The Remarkable Stability of the US Manufacturing Markups*

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Abstract

Many economists believe that US markups have been rising in the latest years. The recent release of the updated NBER-CES database, that aggregates the results of the Survey of Manufactures/Census of Manufactures 1958-2018 (61 years) in 473 industries, allows us to scrutinize this idea in manufacturing. We show that firms' average markups over the last 20 years have been remarkably stable, and confirm this finding using firm-level data from Compustat. We then look at reasons by which it is easy to have illusions of rising markups. Surprisingly, they imply that we cannot discard the fact that the markup was stable the precedent 20 years too.

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1 Introduction

A generalized impression warns that US markups have been rising in the latest years (see, for example, the balanced statement "We believe that (this) research provides persuasive evidence that markups have been raising, although open questions remain about the magnitude and causes of the effect," Berry, Gaynor and Morton, 2019). The recent release of the updated NBER-CES database, aggregating the Survey of Manufactures/Census of Manufacturing data from 1958-2018 (61 years) in 473 industries, allows us to scrutinize this conception in manufacturing.

In what follows we argue that the evidence shows that the average markup of firms over the last 20 years has tended to be completely stable. In fact, an average non-increasing markup is what one would expect from years of intense globalization and sharpened competition. We then check this finding using the Compustat's firm-level manufacturing sample, which allows us to get additional insights on the evolution of markups. The firm-level markups show, for example, a moderate increase in their dispersion.

We look at three reasons by which it is easy to get illusions of rising markups. First, accounting problems in the data. Second, how production elasticities behave in a time of widespread biased technological change. Third, the risk of biases in aggregate indicators built up from firm-level data. Through looking into how these motives can impact the assessment of the markups, we discover -with some surprise- that the fact the markup was also stable the precedent 20 years cannot be discarded.

The main motivation to look at manufacturing is the recent availability of new data; however, it is also the sector of the economy where the claims of raising markups have been made with a broader statistical base. Most of the reasons that we suggest for the confusion affect the other sectors of the economy as well.

We conclude that manufacturing has witnessed the increase in efficiency and market shares of many firms. This has recently been documented with census firm-level data in Kehrig and Vincent (2021), but it has not been translated into average greater markups. Our assessment coincides in this respect with the evidence on profitability contributed by Kwon, Ma and Zimmerman (2022) in analyzing the long-run trends in corporate concentration. It is important to not mistake increases in efficiency for increases in market power, because the implications for economic policy are very different. More research about how biased technological change is affecting market structure and performance is needed.

The rest of the paper is organized as follows. Section 2 explains how the markups are computed and presents the results. Section 3 is a robustness exercise that examines what can go wrong in the estimations. Section 4 is dedicated to the comparison with the firm-level results obtained from Compustat data. Section 5 develops the reasons by which markups can be taken as raising when they are not. Section 6 concludes and establishes a research agenda

2 Results

Measurement

Call μ the markup price over marginal cost $\frac{P}{MC}$. It is easy to see that, if a firm minimizes cost, the following relationship holds

$$\frac{R}{VC} = \frac{\mu}{\nu} \exp(\varepsilon), \tag{1}$$

where R is observed revenue, VC is variable cost, ν is the short-run elasticity of scale or ratio of average variable cost to marginal cost AVC/MC, and ε a mean zero error uncorrelated across time and units.[1] We econometrically estimate ν and compute the log of the short-run markup in the following way

$$\ln \widehat{\mu} = \ln \frac{R}{VC} + \ln \widehat{\nu}. \tag{2}$$

We expect the error ε to tend to cancel in the averages across industries and time, and hence we expect our means to be quite accurate. Formally, if $\widehat{\nu}$ is consistent $E(\ln \widehat{\mu}) = \ln \mu$.[2]

Without the correction for the ratio of average variable cost to marginal cost this measure can be taken as an approximation to gross economic profitability, $\ln \frac{R}{VC} = \ln \frac{1}{1-\pi} \simeq \pi$, where $\pi = \frac{R-VC}{R}$. This latest expression was Bain's (1951) way to measure markups.

We consider short-run costs (average and marginal), it is then important to get an idea of the part of this markup that can be attributed to cover the cost of capital K. In order to do this, no matter how roughly, we compute a user cost of capital uc and calculate a corrected markup as

$$\ln \widehat{\mu}_C = \ln \frac{R}{VC} + \ln \widehat{\nu} - uc\frac{K}{R}.$$

[1] Dividing the numerator and denominator of $\frac{R}{VC}$ by quantity Q, and assuming that the relationship between Q and the cost relevant quantity Q^* is $Q/Q^* = \exp(\varepsilon)$ we have $\frac{R}{VC} = \frac{P}{AVC}\exp(\varepsilon)$. In a cost minimizing firm the elasticity of scale ν equals AVC/MC. The error ε is prevalent in modern microeconomic production analysis, making Q^* unobservable. For an extended discussion, see Doraszelski and Jaumandreu (2019).

[2] $E(\ln \widehat{\mu}) = E[\ln \mu + (\ln \widehat{\nu} - \ln \nu) + \varepsilon] = \ln \mu$.

Production Function

To assess the ratio of average variable cost to marginal cost ν we estimate the simplest production function that can embody the two main types of productivity: labor-augmenting and Hicks-neutral productivity (see Doraszelski and Jaumandreu, 2019). Although still it is unusual, we consider important to allow for labor-augmenting productivity to avoid biases in estimation. The production function turns out to be a translog separable in capital and homogeneous of degree ν in the variable inputs labor and materials. It generalizes the popular Cobb-Douglas (CD) in that the elasticities of the three inputs are variable, with the consequence that the shares in cost can change over time. However, it keeps the sum of the elasticities β_L and β_M, and hence ν, constant.

Calling q the log of output, k, l and m the logs of capital, labor and materials, ω_L the labor-augmenting productivity and ω_H the Hicks-neutral productivity, the production function is

$$\begin{aligned} q_{jt} &= \alpha_0 + \alpha_t + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK} k_{jt}^2 + \alpha_L (l_{jt} + \omega_{Ljt}) + \alpha_M m_{jt} \\ &\quad -\frac{1}{2}\alpha (m_{jt} - l_{jt} - \omega_{Ljt})^2 + \omega_{Hjt} + \varepsilon_{jt}. \end{aligned}$$

We estimate it using 468 six-digit manufacturing industries for which we have observations from 1958-2018 (see Appendix A), treating the industries as if they were the replication of a representative firm. We control for ω_H assuming that it is an autoregressive process of parameter ρ and pseudo-differencing the equation. We control for ω_L replacing it with the expression obtained using the ratio of first order conditions for cost minimization. We estimate using nonlinear GMM, and recover estimates $\widehat{\omega}_L$ and $\widehat{\omega}_H$ for every industry and year.

Estimation

Table 1 shows how the production function fits the data. We present two estimates, one with constant elasticity of capital (as in a CD production function, the two first rows), and a second with varying elasticity of capital (the two following rows), but we will work from now on with the first estimate.[3] For what we are interested in the main results are that MC is estimated to be above AVC by about 8% ($\ln 0.924 \simeq -0.079$) and the elasticity of labor, which shows a sensible dispersion, has been falling systematically (7.5 points in total). The elasticity of substitution is estimated to be $\sigma = 0.635$ on average.

[3] The average elasticity of capital is greater in the second estimation, but the sum of all elasticities or long-run elasticity of scale goes down from 0.964 to 0.907, indicating the possibility of some misspecification.

The production function estimation provides nice estimates of both productivities. We focus of the "output-effect" of labor augmenting productivity or its effect on output (the labor elasticity times labor-augmenting productivity). Two thirds of the average growth of productivity over the whole period are explained by labor-augmenting productivity and one third is explained by Hicks-neutral productivity. If we count the time dummies as neutral productivity growth the relationship is more balanced (see the table notes).

The cross-sectional differences of productivity across industries at the end of the period are estimated with standard deviations in the range $32-40\%$.

Markup

Table 2 reports averages of the markups, their changes across the 468 industries, and the standard deviations of the averaged measures. The average markup is evaluated for the latest 20 years in 34 percentage points. As we later discuss with detail, this level is likely to be a gross overstatement. Census data are based on manufacturing establishments not firms. While revenue is measured more or less accurately, variable cost often misses expenses due to variable inputs that are provided as services to the firm establishments from the firm headquarters or other service establishments not included in the census. But let us for now focus on the variations and relative markups, which is what we are interested most.

