06-14	-0.0247	0.0831	-0.0036	0.0384
	(0.0621)	(0.0549)	(0.0750)	(0.0237)
Constant	-0.1503	0.2365**	0.4294***	0.6610***
	(0.1494)	(0.1202)	(0.0831)	(0.0757)
R-squared	0.380	0.406	0.380	0.443
P-value				
81-89 = 90-05	0.4155	0.9501	0.982	0.9336
81-89 = 06-14	0.9855	0.348	0.3293	0.7889
90-05 = 06-14	0.205	0.5114	0.2425	0.9468
Dependent Variable: Less minus More Detailed Output Elasticity Materials				
Slope Coefficient	0.0409***	-0.0347	0.0407***	0.0251**
	(0.0141)	(0.0231)	(0.0149)	(0.0099)
Slope X 81-89	0.0094	0.0507***	-0.0073	0.0245**
	(0.0099)	(0.0190)	(0.0069)	(0.0104)
Slope X 90-05	-0.0028	0.0415*	-0.0076	0.0162**
	(0.0164)	(0.0232)	(0.0172)	(0.0077)
Slope X 06-14	-0.0196	0.0365	-0.0243	0.0133
	(0.0204)	(0.0232)	(0.0216)	(0.0115)
Constant	-0.0254	0.0857	0.1873***	0.2378***
	(0.0534)	(0.0562)	(0.0266)	(0.0513)
R-squared	0.400	0.420	0.415	0.460
P-value				
81-89 = 90-05	0.01439	0.09292	0.2948	0.0007
81-89 = 06-14	0.1138	0.2238	0.9817	0.0512
90-05 = 06-14	0.00267	0.2267	0.0029	0.6137
Observations	2164000	394000	1924000	472000

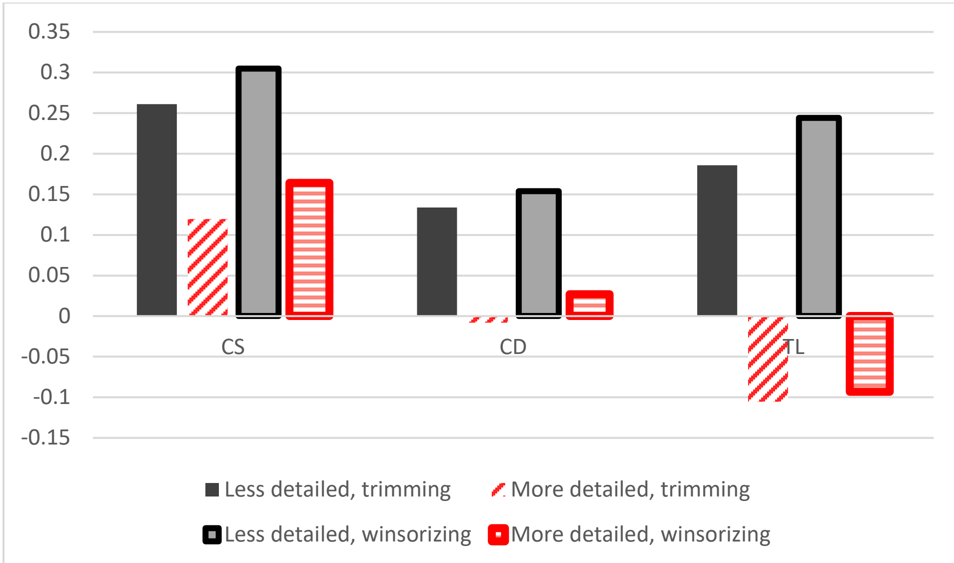
Notes: All specifications control for 6-digit industry by year effects using establishment-level observations. Less minus more detailed markup and output elasticity from translog specification.

