

Rising Markups or Changing Technology?*

Lucia Foster
U.S. Census Bureau

John Haltiwanger
University of Maryland and NBER

Cody Tuttle
University of Texas at Austin

March 2026

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., capital intensity, computer intensity, diversification to non-manufacturing, and relative firm size) and find patterns in support of changing technology underlying those differences.

* Contact information: Foster: Center for Economic Studies, Bureau of the Census, Washington, DC 20233. Haltiwanger: Department of Economics, University of Maryland, College Park, MD 20742. Tuttle: Department of Economics, University of Texas at Austin, Austin, TX 78712. John Haltiwanger and Cody Tuttle were part-time Schedule A(o) employees at Census at the time of the writing of this paper. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release (DRB Approval Numbers: CBDRB-FY20-CED006-0022, CBDRB-FY22-CED006-0016, CBDRB-FY24-CED006-0007). We thank Daron Acemoglu, Jim Bessen, Jan De Loecker, Mert Demirer, Jan Eeckhout, John Eltinge, Cheryl Grim, Devesh Raval, Pascual Restrepo, and participants at the NBER 2021 Summer Institute, the 2022 Montreal Conference on Markets with Frictions, and seminar participants at Dartmouth and the Erasmus School of Economics for their helpful comments on earlier drafts.

I. Introduction

Understanding firm market power and the degree of competition in the economy is a central concern in economics. The first welfare theorem relies on the assumption that firms take prices as given, and 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 for narrowly focused studies. De Loecker and Warzynski (2012), however, introduce a method for identifying markups directly from plant-level production data that can be applied at scale (building on Hall (1988)). 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 examining trends in markups across industries and over time and treating 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. The method has been subject to criticism due to challenges in estimating output elasticities given both measurement and identification issues (e.g., Bond et al. 2021; Doraszelski and Jaumandreu 2023). These challenges are directly related to data limitations. In this paper, we demonstrate the importance of these data limitations by estimating the output elasticities with a much greater granularity over time and across businesses than in the existing literature. To illustrate the empirical relevance 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).

Using the production approach, DEU provide the most definitive evidence for changing markups for the U.S. Their provocative finding is that markups have risen substantially in the U.S. over the last several decades. The primary analysis for DEU is based on Compustat data, which tracks about 10,000 publicly traded firms per year—and only a fraction of those firms are in manufacturing; in contrast, we track more than 50,000 manufacturing establishments per year from the Annual Survey of Manufactures (ASM). In spite of these sample differences, we can largely replicate their findings in the ASM, as long as we estimate output elasticities at the same level of detail (across industries and time). Moreover, this holds true whether we use a control function approach for estimating output elasticities (our preferred method) or a cost-share approach that imposes strong assumptions at disaggregated levels.

A major contribution of our paper is that we can then permit industry to be defined at a more disaggregated level while also estimating flexible functional forms for the production function. Exploiting industry detail in this way is not a trivial distinction—even within 3-digit NAICS industries, there are inherent differences in the production processes across 4-digit NAICS industries. Consider, for example, Computer and Electronic Equipment Manufacturing (NAICS, 334); this 3-digit industry includes Computer and Peripheral Equipment (3341), Communications Equipment (3342), and Semiconductors (3344). Beyond industry detail, our data support time-varying production elasticities and, in our most general translog specification with a control-function approach, establishment-level heterogeneity within industries over time. When we use these more granular estimates of output elasticities, which are only feasible given our rich dataset, the increase in markups is greatly reduced or even eliminated.

While DEU’s main analyses leverage annual firm-level data from Compustat, they also conduct exercises using Economic Census establishment-level data that is closely related to our ASM data. For this robustness analysis, they permit output elasticities to vary by 4-digit NAICS and year. However, since the Economic Census is only available every five years, DEU cannot use the control function method for their robustness analysis.¹ Instead, they use a “cost-share” estimation approach for output elasticities when using the Economic Census. Our secondary exercises follow DEU and employ a cost-share approach; however, this is not our preferred method since it imposes very strong assumptions about constant returns to scale and the variability of all factors of production. Those assumptions become increasingly untenable when permitting variation at more disaggregated levels. Still, as with our preferred control function approach, we find increases in measured markups using the cost-share approach that are attenuated when we use more granular estimates of output elasticities.

Our results are consistent with the hypothesis that the increase in measured markups in U.S. manufacturing largely reflects unmeasured changes in output elasticities across firms and time. These results are the core of our inference of the importance of changing technology. We then dig deeper into these results and provide further evidence connecting our dampened increase in markups to observable changes in technology at the establishment level. There is already strong evidence that businesses in the same industry adopt different technologies (e.g., Acemoglu et al. 2022) and that differences in technology adoption yield differences in output elasticities across firms within the same industry (e.g., Dinlersoz and Wolf 2023, Hubmer and Restrepo 2024). We use observed variation in indicators of changing technology at the

¹ The control function methodology relies on assumptions regarding the serial correlation of idiosyncratic productivity and other shocks. In practice, this method is typically applied at an annual frequency in the literature. Applying this at a five-year frequency would entail pushing the underlying assumptions very hard.

establishment and detailed industry level to investigate the connection between our findings on output elasticities and observable changes in the ways that businesses do business. At the establishment level, we explore measures of capital intensity, computer intensity, diversification, and relative size. We find that all four technology and business structure indicators exhibit increases in the mean and dispersion across establishments over time.

For this analysis of the connection between output elasticities and technology indicators, we compare markups and output elasticities estimated at “less detailed” and “more detailed” levels of variation over time and industry. The “less detailed” level targets a specification that allows the same variation in output elasticities as DEU, whereas the “more detailed” level corresponds to our results using narrower industry by time cells. All four technology and business structure indicators are positively linked to the difference in the “less detailed” and “more detailed” markup estimates at the establishment level. Similarly, all four indicators are positively linked to the difference in the “less detailed” and “more detailed” output elasticity estimates. A simple accounting decomposition suggests that these four technology indicators alone can account for 43 to 73 percent of the widening gap between less and more detailed markup 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. Put simply, the empirical bite of more flexible markup estimation is greatest in businesses and industries undergoing larger shifts in technology.

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 (2024) and Demirer (2025). Hubmer and Restrepo (2024) 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 (2025) also uses Compustat data for the U.S. and develops a novel methodology for estimating production functions. Both 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 measured 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 flexible specification of technologies 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 show that output elasticities for materials are smaller for larger firms. In turn, this implies the shift towards larger firms yields less of an increase in measured markups under more flexible specifications.

A key feature of our analysis is that our data permits us to focus on materials input as the variable factor while analyses with Compustat require using a composite measure of the variable input or constructing an indirect decomposition of the components. As we argue below, the firm adjustment costs literature (see, e.g., Cooper et al. (2024)) suggests that labor should not be treated as a variable factor even at an annual frequency.

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.

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

where μ_{it} is the markup for establishment i in year t , θ_{it}^V is the output elasticity for input v for establishment i in year t , and α_{it}^V is input v 's share of total revenue for establishment i in year t . In other words, the markup is the 'wedge' between the establishment's output elasticity for any variable input v and that input's share of the establishment's revenue.²

The input's share of revenue, α_{it}^V , can be measured directly in firm or establishment-level data. It is the establishment's total expenditure on the input divided by the total revenue in the establishment (i.e., 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

² As noted in equation 1, the markup is defined for any variable input (v). While in theory, the markup is defined to be the same over any variable input, in practice the measured markup may differ. 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).

U.S. manufacturing establishments to estimate production technologies flexibly and demonstrate how estimated markups change when using this flexible approach.

We follow the approach of DEU estimating output elasticities when we do not observe establishment-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):

$$y_{it} = \theta_t^k k_{it} + \theta_t^l l_{it} + \theta_t^m m_{it} + \theta_t^e e_{it} + \omega_{it} + \varepsilon_{it} \quad (2)$$

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, ε_{it} is i.i.d noise, and θ_t^j is the output elasticity for factor j at time t . 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:

$$y_{it} + p_{it} = \theta_t^k k_{it} + \theta_t^l l_{it} + \theta_t^m m_{it} + \theta_t^e e_{it} + \omega_{it} + \varepsilon_{it} + p_{it} - \sum_j \theta_t^j j_{it} \quad (3)$$

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 related to market share.³

³ 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

We implement the control function method using the Wooldridge (2009) GMM estimation method. In practice, we use a version of the Wooldridge-Levinsohn-Petrin estimator described in Petrin and Levinsohn (2012) 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 (2009) 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 (2009) transformation of the revenue function yields revenue as a function of inputs, market share and a nonlinear function of lagged capital and the control. DEU use lagged inputs and market shares as instruments.

Flynn et al. (2019) and Gandhi et al. (2020) have raised questions about identification using this and related approaches. We address these concerns by adding electricity prices that vary by state and year (from the U.S. Energy Information Administration) to the set of lagged instruments. As emphasized by Davis et al. (2013), there is enormous cross-state variation in electricity prices for industrial users given differences in the electricity grid, regulatory factors, and power plant production processes. 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.⁴ For the translog, we include additional interactions of lagged

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.

⁴ 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.

inputs. Identification is facilitated by the assumption of serially correlated productivity shocks and serially correlated input price shocks.

Our data infrastructure permits estimating the output elasticities using the control function method at the 2-digit, 3-digit, 4-digit and 6-digit NAICS level of disaggregation for both the Cobb-Douglas and translog specifications. Moreover, we can permit the output elasticities to vary over time. We follow DEU by using five-year rolling windows centered on any given year – we refer to these as annual estimates but we emphasize that five years of data are used for each year. For both approaches, the estimated coefficients are the same across all establishments in the same industry. This approach permits us to compare results from specifications with similar industry detail to that permitted by DEU to results from specifications more disaggregated to finer industries.⁵ At a given level of industry detail, the estimated parameters of the production technology are the same across establishments within that level of industry. This point bears emphasizing: although the translog yields establishment-specific differences in elasticities, the underlying parameters are industry-specific.

We also estimate output elasticities using a cost-share approach. Using a cost-share approach is common in the firm productivity literature (see, e.g., Syverson 2011). This approach requires the assumption of constant returns to scale and strong assumptions that (at the level of aggregation implemented) all factors of production are treated as variable factors of production. Syverson (2011) has suggested that at the industry-level and aggregated over time this latter assumption is more tenable. In the firm productivity literature, it has been shown that the patterns of measured firm-level TFP are similar using the control function and the cost-share

⁵ The control function approach is best suited to environments with many observations. In what follows, we consider robustness analysis where we restrict attention to the top 50 industries in terms of the number of observations (see Appendix A).

approach (see, e.g., Decker et al. 2020, Blackwood et al. 2023). However, there is the potential for greater sensitivity in the current application since the production approach to markup estimation depends on accurate measurement of the output elasticity of a variable factor of production. That is, the documented similarity for TFP measurement need not carry over to markup estimation under the production function approach since this approach depends critically on the variation in output elasticities for an assumed variable factor of production.