The average markup (see Figure 1), after some initial increase, shows stability in the seventies and then grows steadily during the eighties and nineties. It becomes remarkably stable again during all the 2000's. During the eighties and nineties 80% of the industry markups grow, and the average gain is 8.5 percentage points in 20 years. During the 2000's the average gain is 2 percentage points in 19 years, with the average markup completely stagnant over the latest 10 years, and the proportion of falling markups close to 50%.

Hence, there is a sharp contrast between the first half and the second half of the latest 40 years. From 1980 to the beginning of the 2000's, the average markup gains almost 10 percentage points, while during the 2000's the average markup becomes completely stable.

The correction employing the user cost of capital gives sensible values, very stable since 1980. Te cost of capital accounts for less than $4-5$ percentage points on average. The markup corrected by the cost of capital has again been remarkably stable over the latest 20 years.

3 Robustness

How reliable are the results of applying equation (2)? They are based on the value of $\frac{R}{VC}$ and our estimation of ν. In what follows we briefly discuss these two pieces of our inference. First, we take a look at the share of variable cost in revenue, the inverse of $\frac{R}{VC}$. Second, we dive into the fact that we estimate ν by means of a production function that allows the share of labor in variable cost,[4] and hence the elasticity of labor, to decrease as a result of labor-augmenting productivity. We review why and confirm that this agrees with the data. Third, the framework developed for treating the labor share allows us to ask if we need a similar setting for variable costs. Fourth, as the evolution of the labor share is the result of labor-augmenting productivity, we explore the evolution of this kind of productivity in more detail.

The first panel of Table 3 reports both cost shares, and the second panel moves back to productivity.

The Variable Cost Share in Revenue

We have implicitly commented on VC/R before: this share is stable during the seventies, tends to fall moderately but steadily during the eighties and nineties, and then becomes stable again in the latest 20 years. Of course this fall of the share can be pointing at an autonomous increase in the output prices with respect to average variable cost (a rise in markups). However, there are two additional possible reasons for this movement.

First, the fall could be detecting technological changes in the combination of capital and variable inputs. Investment in fixed capital, in particular intangible capital (software, IT), may have reduced variable costs resulting in a change in the shares of variable cost and capital in total cost and hence in revenue.[5] If this is the case, the elasticity ν should change correspondingly and our markup measurement is wrong. We pursue this discussion after we set the framework for the changes in the labor share.

Second, there can be accounting problems in the measurement of variable costs with respect to revenue. This is a serious alternative explanation for the almost 10 percentage points decrease in the share of variable cost on revenue

[4] For theoretical reasons we focus on the labor share in variable cost, not in revenue. Note that the labor share on revenue, often used in analyses, is the product of the share of labor in variable cost and the share of variable cost in revenue.

[5] Many papers have suggested relationships between an increase in fixed and sunk costs and the rise in markups. See the survey by Berry, Gaynor and Morton (2019). Here we are exclusively concerned with the measurement of markups given any conduct, and hence the issue of interest is the impact of the investments in fixed assets on variable costs. Some papers have started to deal with this issue (see, for example, Ganapati, 2018; Houde, Newberry and Seim, 2020, and De Ridder, 2022), but there is a void of theoretical frameworks about how to treat this.

during the eighties and nineties. We have already mentioned that we find that this share is understated by the census, and this understatement may have changed over time. There are no apparent reasons for the census to be covering an extended amount of variable costs in recent years, hence stabilizing the share, but it is quite likely that firm-level organizational changes impacted variable costs to decrease until the 2000's.

The Labor Share in Variable Cost

The evolution of the labor share in variable cost is depicted in Figure 2. It falls more than 8 percentage points during the whole period and, interestingly, the periods of sharpest decline coincide with the periods of stability of the share of variable cost in revenue. The main fall happens during the seventies. Then it follows a milder, although continuous, fall during the eighties and nineties (2 percentage points in 20 years), and again an accelerated decrease at the beginning of the 2000's (1.8 percentage points in only 10 years). After this, the labor share enters a period of stability or even slight recovery.

Recent microeconomic work has shown the importance of firm-level labor-augmenting productivity (Doraszelski and Jaumandreu, 2018; Raval, 2019; Demirer, 2020; Oberfield and Raval, 2021; Kusaka, Okazaki, Onishi and Wakamori, 2022). This should imply, under quite general conditions, a fall in the firm-level shares of labor and this is what we allow for in our modeling.[6]

For example, since the work by Hicks it is known that, with separable capital, if labor-augmenting productivity is increasing while the elasticity of substitution between labor and materials is less than one, the relative share of labor in variable costs must fall (Hicks, 1932; see Appendix B). This is exactly what happens in our production function estimation.

Figure 3 depicts that labor-augmenting productivity increases continuously since the start of the whole period to grow more moderately in the 2000's and then becomes stagnant in the last decade. (Hicks-neutral productivity, on the contrary, shows stagnation during the eighties and nineties, and a recovery in the 2000's.) The increase in labor-augmenting productivity explains the fall of the labor share in variable cost and the labor elasticity over time. This is a finding that agrees with the facts documented by Kehrig and Vincent (2021): the increases in productivity are strongly associated with falls in the labor share at the firm-level census data 1967-2012, and accompanied by increases in size and hence the market share.[7]

A Variable ν?

Note that the framewok used to analyze the labor share could be extended

[6] Elsby, Hobijn and Sahin (2013) and Grossman and Oberfield (2022) are discussions about the global decline of the labor share.

[7] Kehrig and Vincent (2021) actually base their shares on value added, which in fact makes it more difficult to separate the components of the dynamics.

to analyze the share of variable cost. Suppose a production function with two inputs, capital and a composite variable input, with the composite variable input affected by an idiosyncratic term modeling the productivity increments (implying unit cost reductions) induced by fixed investments.[8] A long-run cost minimizing firm with an elasticity of substitution less than one will show a fall in the share of variable costs (an increase in the share of capital). We speculate with this possible explanation and its implications in section 4.

Labor-augmenting Productivity

The second panel of Table 3 shows that labor-augmenting productivity has been a strong component of the growth of productivity that has tended to fade recently. Under any model of imperfect competition this growth will determine correlated increases of the market shares of the firms. Our subsequent analysis finds that it is important to take into account this growth.

An interesting additional fact about labor-augmenting productivity is that the dispersion of its distribution across industries has tended to fall systematically over time. A more detailed exploration reveals that, while both the labor elasticity and ω_L tend to follow symmetric cross-section distributions across industries, the distribution of the output effect is clearly asymmetric, with a number of quite efficient industries and a long tail of less efficient industries in relative terms. Together these facts point to the spread of gains in labor-augmenting productivity. This suggests some answers to the "Solow paradox," which wonders why the productivity gains of the computerization of the economy are so elusive in the statistics.[9]

4 A comparison with the markups of Compustat

A possible method to evaluate the census markups is through a comparison with the markups of the corresponding individual manufacturing companies available on Compustat. One expects that the markup levels would reveal the difference between two different ways to assess markups. In Compustat, markups come from data on the whole companies, as opposed to the markups assessed using the data corresponding to the collection of manufacturing establishments of each firm. However, the accuracy of the comparison is compromised by the undetermined representativeness of the Compustat

[8] That is, the production function separable in the variable inputs can be written as $Q^* = G(K, \exp(\omega_V)V(\exp(\omega_L)L, M))\exp(\omega_H)$.

[9] See Acemoglu, Autor, Dorn, Hanson and Price (2014) for a recent account of the Solow paradox.

sample, as well as the problems stemming from the use of firm accounting statements.

To maximize the results from the comparison we have carefully determined and characterized the Compustat sample, assessing its representativeness with respect to the whole manufacturing industry as reflected in the aggregate magnitudes of the NBER-CES data. The details are in Appendix C.

Sample

We select all firms that report activity in a four-digit SIC code included in the SIC version of the NBER-CES data. The comparison of total employment between the two samples gives, after 1975, a ratio that fluctuates between 0.4 and 0.6. Before 1975 it seems very clear that the Compustat sample was in continuous expansion, with an intense inflow of firms of smaller size than the firms included from the start. After that, there seems to be no significant trends linked to the entry or exit of firms. It is likely, for example, that the rebound of Compustat relative employment since the middle of the 1990s to 2010 is basically the result of better average behavior of the included firms compared to the rest of manufacturing industry.

When looking at the employment ratios we should consider that not only the firms in Compustat are a self-selected sample of large and good performing firms, but the employment reported is the whole employment in the company, including their operations in non-manufacturing and overseas. However, none of these things seem to constitute a serious handicap for comparing margins and their evolution, at least after 1975.