Table A.6. 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	-0.0022	-0.0235
	(0.0160)	(0.0181)	(0.0170)	(0.0168)
Above med. X 1990-2005	0.2684*	0.1026	0.0806	-0.0736
	(0.1423)	(0.1548)	(0.1401)	(0.1422)
Above med. X 2006-2014	0.1507	0.2654	0.3132	-0.1432
	(0.1876)	(0.2235)	(0.1945)	(0.1993)
Above med.	-0.0454	0.0691	0.0451	0.0010
	(0.0515)	(0.0439)	(0.0471)	(0.0478)
Constant	0.0936***	0.0467	0.0520	0.0744***
	(0.0220)	(0.0332)	(0.0389)	(0.0256)
Panel B. Cobb-Douglas				
Above med. X 1981-1989	-0.0029	0.0226	0.0428**	0.0156
	(0.0215)	(0.0251)	(0.0208)	(0.0219)
Above med. X 1990-2005	0.1661*	0.0680	0.0620	0.1050
	(0.0917)	(0.0994)	(0.0932)	(0.0896)
Above med. X 2006-2014	0.1412	0.2063	0.2430*	0.0999
	(0.1311)	(0.1604)	(0.1389)	(0.1433)
Above med.	-0.0185	0.0921	-0.0524	-0.1447***
	(0.0642)	(0.0579)	(0.0622)	(0.0514)
Constant	0.0765**	0.0311	0.0955*	0.1451***
	(0.0322)	(0.0384)	(0.0509)	(0.0326)
Panel C. Translog				
Above med. X 1981-1989	0.0401	0.0661	0.0039	-0.0118
	(0.0479)	(0.0438)	(0.0460)	(0.0454)
Above med. X 1990-2005	0.2931**	0.2965**	0.1551	0.0615
	(0.1265)	(0.1267)	(0.1232)	(0.1310)
Above med. X 2006-2014	0.2170	0.5248***	0.3725*	0.0201
	(0.2161)	(0.2008)	(0.1913)	(0.2170)
Above med.	0.1113*	0.0727	-0.0453	-0.0996
	(0.0575)	(0.0673)	(0.0568)	(0.0611)
Constant	0.2242***	0.2402***	0.2930***	0.3224***
	(0.0372)	(0.0242)	(0.0263)	(0.0487)
Observations	2,123,000	2,123,000	2,123,000	2,123,000

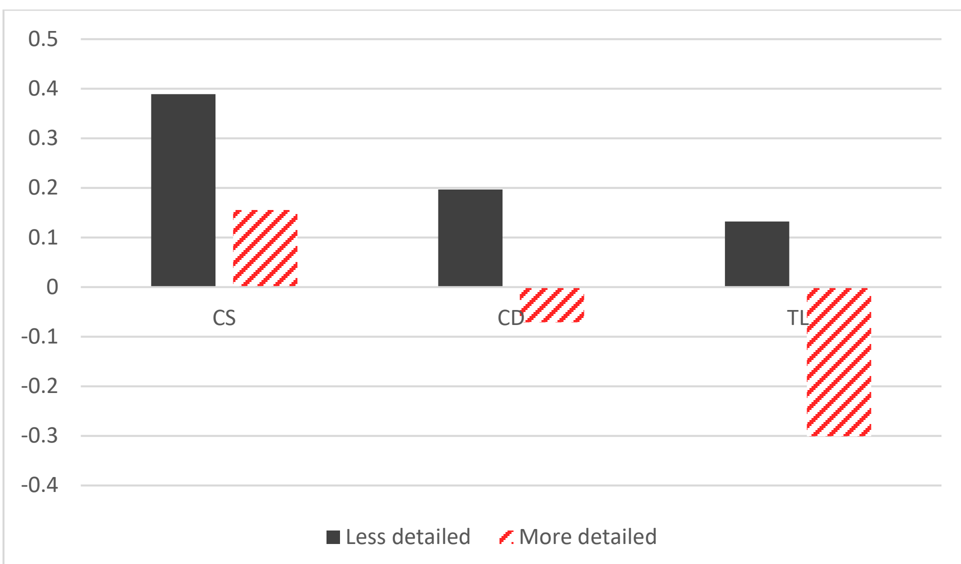
Notes: The markups above are estimated using materials as the variable input. All specifications use revenue weights. Standard errors are clustered at the 6-digit FK-NAICS industry. "Above med." is a dummy variable equal to one if the change in the industry from 1977-2007 is above the revenue-weighted 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 A.1 Long Differences in Markups 1980-2014 Comparing Trimming versus Winsorizing