Allowing for heterogeneity in output elasticities in the same industry using the cost-share approach requires even more stringent assumptions. Specifically, if we assume that the first order conditions hold at the establishment level in each year, then the cost shares of total shares provide estimates of the output elasticities. This approach yields the “accounting measured markup” (denoted as such by Autor et al. (2020)). The very strong (and arguably untenable) assumptions underlying this measure limit the inference for the cost-share approach especially when considering plant-level specific elasticities. We include this approach for completeness and also because, by construction, this approach provides insights into dispersion in cost shares across establishments.

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: $\text{cov}(\varepsilon_{it}, 1/\alpha_{it}) + E(\varepsilon_{it})E(1/\alpha_{it})$. 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.

We apply equation (1) and estimation of output elasticities in (2) and (3) at the establishment level. DEU also use establishment-level variation to estimate output elasticities and markups in their use of Economic Census data. A strong case can be made that the production approach should be implemented at the establishment level – this is the level of aggregation the national accounts use for considering the production process (and why the Economic Censuses, for example, are at the establishment level). Much of the recent research on the production approach for markup estimation for the U.S. uses Compustat data. We regard this as a limitation rather than an advantage given the non-representativeness of Compustat and the

requirement that equation (1) applies at a firm level (where large publicly traded firms typically have many establishments across multiple industries). There is an interesting research agenda for understanding the relationship of markups across establishments in the same firm. We leave that for future research but note that Hottman, Redding and Weinstein (2016) provide guidance that multi-product firms have incentives to charge the same markup across all of their products.

III. Data and Measurement

This paper takes advantage of a dataset 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 salaries 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, as we noted earlier, the firm-level adjustment costs literature provides evidence that labor is not a variable factor of production even at an annual frequency (Cooper, Haltiwanger, and Willis 2024, 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).⁶ For the labor input measure for estimating output elasticities, we use the measure of total hours constructed as the production worker hours times

⁶ See <https://www.nber.org/research/data/nber-ces-manufacturing-industry-database>.

the ratio of salary and wages for all workers to those for production workers. This method includes an adjustment for difference in labor quality for production and non-production workers.

IV. Estimates of Output Elasticities and Markups

We start by providing the results of the output elasticities estimations in three panels of Table 1 where each panel corresponds to one of our three methodologies. Panel A shows the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the Cobb-Douglas (CD) specification. Panel B shows the distribution of estimated output elasticities for materials from control function estimates of the revenue function using the translog specification (TL).⁷ Panel C shows the distribution of estimated output elasticities from cost shares of materials of total costs (CS) at different levels of aggregation. For each estimation, we show the mean and the standard deviation (SD).

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 CD approach rises from 0.03796 to 0.1103 going from 2-digit yearly to 4-digit yearly. The TL specification has a less dramatic increase but starting from a much higher level for the analogous cases: an increase from 0.1889 to 0.2042. The CS approach yields increases from 0.03707 for 2-digit yearly to 0.107 to 4-digit yearly and up to 0.2051 for plant-level yearly. While the latter reflect output elasticities under only very strong assumptions, the CS results highlight heterogeneity in measured cost shares across establishments. Results for estimates of output elasticities for labor show similar patterns and are reported in Tables A.2-A.4.⁸

⁷ We present estimates for the Top 50 industries in Table A.1. Results are robust to this restriction.

⁸ The output elasticities in Tables A.2-A.4 are reported for the primary “less” and “more” detailed specifications.

We now turn to the estimated markups from each of the methodologies (and from varying levels of aggregation).⁹ We show results from three types of exercises. First, we focus our attention on the long differences in markups from 1980-2014 which enables us to demonstrate the impact of greater flexibility in industry detail and time. Second, we show the time series patterns from 1972-2014 of two benchmark cases of markups, one “less detailed” and one “more detailed”. Finally, we present the markups obtained by our different methods for periods associated with Economic Census (to enable comparison to DEU’s cost-share approach).

Our first two sets of analyses are presented in Figures 1 to 3 and show the implied pattern of changing markups on a sales-weighted basis for our three estimation approaches (Cobb-Douglas, Figure 1; translog, Figure 2; cost-shares, 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) of Figures 1-3, as we consider specifications with more industry detail and greater time variation, the increase in markups is substantially dampened. For the preferred control function approach estimates, it is a combination of industry and time variation that is important. Greater industry detail is especially important with the time-varying

⁹ 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.

elasticities. These patterns of implied markups are robust to limiting to the top 50 industries (see Figure A.2).¹⁰

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 little change using the Cobb-Douglas specification (CD), a decline using the translog specification (TL), and only a moderate increase in markups using the cost-share approach (CS). As noted above, we interpret the CS results with caution given the strong assumptions underlying this approach.

The most dramatic differences emerge from the translog specification using the control function approach. At the 2-digit level with time-invariant parameters (a specification DEU considered in robustness exercises), we show that the average sales-weighted markup with this approach increases by 36% from 1977 to 2007 and by 23% from 1977 to 2012. However, the corresponding changes using a translog specification at the 4-digit level with annual estimates (based on rolling five-year windows) are -10% and -12%, respectively. For our Cobb-Douglas (CD) specification, using a control function approach at the 2-digit level with annual estimates (again, using a five-year rolling window), we show the sales-weighted markup increases by 24% from 1977 to 2007 and 8% from 1977 to 2012. The corresponding changes using a 4-digit

¹⁰ 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.

specification with annual estimates yield only a 6% increase from 1977 to 2007 and a decline of -4% from 1977 to 2012.

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 1-3 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 3 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 12 of DEU 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.¹¹ 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

¹¹ The more detailed translog case does not exhibit a rise in markups, and thus there is no corresponding decrease.

three less detailed specifications, markups decrease by about 20% from 2005 to 2014, returning to the levels estimated for the mid-to-late 1990s. Although we find a smaller rise in the more detailed cases using cost share and Cobb-Douglas approaches, we likewise find a smaller decrease of around 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, Appendix 12). 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.

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 four potential factors driving differences in results. These are measurement issues (aggregation and weights); shifting shares as evidenced through decompositions; observable changes in production technology as captured by capital intensity, computer intensity, diversification, and relative firm size; and measurement or specification error.

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:

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

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:¹²

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

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 declines under Cobb-Douglas (CD), increases under the translog (TL) but much less than implied by Figure 3, and exhibits little change for the cost share (CS) approach. For the more detailed specification, the naïve markup declines for the Cobb-Douglas (CD) and translog (TL) specifications.

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

We analyze these two moments in Figures 5 and 6. Figure 5 shows the long difference in output elasticities for materials.¹³ Figure 6 shows the sales-weighted revenue cost shares for all

¹² 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.

¹³ Figure A.5 shows the analogous plot for labor.

inputs (materials (M) as well as labor (L), energy (E), and capital (K)) as well as the ratio of sales-weighted total costs to sales-weighted revenue (TC). 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. 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.¹⁴ We are interested in whether the differences we observe are driven by specific components. The decomposition is given by:

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

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

¹⁴ 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.

detailed” specifications. The rising dispersion and skewness are, in general, mitigated by the “more detailed” specifications. 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 the 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 finding is *prima facie* evidence that changing technology (i.e., changes in the output elasticities across firms and time) underlies a substantial portion, if not all, of the measured increase in markups for U.S. manufacturing.

To provide additional evidence, in this section we explore 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.¹⁵ The share of the parent firm’s sales in industry sales is measurable in Economic Census years when all establishments are covered.¹⁶

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.¹⁷ These findings are important indicators that establishments are changing the way they are doing business with increased differentiation across establishments. The log firm share is related to changing market structure with the shift towards superstar firms. As discussed in both DEU and Autor et al. (2020), the shift towards superstar firms is connected to rising measured markups as larger firms have higher measured markups. However, it may be that this reflects differences in output elasticities between smaller and larger firms as well as differences in the covariance between output elasticities and cost shares across firm size. We investigate that question as we explore the connection between the “less detailed” and “more detailed” measured markups and estimated output elasticities and these indicators of changing technology and changing structure of the economy.

Before presenting regression results that investigate this question, we provide summary statistics for the dependent and explanatory variables in Table 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

¹⁵ Specifically, we measure the ratio of non-manufacturing to manufacturing employment for the parent firm.

¹⁶ 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 $(x_{it} - \bar{x}) / (0.5 * (x_{it} + \bar{x}))$ which is a second order approximation of the log difference of x_{it} from its grand mean \bar{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).

¹⁷ 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.

specification to these technology/business structure measures. All specifications control for detailed industry (6-digit) by year effects. Such controls allow us to highlight differences associated with indicators of technology use within narrow industries. 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.¹⁸

These findings are consistent with the hypothesis that establishments that have adopted different ways of doing business within industries have systematically different estimated markups and output elasticities. The results on log firm size imply that larger firms have smaller estimated output elasticities of variable factors (and smaller measured markups) when using specifications that permit greater differences in output elasticities across establishments within and across industries as well as time. In turn, this implies the shift towards larger firms yields less of an increase in measured markups taking into account the more flexible specifications.

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.¹⁹ 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,

¹⁸ In Appendix Table A.5, we explore whether the relationships in Table 4 have changed over time. For the most part, the answer is no. However, for firm size there is evidence that the less minus more detailed estimates have a greater gap in the post 1980 period.

¹⁹ Hubmer and Restrepo (2024) 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.

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).²⁰ The logic is that there are fixed costs associated with changing technology. The results on capital intensity, computer intensity 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 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 gauge the quantitative importance of observable technology changes for the gap between the "less detailed" and "more detailed" markup estimates, we conduct a simple accounting decomposition. Focusing on the translog specifications, the gap between less and

²⁰ 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).

more detailed markups widens by approximately 0.41 from 1977 to 2012. Using the changes in the means of our four technology indicators over the same period (from Figure 10) and the establishment-level relationships between each indicator and the less minus more detailed markup (from Table 4), we compute the share of the change in the gap attributable to each indicator. Table 5 shows that capital intensity alone accounts for approximately 43 percent of the widening gap between the less and more detailed markup estimates. Computer intensity, diversification, and relative firm size can each account for approximately 7-13%. Assuming each technology indicator contributes independently, the sum of these shares is an upper bound on the portion of the gap explained by these factors. On the other hand, the share explained by capital intensity offers a lower bound. This suggests these four changes in technology alone can account for 43-73% of the rising gap between the less and more detailed markup estimates. In sum, this exercise supports the claim that markup estimates based on higher levels of industry and time aggregation are influenced by observable changes in technology and business structure.

Further evidence that technological change affects measured markup changes under the less detailed estimation specifications is provided in Appendix C. We classify industries based on whether they experienced above or below median changes in computer intensity, capital intensity, firm diversification, and concentration over the 1977 to 2007 period. We find that industries with above-median changes in the first three measures exhibit a widening gap between markups estimated under the less detailed specifications and those estimated under the more detailed specifications.

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 between the “less detailed” and “more detailed” estimates of markups and output elasticities.²¹ 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.