Compustat Markups

To compute markups, we use three different measures of variable expenses as the denominator of the ratio of revenue to variable costs. The first is the variable "Cost of the Goods Sold" or *cogs*, the second is the sum of the variables *cogs* and "Selling, General and Administrative Expense" or *xsga.* The first measure is likely to exclude several variable cost expenses, as it has been pointed out in different contributions to the measurement of markups (Traina, 2018; Basu, 2019), but the second is likely to include several expenses that have a fixed character. To mitigate this fact, we subtract the R&D (*xrd*) and the Advertising expenses of the firm (*xad*) from the previous measurement. This provides a sensible third alternative, even if it is likely to still contain some fixed expenses (as, for example, an unknown part of white-collar payments).

To ensure a proper measurement of the markups and to check the consistency of Compustat information against the information of the NBER-CES database, we carry out the estimation of the same translog specification of the production function as in section 2, now with firm-level data. To make this possible we have, however, to impute a wage for most of the firms (the average wage of the NBER-CES SIC industry the firm belongs to). The results, described in detail in the Appendix, are good. The elasticity of capital, the short-run elasticity of scale, the evolution of the elasticity of labor and productivities are very sensible and fully compatible with our NBER-CES data results. The MC is estimated above AVC by about 13% ($\ln 0.875 \simeq -0.134$). We apply equation (2) with the Compustat ratios $\frac{R}{VC}$ obtained by using $VC = cogs$ and $VC = cogs + (xsga - rd - adv)$ alternatively, in combination with the estimate of the short-run parameter of scale. The results are reported in Table 4 and Figure 4, where we reproduce our markup estimate using the NBER-CES data for convenience.

Comparison

The Compustat markup computed using only *cogs* as variable cost is even greater than the NBER-CES markup, confirming that using *cogs* understates VC. The use of the alternative that also accounts for the general expenses minus $R\&D$ and advertising gives perfect competition for all years (price equal to marginal cost!) It seems clear that there are fixed costs that are unnoticed inside *xsga*.

The only way a case for rising markups in the latest 20 years could be made is through use of *cogs* as the exclusive valid measure for variable costs, however we have seen that excludes many variable items. And, more importantly, the complete stability of $cogs + (xsga - rd - adv)$ would force us to conclude that the entire accounting cost tranfer that seems to be between *cogs* and $xsga$ over time is due to the substitution of fixed for variable costs. A quite unlikely story.

The most important insights are, first, the true markup level must be in between the two bottom measurements of Table 4 (between 0% and 30%, say, probably closer to the bottom than to the top of the bracket). Second, our bottom Compustat calculation shows solid basic stability of the firm-level markups during the entirety of the 2000's that strongly reinforces the main statement of this paper. Third, the basic stability of our bottom Compustat calculation during 1980 to 2000 suggests that the slight upward trend of the markup computed with the NBER-NCES during the same period (recall, a gain of no more than 10%) is related to accounting problems that exclude some variable costs over time.

5 Rising markups?

There are three motives by which it is easy to perceive markups as rising even if they are not.[10] They are: data accounting problems, an inadequate use of production elasticities, and the risk of biases in firm-level based measurements. Here we briefly explore these three motives under the insights from our empirical exercise.

Data Accounting Problems

Markups should ideally be accounted for using firm-level data on revenue and the variable expenses incurred to get this revenue.[11] Notice that the problem of multiproduct firms is not important per-se, because the revenue over variable cost of a firm is simply the cost weighted average of the ratios of revenue over variable cost for each product.[12]

However, we are using census data which is based on manufacturing establishments, not firms.[13] It is quite likely that, while establishments revenue is measured more or less accurately, variable cost misses the expenses due to some variable inputs that are provided as services to the firm establishments from the firm headquarters and other auxiliary establishments (not included in the census). This can explain why average markups are so high (some relevant expenditures are missing) and, worse, can induce systematic changes over time linked to changes in the organization of the activity by multi-establishment firms (and multiproduct firms if they are systematically multi-establishment).

For example, Fort and Klimek (2018) explain how headquarters and auxiliary establishments are classified by NAICS in different service codes, in a way that skimps variable costs (e.g. trunk transportation, storage, repair and maintenance). On the other hand, the extent and accounting effects of the so-called factory-less production (parts and pieces under contract without materials) is unknown. The recent work addressing the startling heterogeneity of multifactor productivity inside narrowly defined industries by Cunningham, Foster, Grim, Haltiwanger, Wulff, Stewart and Wolf (2021) points to how much output is in fact left without input explanation, as Syverson (2011) remarked earlier.

[10] Here we focus on the problem of finding rising markups, a discussion of the risk of wrong correlation with explanatory variables is presented in Doraszelski and Jaumandreu (2021).

[11] Even this, as commented on the previous section, is not without problems because of the difficulties to separate variable costs. For recent dicussions see Traina (2018) and Basu (2019).

[12] $\frac{R}{VC} = \sum_i \frac{VC_i}{VC} \frac{R_i}{VC_i}$, where i indexes products.

[13] Benkard, Yurukoglu and Lee Zhang (2021) is a paper that recalls this through an exploration of the difficulties of adequately measuring market concentration.

This creates sensible doubts. Is the increase in markups that we have reported for the eighties and nineties real? One plausible explanation is a systematic displacement of establishments' variable cost activities towards the firms' headquarters, in a cycle of firms' organizational changes ending at the beginning of the 2000's.

Instead, it seems unlikely that variable costs allocated to establishments have recently increased over time for organizational reasons. Hence, the stability of the markups during the latest decade seems better harbored from criticisms of miscounting.

We conclude that the data shows stability of the markup in the latest 20 years and suggest that some organizational changes of the firms' activities could be the reason for the increase of markups by almost 10 percentage points during the eighties and nineties. Perhaps the real average manufacturing markups have been basically stable during the latest 40 years.

Production elasticities in times of biased technological change

Economic theory suggests computing markups from expressions involving observables and production elasticities, as in equation (1). The equation is based on the fact that economic data allows us to observe (with some noise) the ratio of price to average variable cost. If we are able to estimate the ratio of average variable cost to marginal cost or elasticity of scale ν, we can compute an estimate of the markup. However, the choice of how to complete the observed data with parameters and how to consistently estimate these parameters requires careful consideration.

For example, it has been suggested to use the variable input elasticities instead of the elasticity of scale $\nu = \beta_L + \beta_M$. That is, to start from $\frac{R}{W_X X} = \frac{\mu}{\beta_X} \exp(\varepsilon)$ where $X = L, M$. However, under cost minimization $\beta_X = \nu S_X$, where S_X stands for the share of the input in variable cost $\frac{W_X X}{WL + P_M M}$, and individual input equations collapse to expression (1). This shows that there is no advantage to using this method except for the reason of a lack of data.[14]

On the contrary, there are clear disadvantages. The individual elasticities of the variable inputs are likely to vary much more than their sum. The two main reasons for this are the relative adjustment costs of the variable inputs and the presence of labor-augmenting productivity.[15] Individual varying elasticities are not trivial to estimate (although here we use an easy method to do so) and, if replaced by constants in $\widehat{\mu} = \frac{\beta_X}{S_X^R} \exp(-\varepsilon)$, the underlying ne-

[14] It has been said that a "fully variable" input should be used, because it overcomes the presence of a shadow price different from W_X. However, the need to account for shadow prices only disappears with constant elasticities, because varying elasticities depend on both prices through the shares in variable cost.

[15] The first reason induces cyclical movements in the elasticities and the second induces a systematic fall over time in the elasticity of labor.

glected variation can easily produce spuriously "rising" markups (if S_L falls, say) or "falling" markups (because $S_M = 1 - S_L$ rises).[16]

It is therefore clear that the estimation of ν is key for a proper markup measurement. This makes the estimation of the markup sensitive to the estimation of the production function. Several observations are pertinent.[17] The first is that a consistent estimation of ν is difficult. It needs to account for the presence of unobserved productivity in the production function. We need to control for Hicks-neutral productivity, which affects all inputs. But we also need to control for labor-augmenting productivity, something that has only recently come into focus (see Doraszelski and Jaumandreu, 2018; Raval, 2019, 2021; Demirer, 2020).

The OP/LP procedures to estimate the production function under Hicksian productivity are based on inverting the first order conditions of profit maximization or cost minimization to replace the unobservable. However, these first order conditions include the heterogenous markups in which we are interested, and which still have not been estimated. Hence these procedures are unfortunately not applicable. This is why we pseudo-differentiate the equation, a method in the tradition of "dynamic panel" estimation.[18]

On the other hand, the absence of control for labor-augmenting productivity produces systematically an upward estimate of ν[19],[20] and hence an implicit upward bias of the markup (see equation (2)).