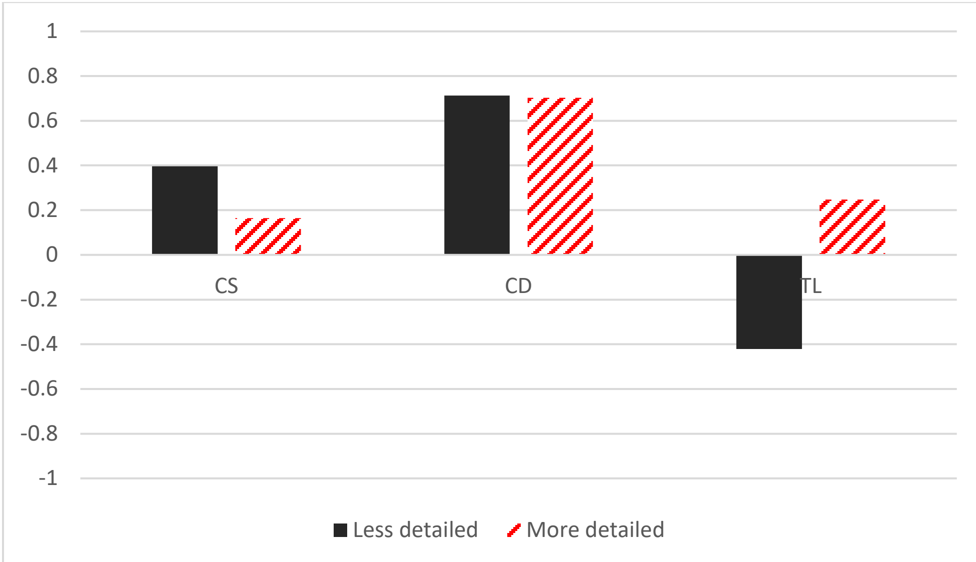
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.2 Long Difference in Markups 1980-2014, Top 50 Industries



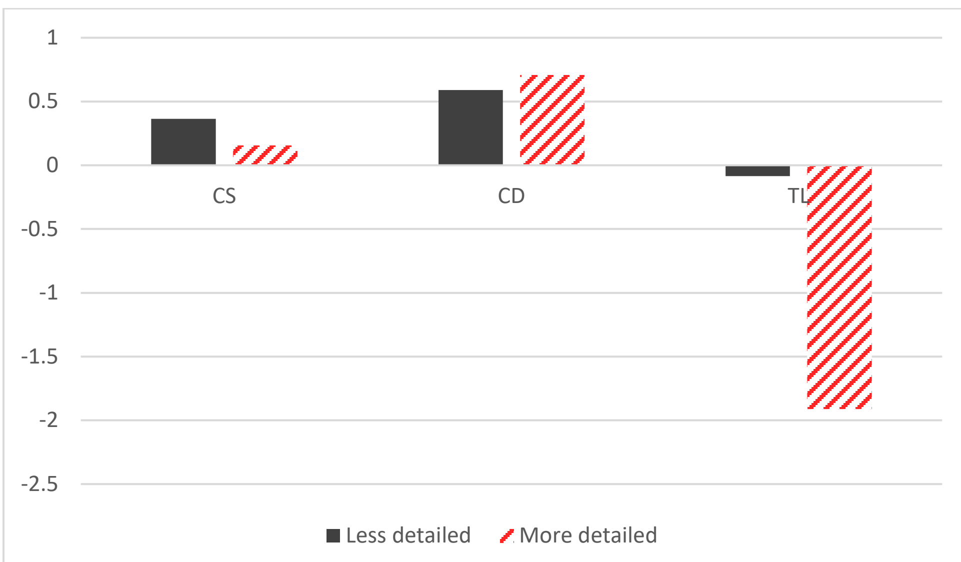
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.3 Long Difference in Markups 1980-2014



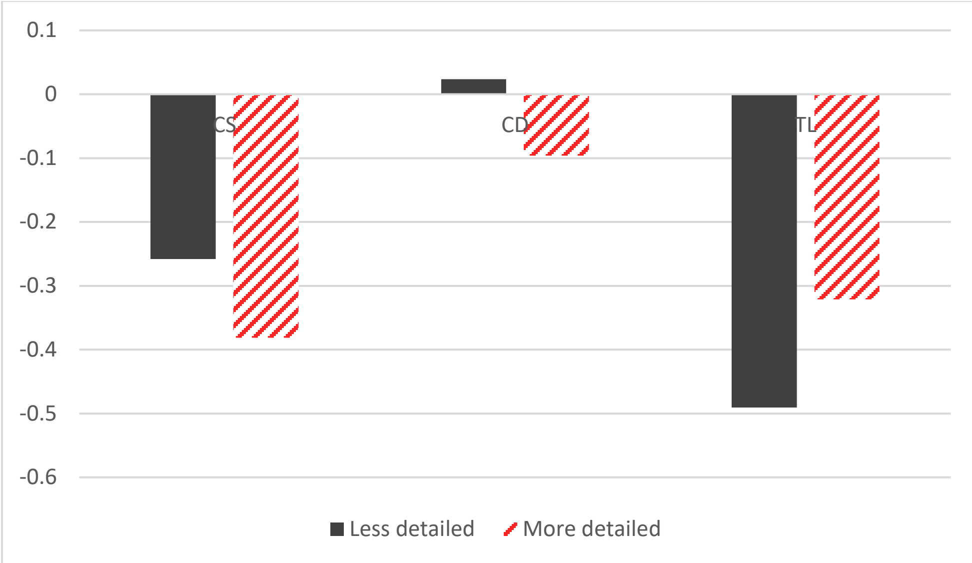
Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.4 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 A.5 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 Manufactures (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 real revenue as $Q_{jt} = (TVS_{jt} + DF_{jt} + DW_{jt})/PISHIP_t$, 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. (2023)). 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. (2023) 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. (2023).