D. Measurement Error

We find the evolution of markups over time is much flatter once we estimate output elasticities at finer levels of industry-by-time. Above, we argue that these patterns are consistent with dramatic, industry-specific changes in technology over the past several decades, which are obscured when the estimated production technology is forced to be the same at very broad levels. However, an alternative interpretation is that, by making the industry-time cells more narrow, we stretch the limits of our data, increase the noise in our estimates of output elasticities, and

²¹ 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.

attenuate the markup estimates. There are four primary reasons this alternative explanation does not comport with the data.

As a starting point, we compare our industry-by-time cell sizes to those used in DEU. We estimate the average cell size in our data using publicly available statistics from the Business Dynamic Statistics, assuming that roughly one in six manufacturing establishments are sampled in the ASM. At the level of four-digit industry and five-year rolling window, the mean cell size is approximately 2,700 establishments. In contrast, we estimate the mean cell size in Compustat is approximately 900 firms when DEU use 2-digit by five-year rolling windows and approximately 11,000 firms when DEU use 2-digit time-invariant cells.²² For our Cobb-Douglas comparisons, we gather that our cells are, in fact, three times larger than the cells used in DEU, although for our translog comparisons, our cells are roughly one-fourth of the size of their cells. It does not appear that issues of small cell sizes can readily explain the difference between our more and less detailed estimates using Cobb-Douglas.

However, we do not believe small cell sizes and potentially related measurement error is a concern even in the case of the translog approach. The second piece of evidence against the measurement error explanation comes from our robustness tests using the top 50 industries. Even for these large industries, we find marked differences between the more and less detailed estimates, using both Cobb-Douglas and translog approaches. For the top 50 manufacturing industries, we estimate that the mean cell size at the level of 4-digit industry and five-year window is roughly 4,400 establishments. Despite almost doubling the cell size, we do not find

²² DEU report 247,644 firms in their main estimation sample, over a period of 61 years. To approximate average cell size using 2-digit industries and five year windows, we calculate $(247,644 \text{ firms} / 22 \text{ 2-digit industries} * (61 \text{ years}/5\text{-year windows})) = 923 \text{ firms per 2-digit by five-year window}$. To approximate average cell size for their 2-digit time-invariant approach, we calculate $(247,644 \text{ firms} / 22 \text{ 2-digit industries}) = 11,257 \text{ firms per 2-digit industry}$.

more of an increase in markups using the translog approach, in fact, we find the gap between our more and less detailed approaches is even larger.

Aside from looking at cell size directly, we also point to two empirical patterns that are difficult to reconcile with a measurement error explanation. First, Figures 1-3 show that the sales-weighted markup estimates from the “less detailed” and “more detailed” specifications are similar early on in our sample period but depart significantly in the middle part of our sample. The gap between these two approaches then remains steady or shrinks in the last ten years. These time series patterns can only be reconciled by a measurement error explanation if one believes that measurement error played an especially large role in the middle of the sample, but a dampened role or no role at all in the beginning and end of the sample. Finally, in the subsection above, we document several strong correlations between the gap in the more and less detailed estimates and industry-specific changes in technology. Were this gap simply a consequence of estimation noise, there is no reason for it to be correlated with changes in capital per worker or computer intensity.

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.

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 2014.²³ These data permit much greater flexibility in estimating output elasticities across establishments.

Using the preferred control function estimation method, 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 a Cobb-Douglas revenue estimation approaches.

²³ The CMP data underlie the public domain Dispersion Statistics on Productivity (DiSP) data on within industry productivity dispersion (Cunningham et al. 2023 and <https://www.census.gov/data/experimental-data-products/dispersion-statistics-on-productivity.html>).

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

Our results are consistent with the hypothesis that much of measured increases in markups instead reflect changing production technology. That is, much of the measured increase is mitigated when indicators of differences in output elasticities across firms and time are allowed to be sufficiently flexible. We present additional 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.²⁴ 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 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 potentially 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; Acemoglu et al. 2022) may be helpful for this important research agenda of characterizing differences across businesses in how they conduct business.

²⁴ Hubmer and Restrepo (2024) is an important step in this direction for publicly traded firms.

References

Acemoglu, Daron and Pascual Restrepo (2018) “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,” *American Economic Review*, 108(6), 1488-1542.

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

Acemoglu, Daron, Gary Anderson, David Beede, Catherine Buffington, Eric Childress, Emin Dinlersoz, Lucia Foster, Nathan Goldschlag, John Haltiwanger, Zachary Kroff, Pascual Restrepo, and Nikolas Zolas (2022) “Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey,” Paper Presented at NBER/CRIW Conference in March 2022.

Autor David, David Dorn, Lawrence F. Katz, Christina C. Patterson, and John Van Reenen (2020) “The Fall of the Labor Share and the Rise of Superstar Firms,” *Quarterly Journal of Economics*, Vol. 135, No. 2, pp. 645-709.

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

Baqae, David Rezza and Emmanuel Farhi (2020) “Productivity and Misallocation in General Equilibrium,” *Quarterly Journal of Economics*, Vol. 135, No. 1, pp. 105-163.

Blonigen, Bruce A. and Justin R. Pierce (2016) “Evidence for Effects of Mergers on Market Power and Efficiency,” working paper.

Bond, Steve, Arshia Hashemi, Greg Kaplan, Piotr Zoch (2021) “Some Unpleasant Markup Arithmetic: Production Function Elasticities and Their Estimation from Production Data,” *Journal of Monetary Economics*, Vol. 121, pp. 1-14.

Chen, Jiafeng and Jonathan Roth (2023) “Log-like? Identified ATEs defined with zero-valued outcomes are (arbitrarily) scale-dependent,” working paper.

Cooper, Russell, John Haltiwanger, Jonathan Willis (2024) “Declining Responsiveness at the Establishment Level: Sources and Productivity Implications,” NBER Working Paper No. 32130.

Cooper, Russell, John Haltiwanger, and Laura Power (1999) “Machine Replacement and the Business Cycle: Lumps and Bumps,” *American Economic Review*, 89 (4): 921-946.

Cunningham, Cindy, Lucia Foster, Cheryl Grim, John Haltiwanger, Sabrina Wulff Pabilonia, Jay Stewart, and Zoltan Wolf (2023) “Dispersion in Dispersion: Measuring Establishment-Level Differences in Productivity,” *Review of Income and Wealth*, 69(4), December 2023.

Davis, Steven, John Haltiwanger, and Scott Schuh (1996) *Job Creation and Destruction*, Cambridge, MA: MIT Press.

Davis, Steven J., Cheryl Grim, John Haltiwanger, and Mary Streitwieser (2013) "Electricity Unit Value Prices and Purchase Quantities: U.S. Manufacturing Plants, 1963–2000," *The Review of Economics and Statistics*, MIT Press, vol. 95(4), pages 1150-1165, October.

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

De Loecker, Jan, Jan Eeckhout, and Simon Mongey (2022) "Quantifying Market Power and Business Dynamism in the Macroeconomy," working paper.

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

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger (2019) "The Rise of Market Power and the Macroeconomic Implications," Working Paper, November.

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

De Ridder, Maarten, Basile Grassi, and Giovanni Morzenti (2022) "A Hitchhikers Guide to Markup Estimation," mimeo.

Decker, Ryan, John Haltiwanger, Ron Jarmin and Javier Miranda (2020) "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," *American Economic Review*, December.

Demirer, Mert (2025) "Production Function Estimation with Factor-Augmenting Technology: An Application to Markups," Conditionally Accepted, *Econometrica*.

Doraszelski, Ulrich and Jordi Jaumandreu (2023) "Reexamining the De Loecker & Warzynski (2012) method for estimating markups," working paper.

Dunne, Timothy, John Haltiwanger, and Kenneth R. Troske (1997) "Technology and Jobs: Secular Change and Cyclical Dynamics." *Carnegie-Rochester Public Policy Conference Series* 46 (June): 107–78.

Dunne, Timothy, Lucia Foster, John Haltiwanger, and Kenneth R. Troske (2004) "Wages and Productivity Dispersion in U.S. Manufacturing: The Role of Computer Investment," *Journal of Labor Economics*, April.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu (2018) "How Costly are Markups," NBER Working Paper No. 24800.

Flynn, Zach, Amit Gandhi, and James Traina (2019) “Measuring Markups with Production Data”, working paper.

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

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

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

Gandhi, Amit, Salvador Navarro and David A. Rivers (2020). "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, University of Chicago Press, vol. 128(8), pages 2973-3016.

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

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

Hsieh, Chang-Tai and Peter J. Klenow (2009) “Misallocation and Manufacturing TFP in China and India,” *The Quarterly Journal of Economics*, 124 (4), 1403-48.

Hottman, Colin, Redding, Stephen, and Weinstein, David (2016) “Quantifying the Sources of Firm Heterogeneity”, *The Quarterly Journal of Economics*, 1291–1364.

Hubmer, Joachim and Pascual Restrepo (2024) “Not a Typical Firm: The Joint Dynamics of Firms, Labor-Shares and Capital Substitution,” *American Economic Journal: Macroeconomics* (forthcoming).

Liu, Yongzheng and Jie Mao (2019) “How Do Tax Incentives Affect Investment and Productivity? Firm-Level Evidence from China,” *American Economic Journal: Economic Policy*, 11 (2), 261-291.

Mullahy, John and Edward C. Norton (2022) “Why Transform Y? A Critical Assessment of Dependent-Variable Transformations in Regression Models for Skewed and Sometimes-Zero Outcomes,” Working Paper 30735, National Bureau of Economic Research.

Petrin, Amil, and James Levinsohn (2012) “Measuring Aggregate Productivity Growth Using Plant-Level Data.” *The RAND Journal of Economics* 43(4), 705–25.

Raval, Devesh (2023) “Testing the Production Approach to Markup Estimation” *Review of Economic Studies* (2023) 90, 2592–2611.

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

Syverson, Chad (2011) “What Determines Productivity?” *Journal of Economic Literature*, 49(2):326-365.

Törnqvist, Leo, Pentti Vartia, and Yrjö O. Vartia (1985) How Should Relative Changes be Measured?, *The American Statistician*, 39:1, 43-46.

Wooldridge, Jeffrey (2009) “On Estimating Firm-Level Production Functions using Proxy Variables to Control for Unobservables,” *Economic Letters*, 104 (112-114).