Second, the estimation of ν affects not only the level but also potentially the evolution of the markup. Is it correct to specify a constant ν as we do in our exercise? The use of a constant ν with varying β_L and β_M is a generalization of the Cobb-Douglas which has the big advantage of simultaneously allowing for input-biased technological change and tractability. However, this is an empirical question and researchers should look carefully at the data that they have to explain, in particular the share of variable costs

[16] Notice that $S_X^R = \frac{VC}{R} S_X$.

[17] What follows is based on the work contained in Doraszelski and Jaumandreu (2019 and 2021).

[18] This is also the option proposed by Bond, Hashemi, Kaplan and Zoch (2020).

[19] Labor-augmenting productivity is associated, for a given technology and input prices, to a greater materials to labor ratio. As productivity is persistent, this correlation happens for all the lags that is common to use as instruments. The elasticity of materials is typically biased up by more than the elasticity of labor is biased down, and the result is an upward bias in the estimation of ν.

[20] See, for example, the 1.2 short-run scale estimate of De Loecker (2011); Aw, Roberts and Xu (2011) directly assume a unity value of the short-run elasticity to avoid this kind of problem. But economic theory strongly suggests that ν should be less than unity. Kusaka, Okazaki, Onishi and Wakamori (2022) find a similar problem with the value added elasticity of scale.

in revenue. A constant ν might be ignoring a pattern in the elasticities that biases the assessment of the evolution of the markup.

What are we implying in the US manufacturing data by assuming a constant ν? It could be that the fall in variable costs over revenue (recall, during the eighties and nineties) that we observe is related to some downward variation of ν We have quoted claims on rising fixed and sunk costs as a way to reduce variable costs. We could use the model suggested in section 2 to test for the increase in efficiency of variable inputs and thoroughly explore the possible variation of ν. If we accounted for this, when $\frac{R}{VC}$ raises the variation in the estimated $\widehat{\nu}$ in equation (2) would bring down the estimated markup. Without varying ν we can be too optimistic about the evolution of the markup. This turns out to be a possible alternative explanation for the increase of the markup during the eighties and nineties. Recall that the comparison with Compustat suggests stability of the markup for the eighties and nineties too.

We are extending our research in this direction. But note that this work will likely contribute to alternative evidence and explanations on the stability of the average markups, not to changing the view that there is no increase in sight.

Risk of biases in firm-level based measurements

Some results of increasing markups are an artifact of the way firm-level data is treated. To understand this, it is convenient to start by reflecting what our aggregate data can show and cannot. Our analysis with aggregate data is by necessity blind to the underlying firm-level heterogeneity and its changes. For a given industry, the ratio of revenue to variable cost can be written as $\frac{R}{VC} = \sum \frac{VC_j}{VC} \frac{R_j}{VC_j} = \sum w_j^{VC} \frac{R_j}{VC_j}$, a variable cost weighted sum of the individual ratios $\frac{R_j}{VC_j}$. Any computation done with the industry magnitudes ignores the changes that may happen in the distribution of the ratios and the weights.

This is why it is highly desirable to complete analyses with firm-level data. For example, the firm-level data presented before shows a moderate increase in the dispersion of the markups which complements our mean stability conclusion. However, the analysis of individual data per-se is not free of pitfalls and biases that can be amplified by not being conscious of them. In what follows we explain how one can get raising markups, for example, when the markups do not change at all.

Suppose that, in an analysis with individual data, a researcher specifies a production function that ignores the presence of labor-augmenting productivity. The true individual elasticities of labor β_{Lj}, that depend on ω_{Lj}, are hence replaced by a "representative" constant elasticity $\widehat{\beta}_L$ (or a set of them, we use only one to simplify notation). The researcher estimates the individual markups as $\widehat{\mu}_j = \frac{\widehat{\beta}_L}{S^R_{Lj}}$ and defines an aggregate "market power" estimate as $\widehat{\mu} = \sum_j w_j \widehat{\mu}_j$, where the w_j are revenue weights. It is easy to see that

$$\widehat{\mu} = \mu + \sum_j w_j (\frac{\widehat{\beta}_L - \beta_{Lj}}{\beta_{Lj}}) \mu_j,$$

where μ is the true aggregate markup. The term $\sum_j w_j (\frac{\widehat{\beta}_L - \beta_{Lj}}{\beta_{Lj}}) \mu_j$ constitutes a positive bias that, in an analysis over time, is continuously increasing. The reason is that $\frac{\widehat{\beta}_L - \beta_{Lj}}{\beta_{Lj}}$ is positively correlated in the cross-section with labor-augmenting productivity and the same happens for the revenue shares, and this correlation increases over time as productivity grows.

The mechanism is the following. Assume that labor-augmenting productivity increases heterogeneously across firms. The firms that experience greater increases see a larger decrease in their labor elasticity as a result of the relative abundance of labor (an effect that is reflected in the decrease of the labor share on cost and hence on revenue).[21] At the same time, marginal cost decreases by more than it does for the rivals and, in any imperfect competitive setting, this leads to an increase in the revenue market shares of these firms. This increase is less than in perfect competition, and accords to the particular game that characterizes competition in the market, but still significant.[22] For example, under monopolistic competition with a common and constant level of market power μ (a standard model for many economic analyses), we have

$$\frac{\widehat{\mu}_t - \mu}{\mu} = \sum_j w_{jt} \frac{\widehat{\beta}_L - \beta_{Ljt}}{\beta_{Ljt}}.$$

It follows that the researcher's "aggregate" markup will sharply increase even if firm-level market power doesn't change for any individual. Firm-level data will show an increase in the revenue shares of the firms with greater efficiency gains, and these firms will exhibit smaller labor shares in revenue. The index built by the researcher confounds efficiency gains with market power gains.

We check the effects of the underlying variation of the labor elasticity and the bias of aggregation with our Compustat data. We compute markups $\widehat{\mu}_j =$

[21] This is the result of the adjustment of the firm to a new equilibrium after an exogenous change in labor-augmenting productivity.

[22] With greater competition, the cost reductions will tend to have a larger effect on market shares For example, with Cournot competition the effect on revenue shares will tend to be less than with Bertrand competition

$\frac{0.291}{S^R_{Lj}}$, where 0.29 is the translog mean estimate of labor elasticity, and average these markups without and with revenue weights. Figure 5 compares these measures with the bottom markup estimate of Table 4 (where μ is virtually 1 during the entire period). The simple mean of the constant elasticity markups steadily increases over time up to 1.6, and the weighted aggregation grows crazily due to the covariance of the computed markups with the revenue weights (this could be moderated using industry and period specific elasticity estimates). With the same data we would conclude, completely wrongly, that markups had been raising.

6 Concluding remarks

Using the recent update of the NBER-CES manufacturing database we fit a production function to the 468 six-digit industries with data from 1958-2018, allowing for industry and time specific labor-augmenting productivity and Hicks-neutral productivity. The production function estimation provides a ratio of average variable cost to marginal cost that can be used to measure markups, and also helps us to discuss what is in the data. We then explore what can be safely said about the US manufacturing markups during the latest years.

We establish that the average markup of the latest 20 years was stable. Also, the evidence suggests that the limited variation of the average markups that we report for the previous 20 years (8.5 percentage points from 1980 to 2000) is not a real increase in market power. The increase can be explained by the accounting specificities of building markups by combining data on only manufacturing establishments with changes in organization undergone by multi-establishment firms.

There is another possible explanation, that also downplays the increase of market power. If investment in fixed and sunk costs has reduced unit variable costs, the computation of markups should be done with a decreasing elasticity of output with respect to variable inputs, something that we have not done until now. We leave this for the continuation of our research.

A comparison with the firm-level markups of the sample of Compustat manufacturing firms highlights the census under-reporting of variable costs and confirms the stability of markups in the latest 20 years. Moreover, the stability of Compustat markups during the eighties and nineties lends support to the likelihood of a more extended period of stability.

Our production function provides sensible estimates of labor-augmenting and Hicks-neutral productivity, with labor-augmenting productivity playing a dominant role. Labor-augmenting productivity implies an associated decrease of the labor share in variable cost and of labor elasticity (given the presence of less than unit substitution). We find that serious mismeasurement can happen by ignoring the elasticity implications of biased technological change, both in computing firm-level markups and in getting a unique aggregate indicator. Future research should check that we do not have the same problems with the joint elasticity of the variable inputs.