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.

Appendix C. Estimation Issues

We follow the approach of DEU in recognizing that in estimating output elasticities that we don't observe establishment (firm) level output or input prices. We illustrate the implied estimation issues with a Cobb-Douglas specification but the same issues apply for the more general translog specification. Consider a production function for a given industry and time period (all variables logged):

(A1) $$y_{it} = \theta_t^k k_{it} + \theta_t^l l_{it} + \theta_t^m m_{it} + \theta_t^e e_{it} + \omega_{it} + \varepsilon_{it}$$

Where y_{it} is output, k_{it} is capital, l_{it} is labor, m_{it} is materials, e_{it} is energy, ω_{it} is a serially correlated productivity shock and ε_{it} is i.i.d noise. Beyond the well-known issues of endogeneity of inputs that the control function approach addresses, the additional challenge is prices of both outputs and inputs at the micro level are not observed. Thus, the relevant revenue equation (building on equation (29) of Appendix A of DEU) is given by:

(A2) $$y_{it} + p_{it} = \theta_t^k k_{it} + \theta_t^l l_{it} + \theta_t^m m_{it} + \theta_t^e e_{it} + \omega_{it} + \varepsilon_{it} + p_{it} - \sum_j \theta_t^j j_{it}$$

where *j* indexes inputs. The error term thus includes the wedge between output and input prices (the latter weighted by technology parameters). We follow DEU by assuming that this wedge is linearly related to market share.

We implement the control function method using Wooldridge (2009) GMM estimation method. In practice, we use a version of the Wooldridge-Levinsohn-Petrin estimator described in Petrin and Levinsohn (2012) that implements a version of Wooldridge (2009) using equation (2.11) in Wooldridge (2009) for estimation. Specifically, we use the conditional input demand for energy as the control as a nonlinear function of productivity and capital. However, following Wooldridge we also allow for a nonlinear relationship between current and lagged productivity. We also include market share of the establishment at the 4-digit level as in DEU to account for variation in input and factor markets. The Wooldridge transformation of the revenue function yields revenue as a function of inputs, market share and a nonlinear function of lagged capital and the control (see equation 2.11 in Wooldridge). DEU use lagged inputs and market shares as instruments.

Flynn et al. (2019) and Gandi et al. (2020) have raised questions about identification using this and related approaches. We address these concerns by adding to the lagged instruments electricity prices that vary by state and year (from the US EIA). As emphasized by Davis et al. (2013) there is enormous variation in electricity prices for industrial users across locations given differences in the electricity grid and power plant production processes across location. As discussed in Davis et al. (2013), such variation is plausibly exogenous to the establishments. Thus, our instruments include lagged inputs, market shares, and electricity prices. For the translog we include additional interactions of lagged inputs. Identification is facilitated by the assumption of serially correlated productivity shocks and serially correlated input price shocks.

As noted in the main text, DEU implement their control function estimation only for the COMPUSTAT data which are quite distinct from the establishment-level data we use. When DEU use the Economic Census data they focus on cost shares. Thus, the most comparable results with ours are the cost share based output elasticities. Moreover, the details of their implementation of the control function estimation differ from ours especially given the differences in the firm vs establishment level data. However, we note that when we implement a control function estimation with the establishment-level data for manufacturing, we obtain results when using Cobb-Douglas or Translog (see our Figures 2 and 3) that are similar to those in Figure 12.1 (in Appendix 12 of the 2019 Draft of DEU) when we use similar levels of aggregation in terms of industry and time.[2] We interpret these patterns as implying that using our data and methods that we can largely replicate their findings using what we denote as the "less detailed" estimates.

[2] An exception is that they do not find a decline in markups post 2007 in their control function based results for COMPUSTAT for manufacturing. However, we note that they do find such a decline using the cost share based results for manufacturing using Economic Census data.