Table 1. Output Elasticities for Materials, Alternative Approaches

Level of Aggregation	Mean	SD
Panel A. Cobb Douglas (CD)		
2-digit, constant over time	0.5384	0.0173
3-digit, constant over time	0.5284	0.07718
4-digit, constant over time	0.5138	0.09567
6-digit, constant over time	0.4992	0.1214
2-digit, yearly	0.5301	0.03796
3-digit, yearly	0.5154	0.08882
4-digit, yearly	0.4875	0.1103
Panel B. Translog (TL)		
2-digit, constant over time	0.5699	0.1849
3-digit, constant over time	0.5518	0.1928
4-digit, constant over time	0.527	0.1943
6-digit, constant over time	0.5109	0.2111
2-digit, yearly	0.5652	0.1889
3-digit, yearly	0.5432	0.1966
4-digit, yearly	0.4959	0.2042
Panel C. Cost Share (CS)		
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

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
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
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

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)**

<i>Variable</i>	<i>Mean</i>	<i>SD</i>
Less minus more detailed markup	0.6403	1.009
Less minus more detailed output elasticity	0.242	0.2244
Capital Intensity (log (K/L))	4.908	1.325
Computer Intensity (DHS Comp Inv Per Worker)	-0.7437	1.363
Diversification Index	-0.9281	1.012
Relative Firm Size (log(firm share))	-3.494	1.954

Notes: Summary statistics for the dependent and explanatory variables in Tables 4. All variables are measured at the establishment level. The less minus more 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 relative firm size 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

Less minus More Detailed Markup				
	Capital Intensity	Computer Intensity	Diversification Index	Relative Firm Size
Slope Coefficient	0.1541*** (0.0249)	0.0384*** (0.0109)	0.0978*** (0.0166)	0.1250*** (0.0154)
Constant	-0.1158 (0.1224)	0.6722*** (0.0081)	0.7416*** (0.0154)	1.045*** (0.0538)
R-squared	0.371	0.394	0.366	0.430
Less minus More Detailed Output Elasticity, Materials				
Slope Coefficient	0.0438*** (0.0055)	0.0109*** (0.0028)	0.0284*** (0.0044)	0.0418*** (0.0037)
Constant	0.0270 (0.0270)	0.2569*** (0.0021)	0.2710*** (0.0041)	0.3844*** (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 3.

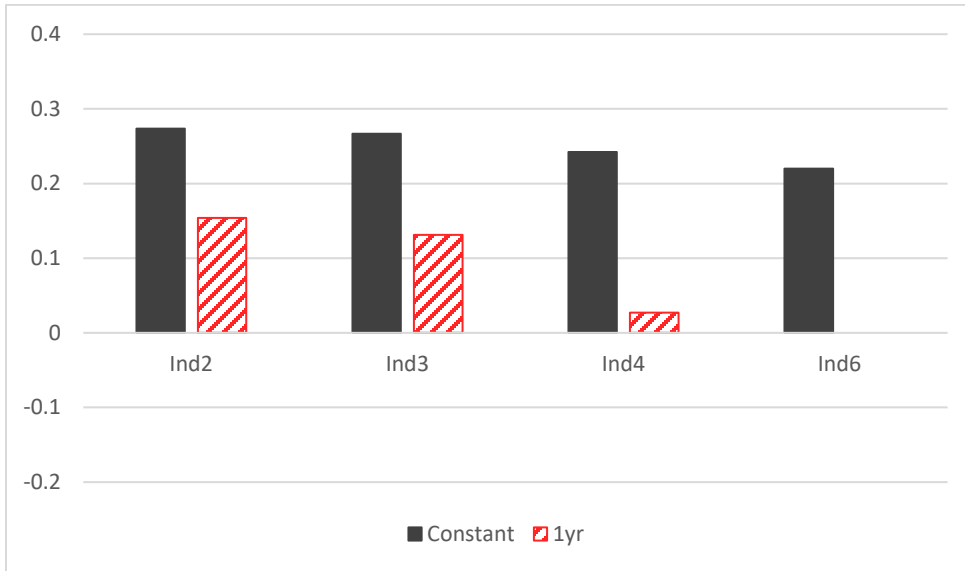
Table 5: A Simple Accounting Decomposition of Change in Less minus More Detailed Markups Based on Technology Change Alone

	Change in Technology	Rel. between Tech. and (Less-More) Gap	Predicted Change in Gap	Share of Change in (Less-More) Gap Accounted for
Capital Intensity	1.155	0.154	0.178	43.4%
Computer Intensity	1.353	0.038	0.052	12.7%
Diversification	0.275	0.098	0.027	6.6%
Relative Firm Size	0.348	0.125	0.044	10.6%
Sum			0.300	73.3%

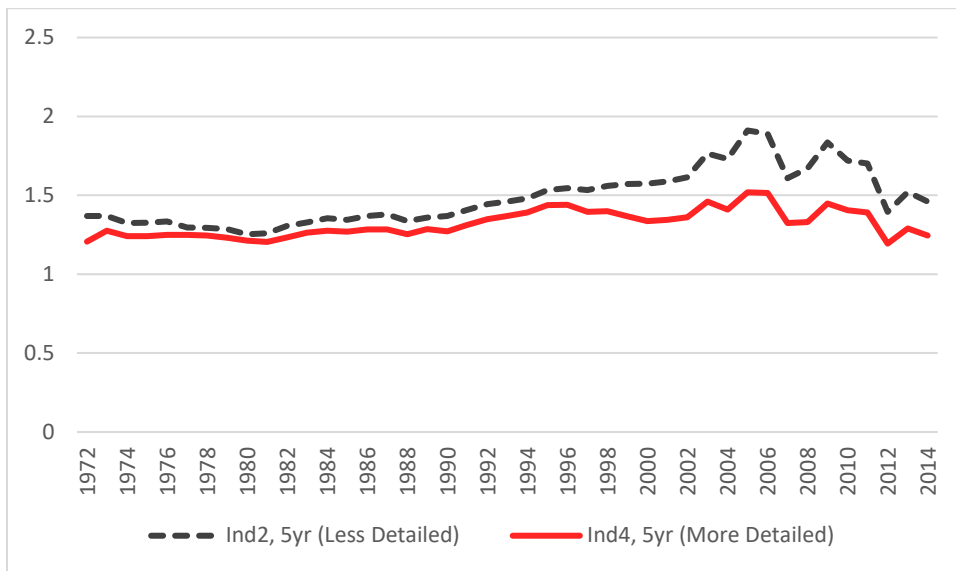
Notes: Column 1 reports the 1977-2012 change in each technology measure from Figure 10. Column 2 reports the relationship between the less minus more detailed markup and each technology measure from Table 4. Column 3 multiplies column 1 and column 2 to arrive at the predicted change in the less minus more detailed markup from 1977-2012 based on each technology measure in isolation. Column 4 reports the share of the actual 1977-2012 change in the less minus more detailed markup accounted for by the changes in each technology measure. In this table, the less minus more detailed markup refers to the translog specifications.

Figure 1. Markups Estimated Using Cobb-Douglas (CD)

(a) Long difference in markups 1980-2014



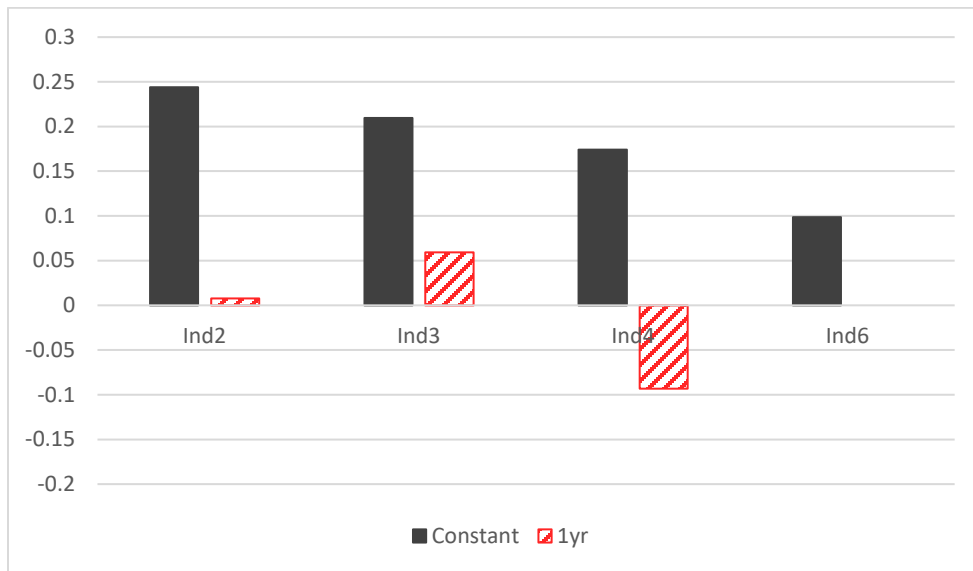
(b) Markups from 1972-2014, benchmark cases



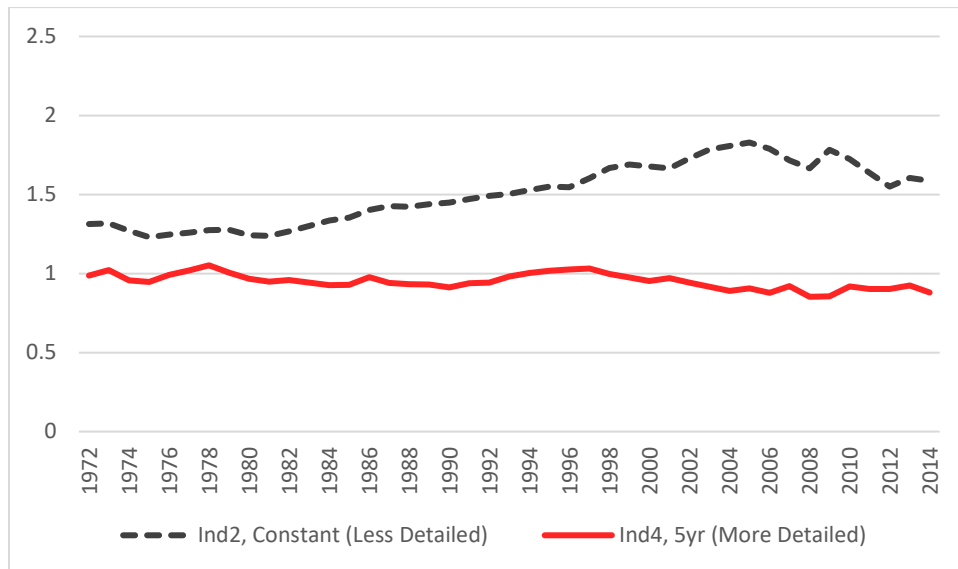
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 2. Markups Estimated Using Translog (TL)

(a) Long difference in markups 1980-2014



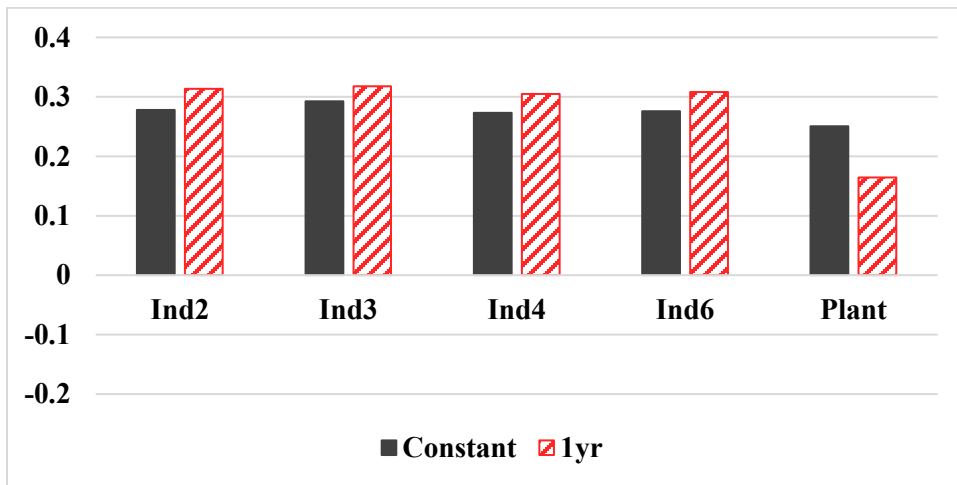
(b) Markups from 1972-2014, benchmark cases