Manufacturing has experienced increases in efficiency and market shares of many firms, but this has not been translated into greater markups. These outcomes suggest the importance of more research focused on how technologically biased productivity affects market structure and firms' performance, assessing the underlying trends with firm and establishment-level data.

Appendix A

The database used is the Survey of Manufactures/Census of Manufactures as aggregated in the NBER-CES database, at six-digits of NAICS 1997, in 473 industries. The database is available at https://www.nber.org/research/data/nber-ces-manufacturing-industry-database, and documented in Becker, Gray and Marvakov (2021).

We drop 5 industries for which the series lacked of data for some years: NAIC codes 311811, 326212, 334611 and 339116, without data 1958-1996, and code 315192, which lacks data between 2012-2018. This gives 468 industries, 61 years for each of them, resulting in a total of 22,448 observations.

We use the variables EMP (employment), VSHIP (shipments), MATCOST (cost of materials), CAP (real capital) and the deflators PISHIP (shipments), PIMAT (materials), and PIINV (investment).

All industries lack the variables investment, deflator of investment and the three capital constructs (capital, equipment and plant) for the years 2017 and 2018. We expand the capital series by assigning a industry capital rate of growth equal to the mean industry capital growth 2000-2016, and extend the investment and deflator of investment series replicating the data of 2016 twice.

There is a SIC version of the database that we use for the comparison with Compustat (where firms are assigned to SIC codes).

Appendix B

Consider the production function

$$Q^* = G(K, F(L^*, M))e^{\omega_H},$$

where K is capital, $L^* = \exp(\omega_L)L$ is labor in efficiency units, M is materials and $F(\cdot)$ is homogeneous of degree ν. The first order conditions of cost minimization for the variable inputs are

$$\begin{aligned} MC\frac{\partial G}{\partial F}\frac{\partial F}{\partial L^*}e^{\omega_H} &= W^*, \\ MC\frac{\partial G}{\partial F}\frac{\partial F}{\partial M}e^{\omega_H} &= P_M, \end{aligned}$$

where $W^* = \frac{W}{\exp(\omega_L)}$ is the unit cost of efficient labor and P_M the price of materials. Multiplying the first FOC by L^* and the second by M, we can write the ratio of FOCs as

$$\frac{\frac{\partial F}{\partial L^*}L^*}{\frac{\partial F}{\partial M}M} = \frac{WL}{P_M M} = \frac{S_L}{1-S_L},$$

where we use the fact that $W^*L^* = WL$, and S_L denotes the labor share in variable cost $S_L = \frac{WL}{WL+P_M M}$.

Because homogeneity of $F(\cdot)$

$$\frac{\frac{\partial F}{\partial L^*}(1, \frac{M}{L^*})}{\frac{\partial F}{\partial M}(1, \frac{M}{L^*})}\frac{1}{\frac{M}{L^*}} = \frac{S_L}{1-S_L},$$

and it is clear that S_L can be expressed as a function of $\frac{M}{L^*}$ alone. To simplify notation write $r = \frac{M}{L^*}$ and $rmp = \frac{\frac{\partial F}{\partial L^*}}{\frac{\partial F}{\partial M}}$. The ratio of FOCs define the implicit function

$$\ln rmp - \ln r - \ln S_L(\ln r) + \ln(1 - S_L(\ln r)) = 0.$$

The elasticity of substitution can be computed as

$$\sigma = \frac{d\ln r}{d\ln rmp} = \frac{1}{1 + \frac{d\ln S_L}{d\ln r} + \frac{dS_L}{d\ln r}\frac{1}{1-S_L}} = \frac{1}{1 + \frac{1}{S_L(1-S_L)}\frac{dS_L}{d\ln r}}.$$

It turns out that $\frac{dS_L}{d\ln r} \gtrless 0$ if $\sigma \lessgtr 1$.

We measure (log) efficient labor as $l^* = l+\omega_L$ and hence $\ln r = m-l-\omega_L$. With $\sigma < 1$, an increase ceteris paribus in labor-augmenting productivity brings down the labor share: $\frac{dS_L}{d\omega_L} < 0$.

Appendix C

We downloaded the Compustat data from Wharton Research Data Service (WRDS) in September 15, 2021. We use all available firms classified as manufacturing in the Fundamentals Annual North America Compustat Data from 1958 to 2018, as assigned by the four-digit SIC codes. This gives a total of 7,020 manufacturing firms and 103,448 firm-year observations. The sample has 314 companies in 1958, reaches a maximum of 2,654 companies in 1995 and decreases to 1,499 companies by 2018 (see Figure A1).

Information-Available Sample

To employ an identical sample throughout the different measurements we keep a firm-year if it has no missing value (or zero or negative value) in any of the variables measuring sales, employment, variable costs and assets (*sale*, *emp*, *cogs*, *xsga*, *ppent* and *ppegt*). It turns there are no years left for 1,137 firms, and only one year or non-adjacent single years for 348 firms. We are also going to compare employment and there are 173 firms for which, since 1997, there is no information on the employment of the corresponding four-digit SIC code of the NBER-CES database.[23] We drop all these firms, while we keep all the disjoint time sequences (more than a single year) in which some firms are split. This implies a sample with 5,362 firms (76.4% of the downloaded sample) and 75,889 observations. This information-available sample follows the same pattern as the original over time. However, the effect of missing information tends to somewhat grow over time (see Figure A1).

To check the effects of the unavailability of information we also use an slightly imputed database. To extend the firm-level series that is missing some informationwe replicate the first and/or the last value, and we impute up to two consecutive gaps in the series with an average of the previous and subsequent number. Then we apply the same selection procedure as before. The imputed data base keeps 5849 firms (83.3 %) and 81828 observations. Figure A1 also depicts the evolution of the number of firms in the imputed sample.

Employment Comparison

We start by analyzing the ratio of total employment in our available sample to the employment in the NBER-CES database. The employment variables have different content. Employment in the NBER-CES data is obtained through the addition of every firms' employment in the collection of US establishments that belong to manufacturing. However, employment reported by firms to Compustat encompasses employment in all establishments (manufacturing and non-manufacturing), including employment in subsidiaries,

[23] Codes 2711, 2721, 2731, 2741 and 2771, which all belong to the publishing activity.

domestic and foreign. Employment in Compustat should hence be larger for the same firm, and the discrepancy should be larger for multinational and foreign companies operating in the US. Davis, Haltiwanger, Jarmin and Miranda (2007) estimate that employment of an LBD[24] matched sample is about a quite stable 70% of Compustat employment.

The ratio of employment in our sample to total employment in manufacturing, as given by the NBER-CES data, is depicted in Figure A2. It increases from an initial 29% to 56% in 1976, and then it fluctuates, first decreasing until reaching 38% in 1993, followed by a rebound up to a maximum of 69% in 2012 and a subsequent fall again to 61%. Given the nature of the data (public firms) and the evolution in the number of firms, we interpret the initial increase up to 1976 as an expansion of the coverage of the Compustat sample.

Given the magnitude of the fluctuations after 1975, it is important to ask to what extent they can be attributed either to a different behavior of the sample or to systematic changes in the sample composition with respect to the whole manufacturing. Compustat is a self-selected sample but otherwise can have stable representativeness bias. The answer is not trivial because the ratio of employment tends to decrease when the number of firms goes up (roughly 1975-1995) and tends to increase when the number of firms goes down (roughly 1995-2018). This means that the average employment per firm in the sample behaved quite worse during the first subperiod, and quite better during the second subperiod, than what we see in the aggregate data of the NBER-CES database.

Composition Analysis

To gain insights we compute employment per firm in the Compustat sample and assess the impact of entry and exit in this mean employment. Figure A3 shows that the mean sharply decreases until around 1975 and then follows a much more smooth u-shaped pattern reaching a minimum in 1993. Consider two periods, 1 and 2, denote the total number of workers by L_1 and L_2, and the number of firms by N_1 and N_2. Call the firms that are present in the two periods surviving firms, the firms only present in period 2 entrant firms, and the firms only present in 1 exiter firms. Denote employment and numbers of firms by L_S, L_E, L_X and N_S, N_E and N_X,respectively. It is easy to see that the change in the employment per firm can be written as

$$\frac{L_2}{N_2} - \frac{L_1}{N_1} = \frac{L_{S2} - L_{S1}}{N_S} + (\frac{L_E}{N_E} - \frac{L_{S2}}{N_S})\frac{N_E}{N_2} - (\frac{L_X}{N_X} - \frac{L_{S1}}{N_S})\frac{N_X}{N_1}.$$

The first term on the right-hand side is the average difference in employment

[24] The Longitudinal Data Base (LBD) is likely to include more employment for the firms than the census data.

of the survivors, and the second and third terms can be read as the contribution of entry and exit to the mean difference of employment given the size differences of entrants and exiters with respect to the survivors. Table 1 reports the changes in three subperiods: 1959-1975, 1975-2000 and 2000-2018.

The mean employment of survivors always grows, although at a decreasing rate over the years. The effect of entry in the sample is always negative (entrants are smaller firms), overwhelmingly dominating the first subperiod and with a smaller and non-disimilar effect in the other two. Comparing the two latest subperiods it becomes clear that the rebound in mean employment is partly due to less entry at small size and some more exit of smaller firms. However, entry and/or exit do not drive the ratios. Hence, our conclusion is that there are no reasons to think that the sample embodies a systematic bias due to a change of composition or representativeness after 1975, and it is clear that the average employment of the firms in Compustat tends to perform much better than that of the average manufacturing firms in, say, the last 20 years.

Measuring Variable Cost

Compustat provides two variables related to expenditures that can be used for the specification of the variable costs in order to compute $\ln \frac{R}{VC}$. The first,"Cost of Goods Sold" or *cogs*, is likely to miss several costs that are variable and that may have been varying systematically over the time. For example, costs of employment linked to the sales and distribution of the goods. The second, "Selling, General and administrative Expenses" or *xsga*, is likely to include these costs but it is apparent that also contains expenses that must be considered an investment, as for example R&D and advertising expenditures (*rd* and *adv*). We construct three alternative measurements of the margins using three measurements of VC: *cogs*, *cogs+xsga*, *cogs+(xsga-rd-adv)*.

Table A2 describes the mean values for selected periods of the three alternatives and Figure A4 depicts them. With individual data, average margins $\ln \frac{R}{VC}$ can be very sensitive to the presence of outliers. To avoid this, in the second panel of the table we winsorize the results setting all values below the quantile 0.05 to the value of the quantile and all values above the quantile 0.95 at the value of the quantile. To check the robustness of the estimates we also compute the margins with the imputed sample and report them in the third panel of the table.

Since differences are not dramatic we comment on the first panel of values. The first margin turns out to have an unrealistic average value of 51%. In addition, the margin tends to increase over time, ending at a value of 67%. With the second alternative the opposite happens. The whole average is again an unrealistic value, in this case 2% , and the margin shows negative average values about -6% since 2000. Notice that this is the first indication that we find in the data that some fixed expenses of the firm (wrongly included in this measure) may have been increasing over time. Subtraction of the R&D and advertising expenses, which have been trending continuously up, give an average margin of 11%, a much more sensible number. In addition, the margin defined in this way shows much more stability: 15% before 1980, 11% from the eighties until 2000, and about 8% during the 2000's.

We conclude that the data strongly suggests that using *cogs* gives a margin which increases with the presumable fading of some variable costs over time, using *cogs+xsga* gives margins that systematically decrease with the apparent trend in the (wrongly cost-included) R&D and advertising expenditures, and using *cogs+(xsga-rd-adv)* gives a sensible alternative. This suggests a strong stability of the margins. Notice that our previous conclusion on the representativeness of the sample says that the bias in the measurement of margins in the last 20 years, if any, should be upward. So we cannot discard that this stability may be too rosy of a view.

Production Function Estimation

To carry a proper measurement of the markups and to check the consistency of the Compustat information against the information of the NBER-CES database, we estimate the same translog specification of the production function as in section 2, now with firm-level data.

The main drawback is that Compustat doesn't include information on the wage bill except for a very small subset of firms (473, only 6.6% of the downloaded number of manufacturing firms). However, as we have the employment of firms, when there is no wage information we impute for each firm-year the average observed wage at the SIC industry that the firm belongs to. Then we compute the materials bill by subtracting the wage bill from the total variable costs attributed to the firm according to the measurement *cogs+(xsga-rd-adv)*. This subtraction gives negative numbers in 1.3% of the observations, and then we attribute all variable cost to materials and compute the share of labor as if the inputted wage bill was right. This is admittedly a rough procedure, that works because the regression only uses information on m and s_L. However, at the time of estimation we drop 5% of the sequences, namely those with the most negative margins.

The results of the production function estimation, summarized in Table A3, are good.[25] The elasticity of capital and the short-run elasticity of scale are very sensible, and this time MC is estimated above AVC by about 13% ($\ln 0.875 \simeq -0.134$). The elasticity of labor, which shows a dispersion slightly

[25] The autoregressive parameter is however too large and the implicit elasticity of substitution is too low.

greater than across industries, is detected also be systematically falling (although less than in the aggregate data, 5 percentage points in total).

The growth of productivity in the whole period is explained both by labor-augmenting and Hicks-neutral productivity, with some advantage of the second. In this case the time dummies tend to explain almost nothing. The cross-sectional differences of productivity at the end of the sample have a standard deviation around 50% for the output effect of labor-augmenting productivity, slightly higher than the dispersion across industries shown by the aggregate data, while Hicks-neutral productivity shows a notable dispersion.

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Table 1: Estimating a Translog Production Function with Labor-augmenting and Hicksian Productivity 1959-2018[a]

Production function params.[b,c] (Std. dev.)				Elasticities (Std. dev.) Capital	Labor					Dispersion and growth of productivity (Std. dev.) Output effect $\beta_L\omega_L$		ω_H	
β_K	ν	α	ρ	β_K	β_L	$Q_{0.1}$	$Q_{0.5}$	$Q_{0.9}$	Change over time	Cross-s. std. dev.[d]	Mean growth	Cross-s. std. dev.[d]	Mean growth[e]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0.040	0.924	0.094	0.976	0.040	0.260	0.120	0.262	0.410	-0.076	0.402	0.010	0.318	0.004
(0.013)	(0.027)	(0.011)	(0.003)	-	(0.113)						(0.123)		(0.069)
0.125	0.782	0.062	0.975	0.125	0.224	0.102	0.222	0.347	-0.065	0.401	0.009	0.791	0.013
(0.026)	(0.042)	(0.009)	(0.003)	(0.083)	(0.096)						(0.124)		(0.075)

[a] Survey of Manufactures/Census of Manufactures as aggregated in NBER-CES database at six-digits (468 NAICS industries).
[b] First estimate: capital enters only linearly. Second estimate: adds a quadratic term in capital.
[c] Estimated in pseudodifferences by nonliner GMM. Instruments: constant, time dummies, third degree polynomial in k, variables k_{-1}, l_{-1}, $(m-l), wg_{-1}-p_{-1}$ and $p_{M_{-1}}-p_{-1}$, where wg is the natural logarithm of wage, p_M of price of materials and p of output price. (4 degrees of freedom).
[d] Standard deviation of the level of productivity accross the 486 industries in 2018.
[e] During the whole period time dummies account for about 0.235 and -0.184 respectively, which can be considered adding 0.004 and -0.003 to these means.

Table 2: Markups in US Manufacturing 1959-2018[a]

		1959-2018	1959-1980	1980-2000	2000-2018	2009-2018
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Markup[b], $\ln\widehat{\mu} = \ln\frac{R}{VC} + \ln\widehat{\nu}$	Mean	0.278	0.218	0.286	0.337	0.336
	Std. dev.	(0.159)	(0.118)	(0.152)	(0.181)	(0.178)
	Mean of industry-period changes[c]	0.146	0.039	0.086	0.021	0.002
	Std. dev.	(0.174)	(0.095)	(0.135)	(0.160)	(0.138)
	Prop. of negative changes	0.130	0.252	0.218	0.404	0.479
	$Q_{0.9}$ of changes	0.229	0.093	0.132	0.096	0.069
	$Q_{0.5}$ of changes	0.141	0.046	0.078	0.021	0.006
	$Q_{0.1}$ of changes	0.050	0.009	0.013	-0.051	-0.064
User cost of capital[d], $uc = (r + d - \Delta p_I)$	Mean	0.075	0.045	0.090	0.093	0.087
	Std. dev.	(0.063)	(0.048)	(0.049)	(0.079)	(0.102)
Corrected markup[b], $\ln\widehat{\mu}_c = \ln\frac{R}{VC} + \ln\widehat{\nu} - uc\frac{K}{R}$	Mean	0.243	0.200	0.244	0.292	0.293
	Std. dev.	(0.163)	(0.118)	(0.153)	(0.200)	(0.212)

[a] Averages across industries for each period/subperiod; sample standard deviations.
[b] $\widehat{\nu} = 0.924$ (first estimate of Table 1).
[c] As changes are time differences, and the panel is balanced, the means of period changes equal the change in the means.
[d] The interest rate r is the Weighted-average Effective Loan Rate for All Commercial and Industry Loans, Federal Reserve Bank of Saint Louis, and d and Δp_I as implicit in the capital, investment and investment price of the NBER-CES database.