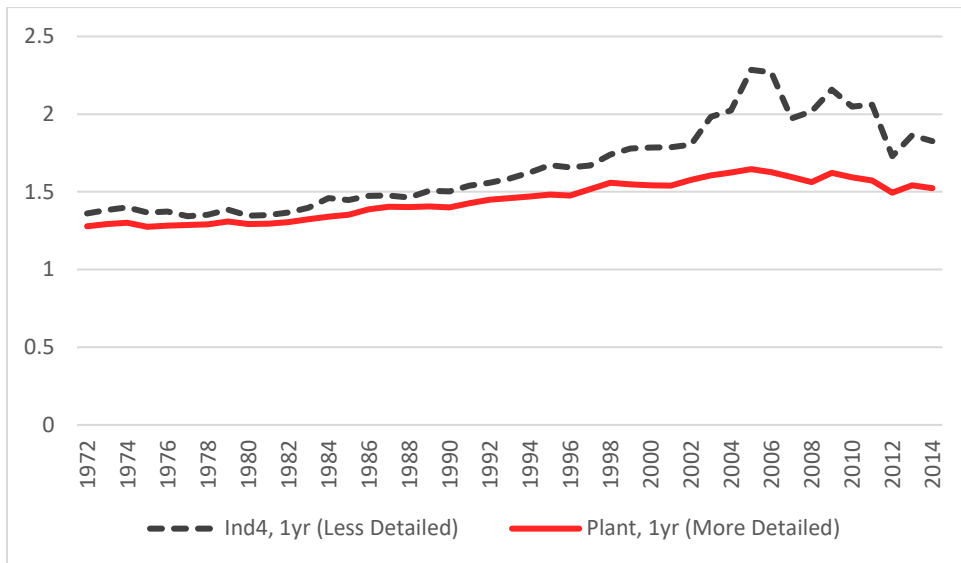
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 3. Markups Estimated Using Cost Shares (CS)

(a) Long difference in markups 1980-2014

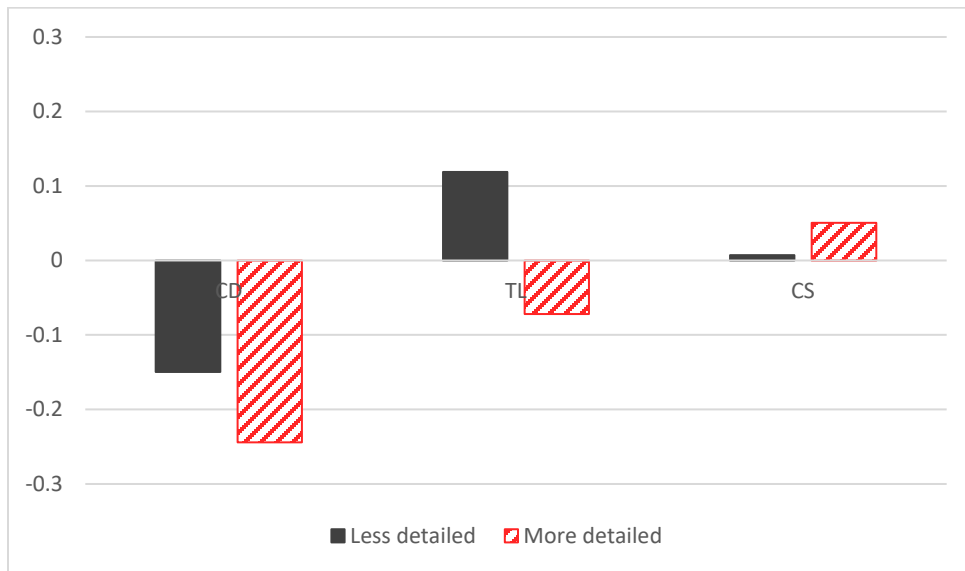


(b) Markups from 1972-2014, benchmark cases



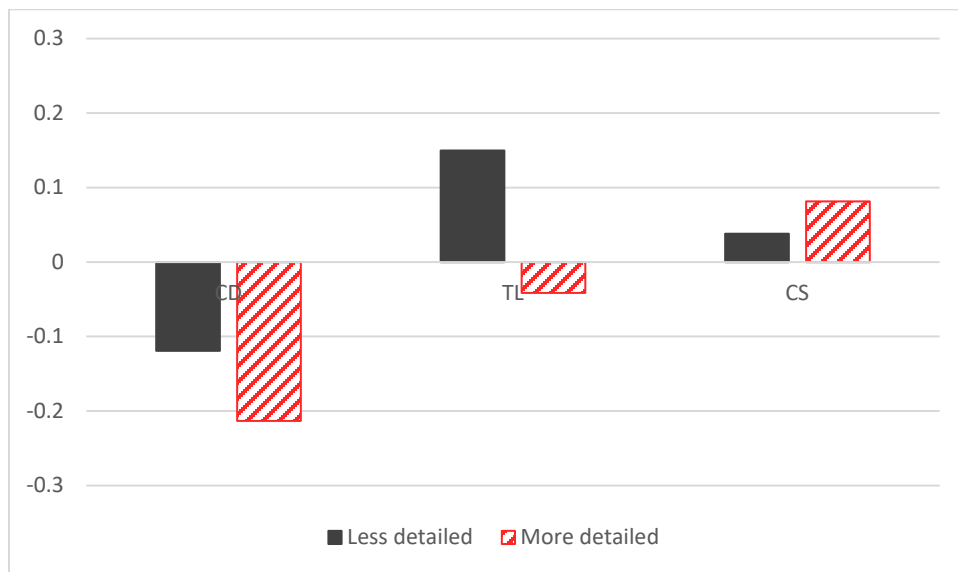
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure 4. Long Difference in Naïve Markups 1980-2014



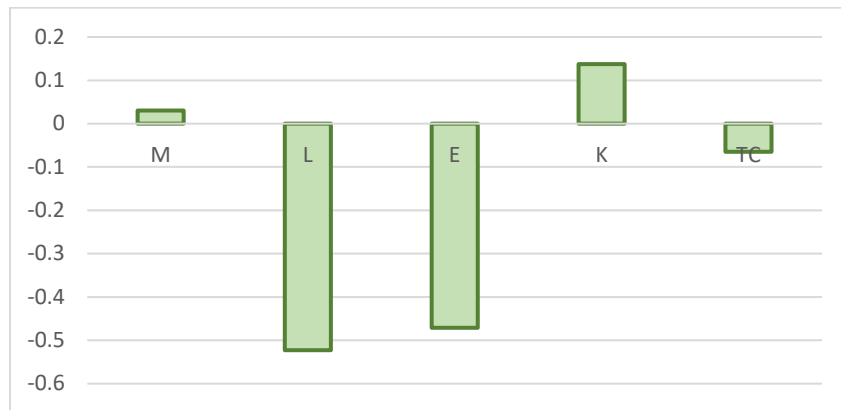
Notes: The markups above are estimated using materials as the variable input. See equation (3) for definition of naïve markup. Long differences are log differences.

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



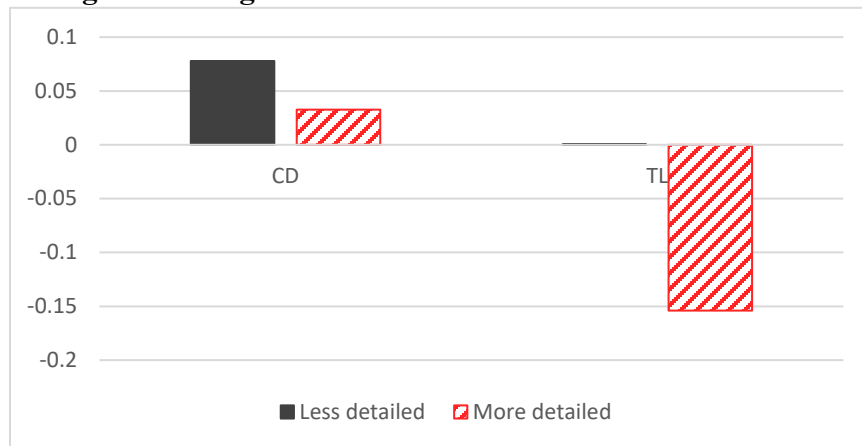
Notes: The output elasticities above are estimated for materials. Output elasticities are revenue-weighted means. Long differences are log differences.

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



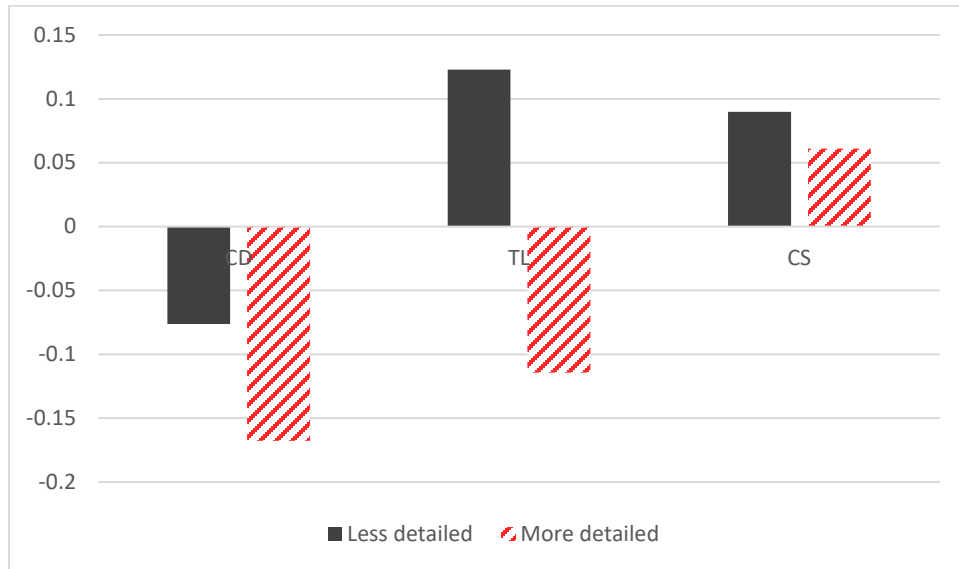
Notes: Input shares of revenue are revenue-weighted means. Long differences are log differences.

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.