Table 3: A Look at the Cost Shares and Productivity[a]

		1959-2018	1959-1980	1980-2000	2000-2018	2009-2018
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable Cost over Revenue, $\frac{VC}{R}$	Mean	0.708	0.748	0.701	0.669	0.670
	Std. dev.	(0.100)	(0.085)	(0.096)	(0.103)	(0.103)
Labor Share in Variable Cost, $S_L = \frac{WL}{VC}$	Mean	0.286	0.322	0.281	0.250	0.242
	Std. dev.	(0.122)	(0.128)	(0.116)	(0.110)	(0.108)
	Mean of period changes[b]	-0.083	-0.045	-0.020	-0.018	-0.002
	Std. dev.	(0.087)	(0.060)	(0.057)	(0.065)	(0.047)
	Prop. of negative changes	0.846	0.814	0.628	0.684	0.553
Output effect of labor-augmenting prod. growth, $\beta_L \Delta\omega_L$	Mean	0.010	0.013	0.011	0.005	-0.002
	Std. dev.	(0.123)	(0.140)	(0.116)	(0.107)	(0.099)
Growth of Hick-neutral prod., $\Delta\omega_H$	Mean	0.004	0.007	0.000	0.006	0.006
	Std. dev.	(0.069)	(0.060)	(0.066)	(0.079)	(0.086)
Dispersion of labor-augmenting prod., $\beta_L \omega_L$	Std. dev.	0.634	0.737	0.571	0.438	0.390
Dispersion of Hick-neutral prod., ω_H	Std. dev.	0.314	0.381	0.228	0.285	0.306

[a] Averages across industries for each period/subperiod; sample standard deviations.

[b] As changes are time differences, and the panel is balanced, the means of period changes equal the change in the means.

Table 4: Markups in Manufacturing[a]: A Comparison of data from NBER-CES[b] and Compustat[c], 1959-2018

		1959-2018	1959-1980	1980-2000	2000-2018	2009-2018
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Compustat[d],	Mean	0.366	0.269	0.357	0.453	0.478
$VC = cogs$, $\widehat{\nu} = 0.875$.	Std. dev.	(0.313)	(0.238)	(0.297)	(0.360)	(0.368)
NBER-CES[e],	Mean	0.278	0.218	0.286	0.337	0.336
$VC = payroll + materials\ bill$, $\widehat{\nu} = 0.924$.	Std. dev.	(0.159)	(0.118)	(0.152)	(0.181)	(0.178)
Compustat[d],	Mean	0.004	0.018	-0.003	0.001	0.010
$VC = cogs + (xsga - rd - adv)$, $\widehat{\nu} = 0.875$.	Std. dev.	(0.183)	(0.117)	(0.180)	(0.226)	(0.233)

[a] Computed as $\ln \widehat{\mu} = \ln \frac{R}{VC} + \ln \widehat{\nu}$.

[b] Survey of Manufactures/Census of Manufactures as aggregated in NBER-CES database at six-digits (468 NAICS industries).

[c] Computed with 5,386 companies and a total of 71,735 observations. Winsorized at the 0.05 and 0.95 quantiles.

[d] Averages of the firm-level markups in the sample corresponding to each period/subperiod; sample standard deviations.

[e] Averages across industries for each period/subperiod; sample standard deviations.

Table A1: The Evolution of Mean Employment in Compustat Manufacturing 1959-2018

	Number of firms[a]			Mean employment		Decomposition of changes			
	N_1	N_2	$\frac{N_S}{N_1}$	$\frac{L_1}{N_1}$	$\frac{L_2}{N_2}$	Mean Variation	Survivors	Entry	Exit
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1959-1975	237	1489	0.759	19822	6233	-13,589	12,656	-29,434	3,188
1975-2000	1489	1588	0.201	6233	4922	-1,311	3,248	-9,258	4,699
2000-2018	1588	788	0.225	4922	8994	4,072	1,990	-5,356	7,437

[a] The sample used drops the first observation of each firm.

Table A2: Margins in Compustat Manufacturing 1959-2018[a]

(1)	(2)		1959-2018 (3)	1959-1980 (4)	1980-2000 (5)	2000-2018 (6)	2009-2018 (7)
Information-available sample[b]	Margin 1[e]	Mean	0.513	0.403	0.493	0.626	0.667
		Std. dev.	(0.436)	(0.266)	(0.386)	(0.563)	(0.601)
	Margin 2[f]	Mean	0.022	0.118	0.026	-0.060	-0.058
		Std. dev.	(0.424)	(0.149)	(0.367)	(0.599)	(0.631)
	Margin 3[g]	Mean	0.108	0.150	0.108	0.072	0.076
		Std. dev.	(0.401)	(0.154)	(0.345)	(0.574)	(0.607)
Information-available sample,[b] winsorized distribution[d]	Margin 1[e]	Mean	0.499	0.402	0.490	0.587	0.612
		Std. dev.	(0.313)	(0.238)	(0.297)	(0.360)	(0.368)
	Margin 2[f]	Mean	0.060	0.117	0.055	0.022	0.029
		Std. dev.	(0.194)	(0.103)	(0.189)	(0.242)	(0.247)
	Margin 3[g]	Mean	0.137	0.151	0.131	0.134	0.144
		Std. dev.	(0.183)	(0.117)	(0.180)	(0.226)	(0.233)
Inputed sample,[c] winsorized distribution[d]	Margin 1[e]	Mean	0.498	0.401	0.491	0.583	0.605
		Std. dev.	(0.321)	(0.240)	(0.304)	(0.372)	(0.381)
	Margin 2[f]	Mean	0.031	0.113	0.028	-0.031	-0.035
		Std. dev.	(0.261)	(0.118)	(0.252)	(0.331)	(0.346)
	Margin 3[g]	Mean	0.114	0.147	0.110	0.093	0.093
		Std. dev.	(0.228)	(0.127)	(0.222)	(0.289)	(0.304)

[a] Computed as $\ln\frac{R}{VC}$. Averages of the firm-level markups in the sample corresponding to each period/subperiod; sample standard deviations.

[b] $5,362$ companies and a total of $75,889$ observations.

[c] $5,849$ companies and a total of $81,828$ observations.

[d] Margins winsorized at the quantiles 0.05 and 0.95.

[e] $VC = cogs$

[f] $VC = cogs + xsga$

[g] $VC = cogs + (xsga - xrd - xad)$

Table A3: Estimating the Translog Production Function with Compustat Data 1959-2018[a]

Production function params.[b,c] (Std. dev.)				Elasticities (Std. dev.)						Dispersion and growth of productivity (Std. dev.)			
				Capital	Labor					Output effect $\beta_L \omega_L$		ω_H	
β_K	ν	α	ρ	β_K	β_L	$Q_{0.1}$	$Q_{0.5}$	$Q_{0.9}$	Change over time	Cross-s. std. dev.[d]	Mean growth	Cross-s. std. dev.[d]	Mean growth[e]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0.046	0.875	0.548	1.013	0.046	0.291	0.122	0.274	0.478	-0.051	0.493	0.018	1.422	0.023
(0.014)	(0.032)	(0.100)	(0.002)	-	(0.144)						(0.417)		(0.323)

[a] Information-available sample of 5,386 firms and 75,889 observations, dropping from estimation the 5% sequences with most negative margins.

[b] Capital enters only linearly.

[c] Estimated in pseudodifferences by nonliner GMM. Instruments: constant, time dummies, third degree polynomial in k, variables k_{-1}, l_{-1}, $(m-l)$, $wg_{-1} - p_{-1}$ and $p_{M_{-1}} - p_{-1}$, where wg is the natural logarithm of wage, p_M of price of materials and p of output price (4 degrees of freedom).

[d] Standard deviation of the level of productivity in 2018.

[e] Time dummies account for very little during the whole period.

Figure 1: Markup in US Manufacturing according to NBER-CES data, 1959-2018.