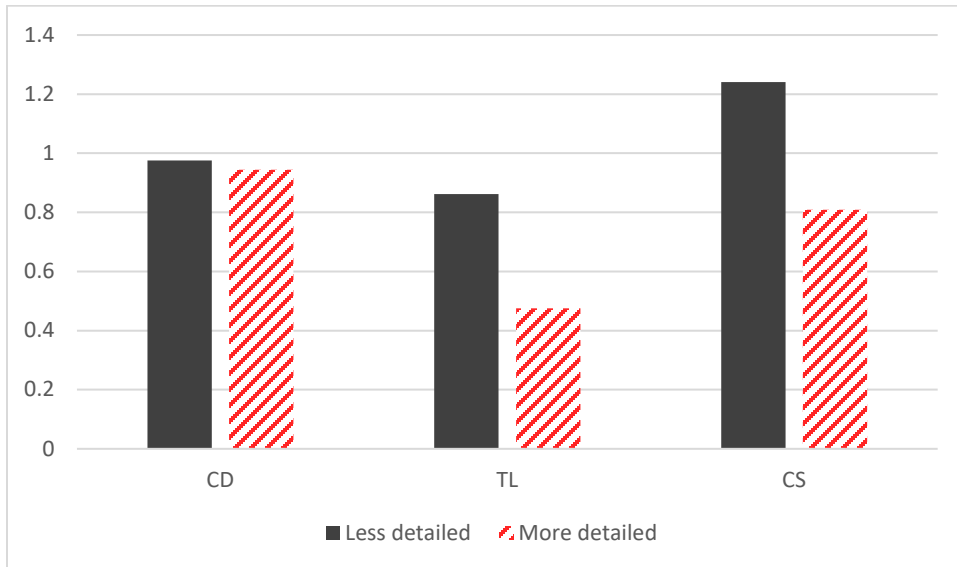
Figure 8. Long Difference of Markups from 1980-2014. Robustness to Total Cost Weighting



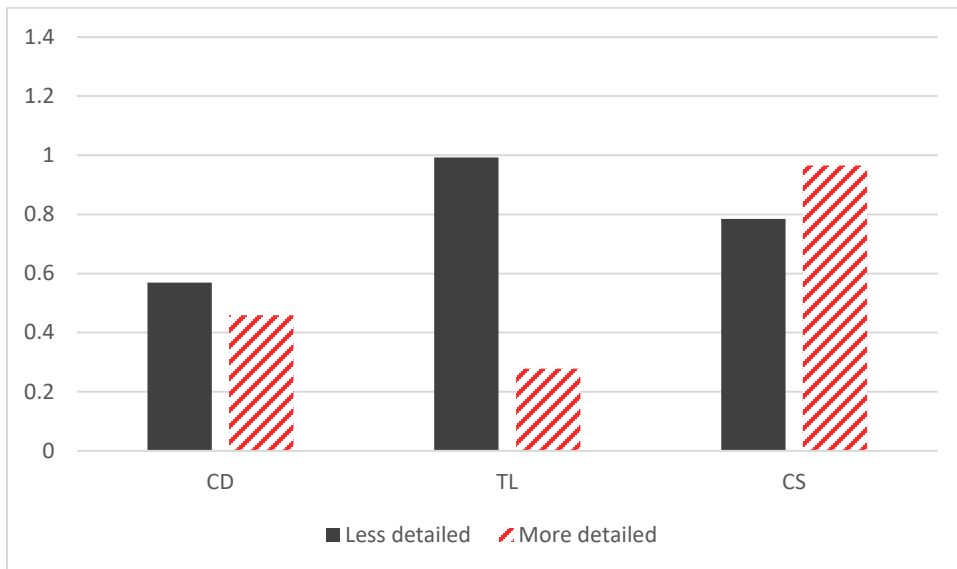
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are total cost-weighted means. Long differences are log differences.

Figure 9. Dispersion in Markups over Time

(a) Long difference in standard deviation 1980-2014



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



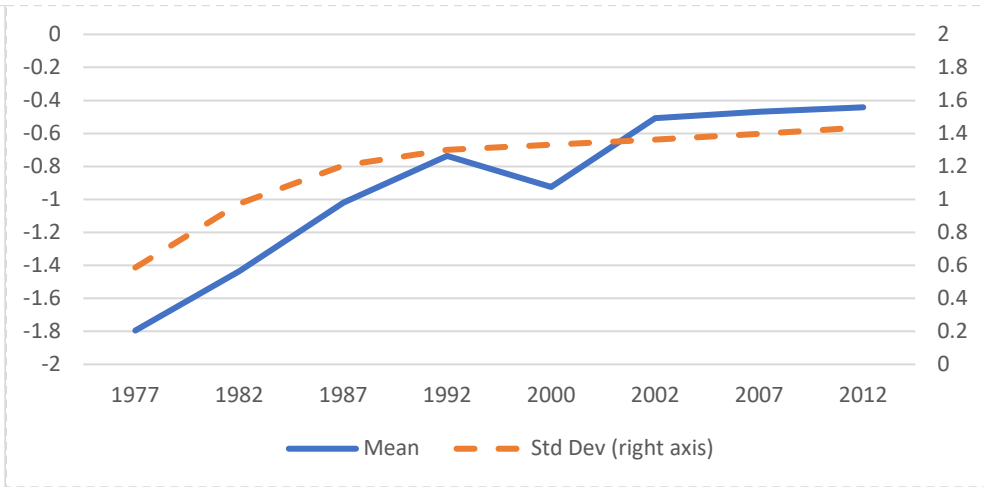
Notes: The markups above are estimated using materials as the variable input. The markup moments are computed from revenue-weighted distribution. Long differences are log differences.

Figure 10. Changes in Indicators of Plant-Level Technology

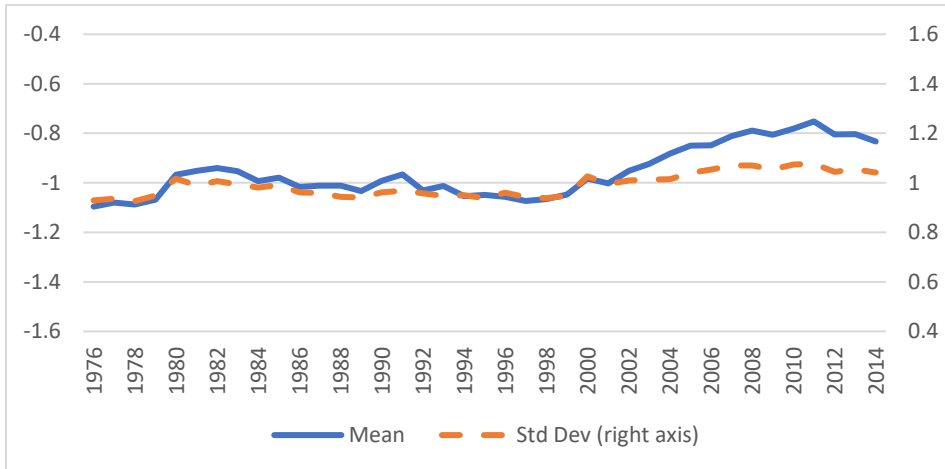
(a) Capital Intensity (log(K/L))



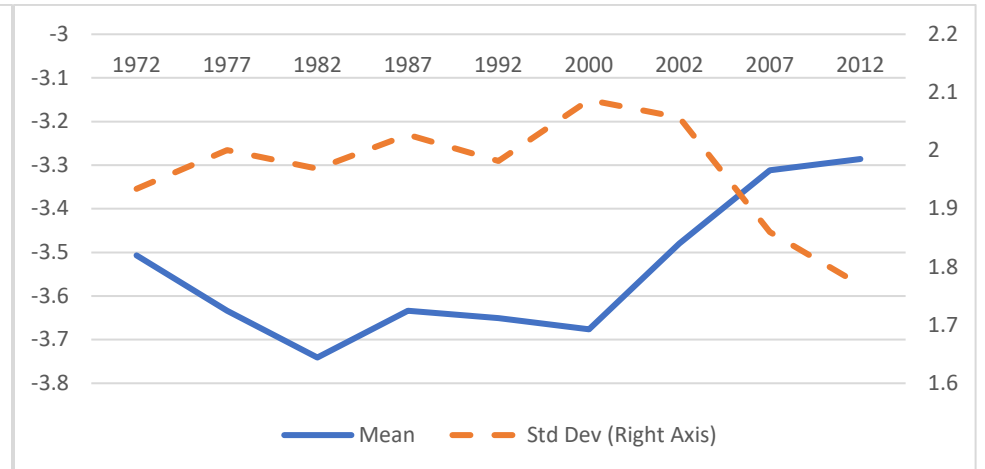
(b) Computer Intensity (Investment Per Worker)



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



(d) Relative Firm Size (log firm share)



Notes: Tabulations from the ASM, CM and LBD. Computer Investment Per Worker uses the DHS transformation as described in the text. The log firm share is the share of sales of the parent firm in total industry sales. These are moments not weighted by activity.

Appendices

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

Level of Aggregation	Mean	SD
Panel A. Cobb Douglas (CD)		
2-digit, constant over time	0.4817	0.02614
3-digit, constant over time	0.4938	0.06064
4-digit, constant over time	0.4766	0.08892
6-digit, constant over time	0.4746	0.1034
2-digit, yearly	0.4712	0.04587
3-digit, yearly	0.4734	0.09125
4-digit, yearly	0.449	0.133
6-digit, yearly	0.4476	0.1418
Panel B. Translog (TL)		
2-digit, constant over time	0.5406	0.2079
3-digit, constant over time	0.5254	0.2084
4-digit, constant over time	0.5056	0.2007
6-digit, constant over time	0.5007	0.2041
2-digit, yearly	0.5323	0.2051
3-digit, yearly	0.4992	0.2103
4-digit, yearly	0.4616	0.2094
6-digit, yearly	0.4569	0.2198
Panel C. Cost Share (CS)		
2-digit, constant over time	0.5761	0.0631
3-digit, constant over time		0.09867
4-digit, constant over time		0.1253
6-digit, constant over time		0.1325
Plant-level, constant over time		0.1911
2-digit, yearly		0.06506
3-digit, yearly		0.1024
4-digit, yearly		0.1286
6-digit, yearly		0.1359
Plant-level, yearly		0.2122

Notes: Simple means and standard deviations reported for the pooled full sample. 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, Cobb-Douglas Proxy Method (CD) Approach

Panel A. All industries		
Level of aggregation	Mean	SD
2-digit, yearly	0.2382	0.05458
4-digit, yearly	0.2307	0.08609

Panel B. Top 50 industries		
Level of aggregation	Mean	SD
2-digit, yearly	0.2313	0.0678
4-digit, yearly	0.2154	0.1004

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

Table A.3 Output Elasticities for Labor, Translog Proxy Method (TL) Approach

Panel A. All industries		
Level of aggregation	Mean	SD
2-digit, constant over time	0.2476	0.1085
4-digit, yearly	0.2438	0.1741
Panel B. Top 50 industries		
Level of aggregation	Mean	SD
2-digit, constant over time	0.2599	0.1287
4-digit, yearly	0.234	0.1826

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

Table A.4 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.5: Relationship Between Less minus More Markups and Output Elasticities and Indicators of Technology and Firm Structure, Time Varying Coefficients

<i>Dependent Variable: Less minus More Detailed Markup</i>				
	Capital Intensity	Computer Intensity	Diversification Index	Relative Firm Size
Slope Coefficient	0.1163*** (0.0377)	-0.0575 (0.0530)	0.0814* (0.0468)	0.0842*** (0.0154)
Slope X 81-89	0.0126 (0.0207)	0.0848** (0.0426)	-0.0048 (0.0216)	0.0368*** (0.0120)
Slope X 90-05	0.0130 (0.0417)	0.0686 (0.0509)	0.0323 (0.0566)	0.0395*** (0.0125)
Slope X 06-14	-0.0247 (0.0621)	0.0831 (0.0549)	-0.0036 (0.0750)	0.0384 (0.0237)
Constant	-0.1503 (0.1494)	0.2365** (0.1202)	0.4294*** (0.0831)	0.6610*** (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
<i>Dependent Variable: Less minus More Detailed Output Elasticity Materials</i>				
Slope Coefficient	0.0409*** (0.0141)	-0.0347 (0.0231)	0.0407*** (0.0149)	0.0251** (0.0099)
Slope X 81-89	0.0094 (0.0099)	0.0507*** (0.0190)	-0.0073 (0.0069)	0.0245** (0.0104)
Slope X 90-05	-0.0028 (0.0164)	0.0415* (0.0232)	-0.0076 (0.0172)	0.0162** (0.0077)
Slope X 06-14	-0.0196 (0.0204)	0.0365 (0.0232)	-0.0243 (0.0216)	0.0133 (0.0115)
Constant	-0.0254 (0.0534)	0.0857 (0.0562)	0.1873*** (0.0266)	0.2378*** (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

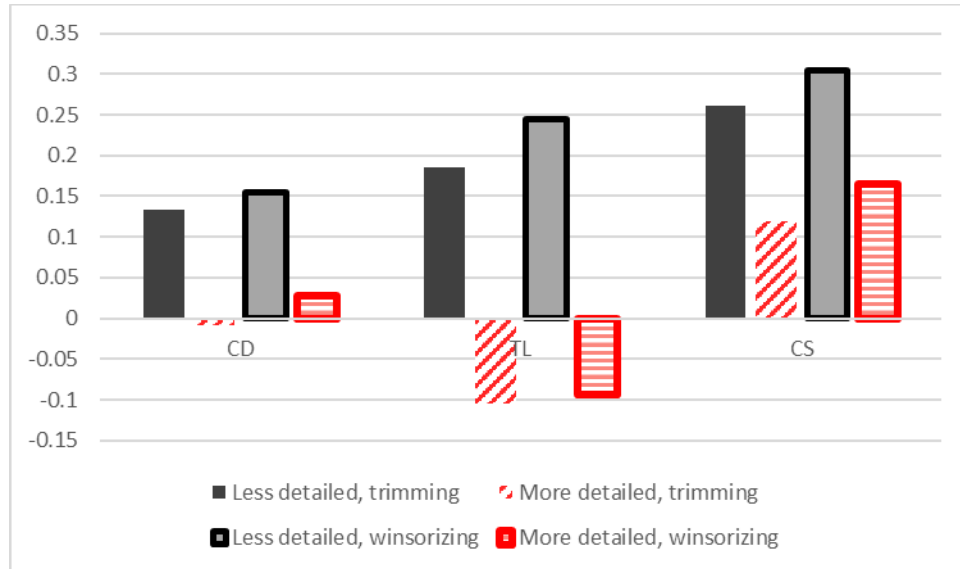
Change in...	Dependent Variable: Less detailed markup – more detailed markup			
	Computer intensity	Capital intensity	Diversification	Concentration
	(1)	(2)	(3)	(4)
Panel A. Cobb-Douglas (CD)				
Above med. X 1981-1989	-0.0029 (0.0215)	0.0226 (0.0251)	0.0428** (0.0208)	0.0156 (0.0219)
Above med. X 1990-2005	0.1661* (0.0917)	0.0680 (0.0994)	0.0620 (0.0932)	0.1050 (0.0896)
Above med. X 2006-2014	0.1412 (0.1311)	0.2063 (0.1604)	0.2430* (0.1389)	0.0999 (0.1433)
Above med.	-0.0185 (0.0642)	0.0921 (0.0579)	-0.0524 (0.0622)	-0.1447*** (0.0514)
Constant	0.0765** (0.0322)	0.0311 (0.0384)	0.0955* (0.0509)	0.1451*** (0.0326)
Panel B. Translog (TL)				
Above med. X 1981-1989	0.0401 (0.0479)	0.0661 (0.0438)	0.0039 (0.0460)	-0.0118 (0.0454)
Above med. X 1990-2005	0.2931** (0.1265)	0.2965** (0.1267)	0.1551 (0.1232)	0.0615 (0.1310)
Above med. X 2006-2014	0.2170 (0.2161)	0.5248*** (0.2008)	0.3725* (0.1913)	0.0201 (0.2170)
Above med.	0.1113* (0.0575)	0.0727 (0.0673)	-0.0453 (0.0568)	-0.0996 (0.0611)
Constant	0.2242*** (0.0372)	0.2402*** (0.0242)	0.2930*** (0.0263)	0.3224*** (0.0487)
Panel C. Cost Share (CS)				
Above med. X 1981-1989	0.0546*** (0.0160)	0.0019 (0.0181)	-0.0022 (0.0170)	-0.0235 (0.0168)
Above med. X 1990-2005	0.2684* (0.1423)	0.1026 (0.1548)	0.0806 (0.1401)	-0.0736 (0.1422)
Above med. X 2006-2014	0.1507 (0.1876)	0.2654 (0.2235)	0.3132 (0.1945)	-0.1432 (0.1993)
Above med.	-0.0454 (0.0515)	0.0691 (0.0439)	0.0451 (0.0471)	0.0010 (0.0478)
Constant	0.0936*** (0.0220)	0.0467 (0.0332)	0.0520 (0.0389)	0.0744*** (0.0256)
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

Online Appendix: Not Intended for Publication

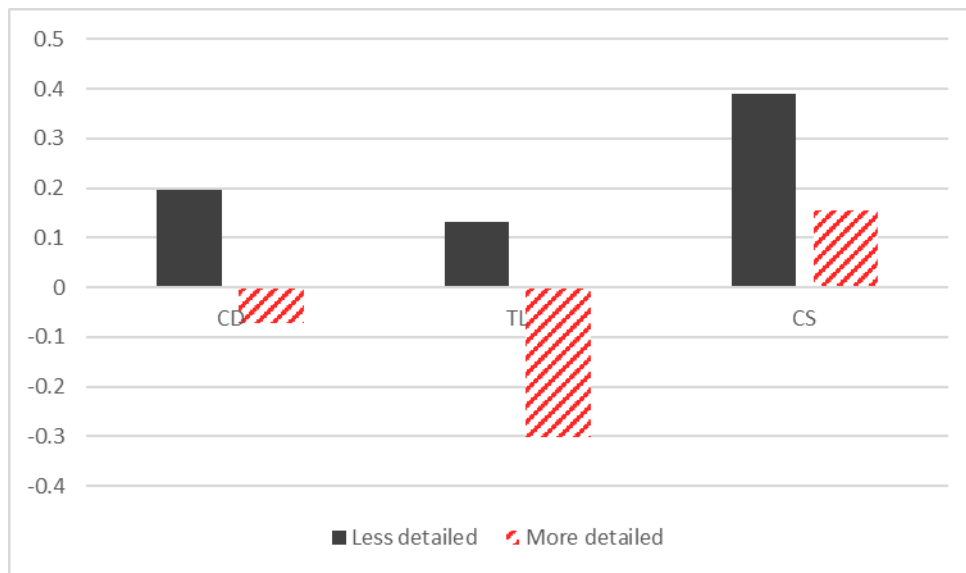
calculating “above med.” in each column. “1981-1989”, “1990-2005”, and “2006-2014” are dummy variables equal to one when the year is in that year range. The reference years for these specifications are 1972-1980.

Figure A.1 Long Differences in Markups 1980-2014 Comparing Trimming versus Winsorizing



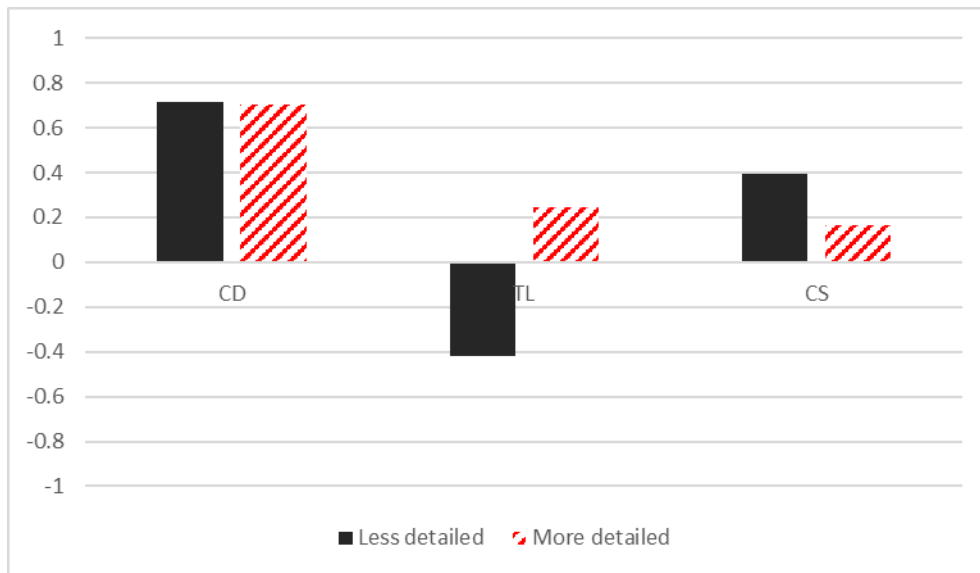
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

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



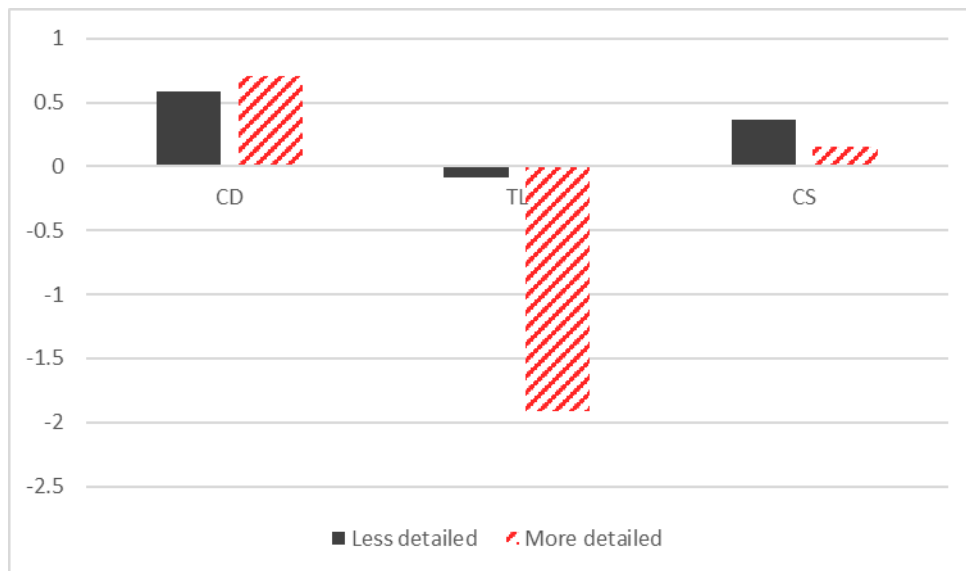
Notes: The markups above are estimated using materials as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.3 Long Difference in Markups 1980-2014



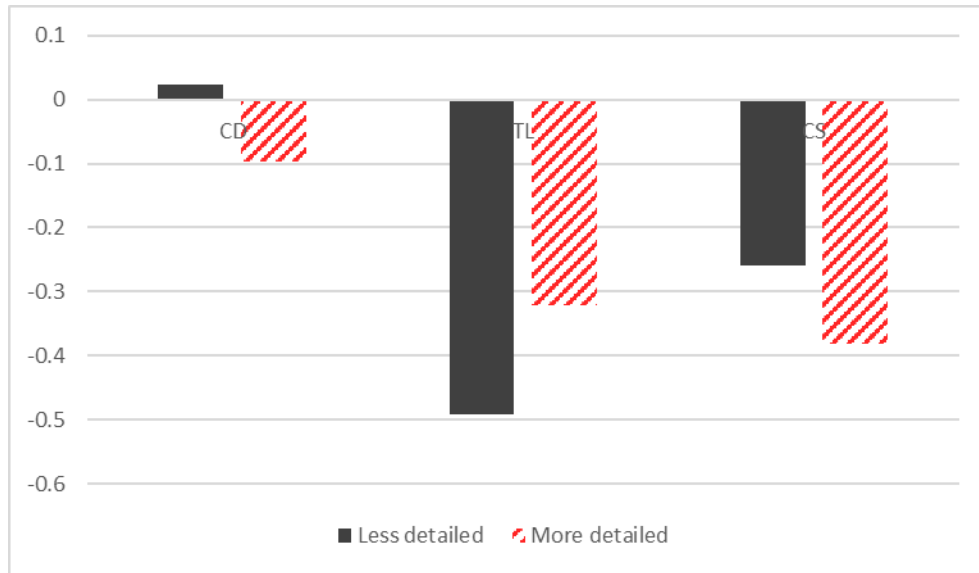
Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.4 Long Difference in Markups 1980-2014, Top 50 Industries



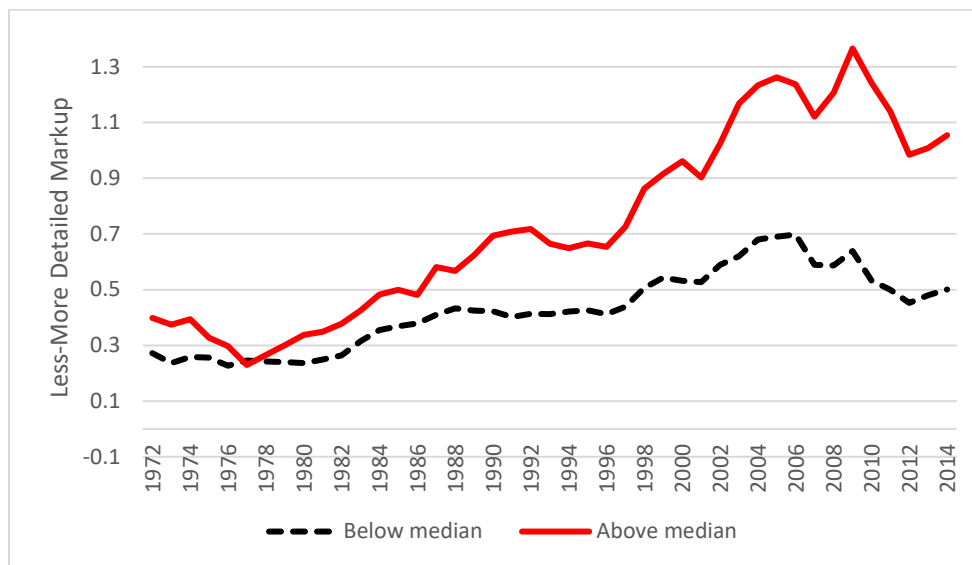
Notes: The markups above are estimated using labor as the variable input. Aggregate markups are revenue-weighted means. Long differences are log differences.

Figure A.5 Long Difference in Labor Output Elasticities 1980-2014



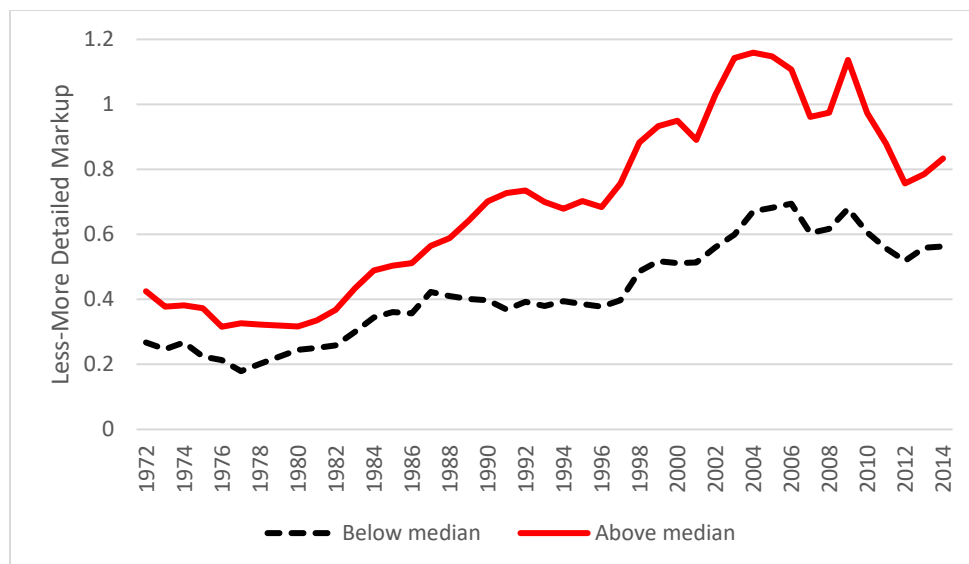
Notes: The output elasticities above are for labor. Output elasticities are revenue-weighted means. Long differences are log differences.

Figure A.6 Markups and Changes in Capital Intensity



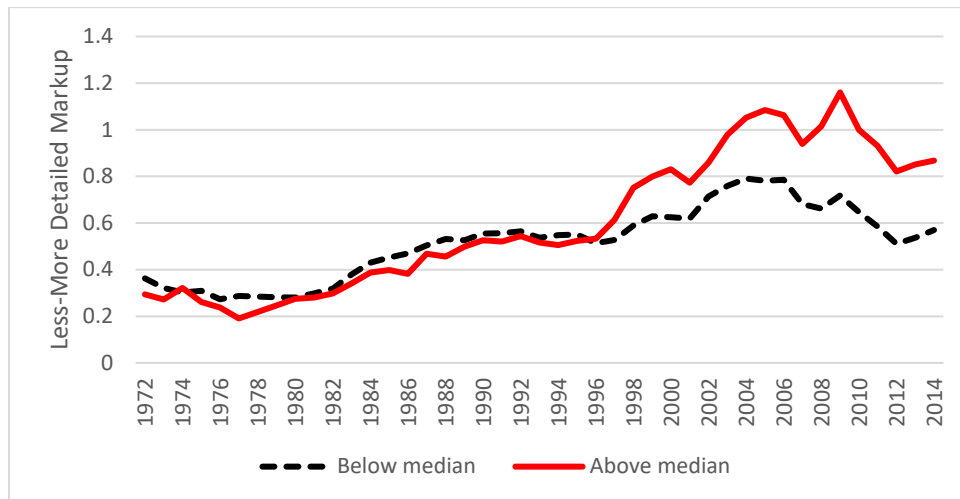
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in rolling annual intervals. Reported are 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 capital per worker (from 1977 to 2007). Aggregate markups are revenue-weighted means.

Figure A.7 Markups and Changes in Computer Intensity



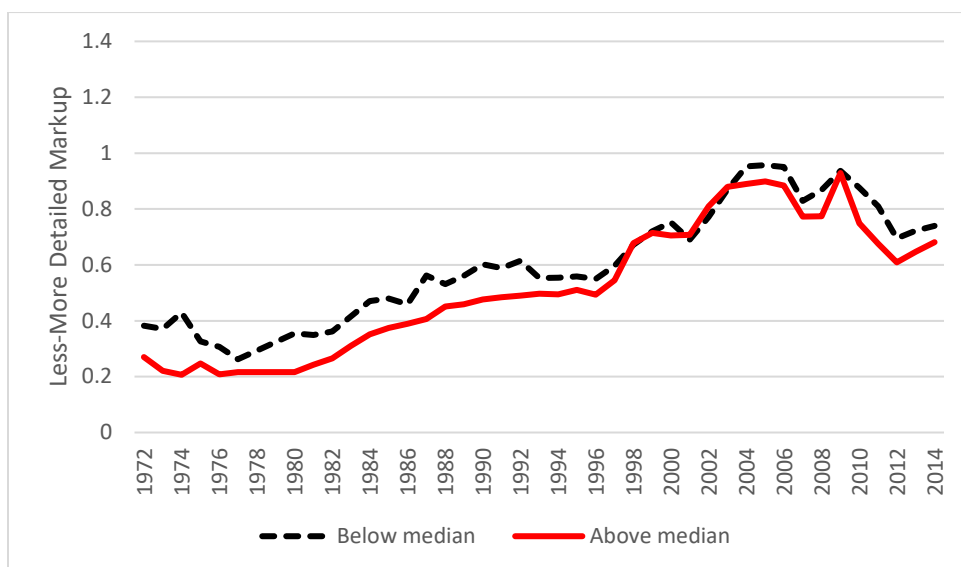
Notes: The markups above are estimated using materials as the variable input. Less detailed is translog with parameters that vary at the 2-digit level and are constant over time. More detailed is translog with parameters that vary at the 4-digit level and vary in rolling year intervals. Reported are 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 A.8. 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 A.9 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.

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:

$$TH_{jt} = \begin{cases} PH_{jt} \frac{SW_{jt}}{WW_{jt}} & \text{if } SW_{jt} > 0 \text{ and } WW_{jt} > 0 \\ PH_{jt} & \text{otherwise} \end{cases} \quad (\text{B1})$$

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. Between Industry Variation in Measured Markups and Indicators of Technology

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)).²

Figures A.6-A.9 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 find that the industries with above median changes in capital intensity (Figure A.6), computer intensity (Figure A.7), and diversification (Figure A.8) exhibit an increasing difference between the less detailed and more detailed based markups. Industries with larger changes in concentration

² 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.

ratios (Figure A.9) 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.

We provide further evidence on the industry long differences in Table A.6. These specifications are broadly similar 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 subperiod 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.