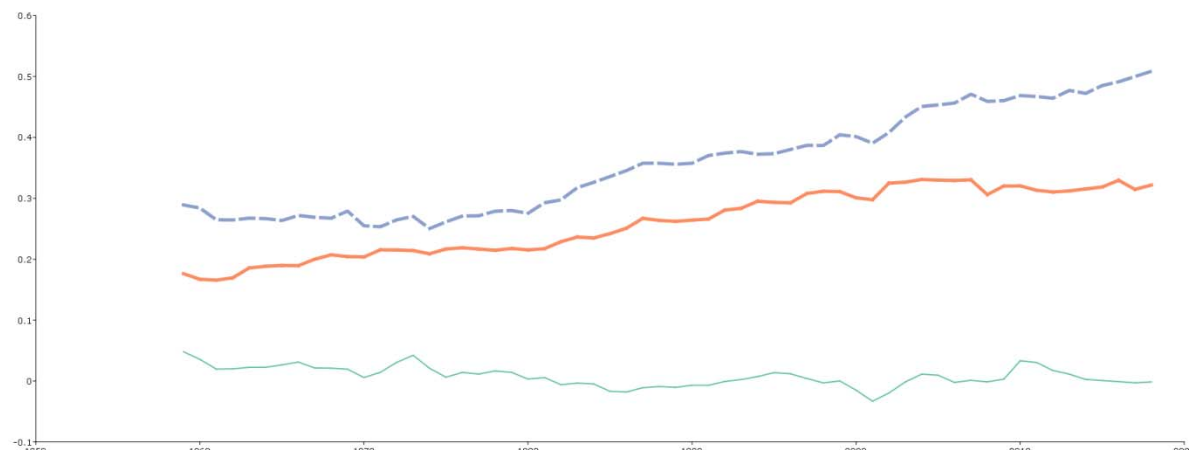
Solid line: Markup computed as reported in Table 2.
Dashed line: Markup corrected by the cost of capital.

Figure 2: Labor Share in Variable Cost 1959-2018.

Figure 3: Labor-augmenting and Hicks-neutral Productivity, 1959-2018.[1]

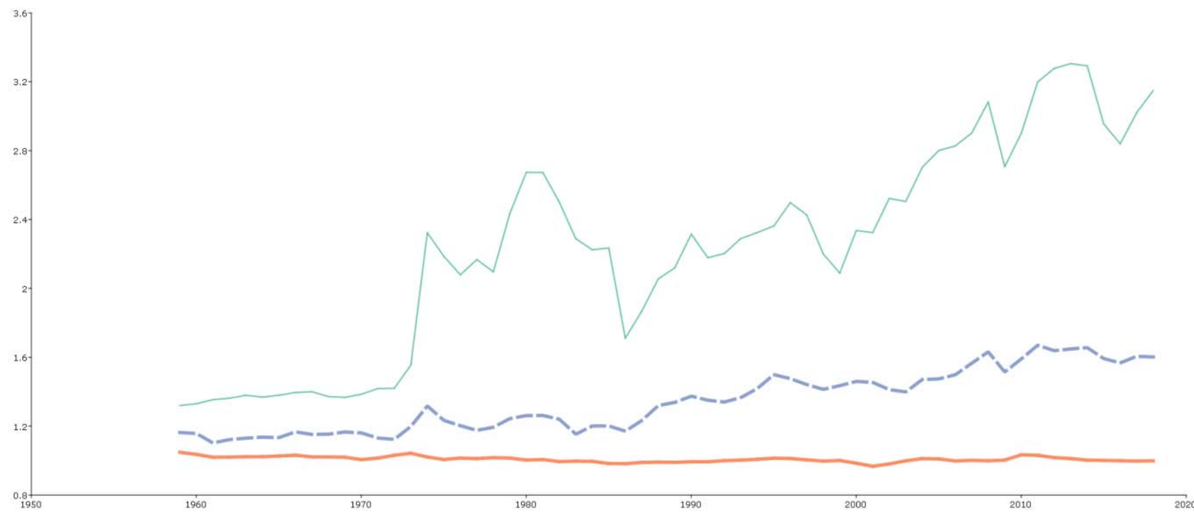
Solid line: Output Effect of Labor-augmenting Productivity
Dashed line: Hicks-neutral Productivity
[1] Series centered at zero at its mean.

Figure 4: The markup according to NBER-CES and Compustat, 1959-2018.



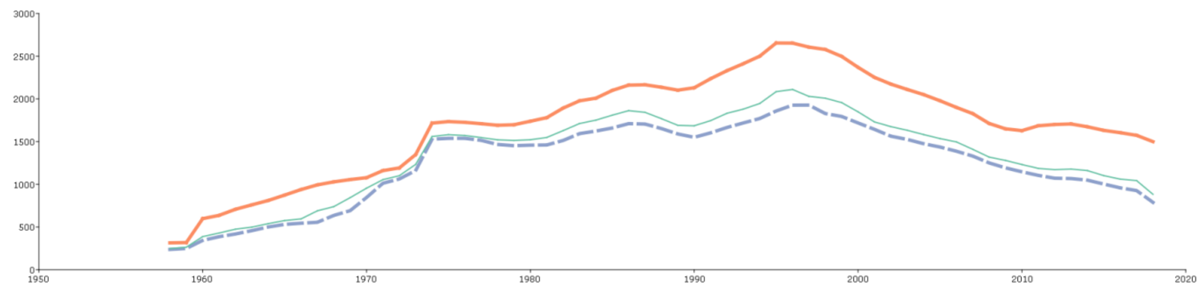
Main solid line: Markup in NBER-CES
Dashed line: Markup in Compustat with VC=*cogs*
Thin solid line: Markup in Compustat with VC=*cogs+xgsa-rd-adv*.

Figure 5: The elasticity and aggregation biases



Solid line: Markup in Compustat with VC=*cogs+xgsa-rd-adv*.
Dashed line: Simple average of markups computed with constant labor elasticity 0.291.
Thin solid line: Revenue weighted average of the markups computed with constant labor elasticity 0.291.

Figure A1: Number of Firms in the Compustat Sample.



Solid line: Original Sample
Dashed line: Information-available Sample
Thin solid line: Inputed Sample

Figure A2: Ratio of Employment Compustat/NBER-CES.

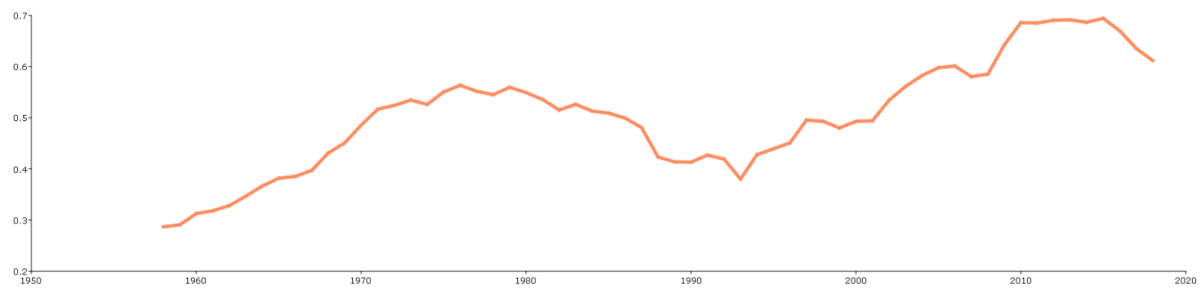


Figure A3: Evolution of Mean Employment in the Compustat Sample (Thousand Employees).

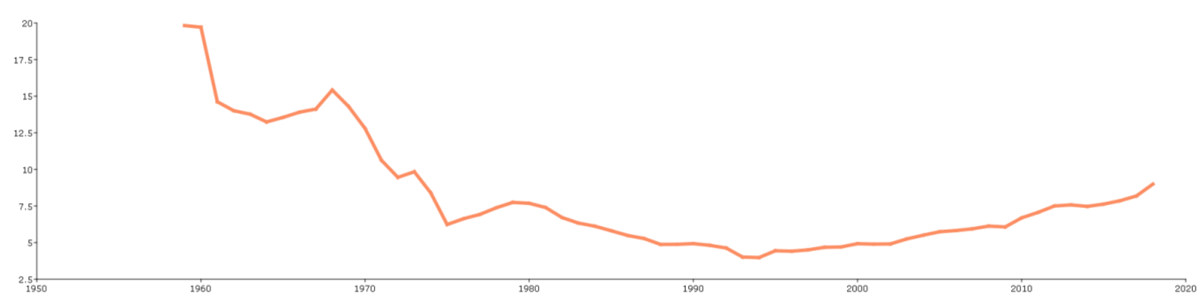
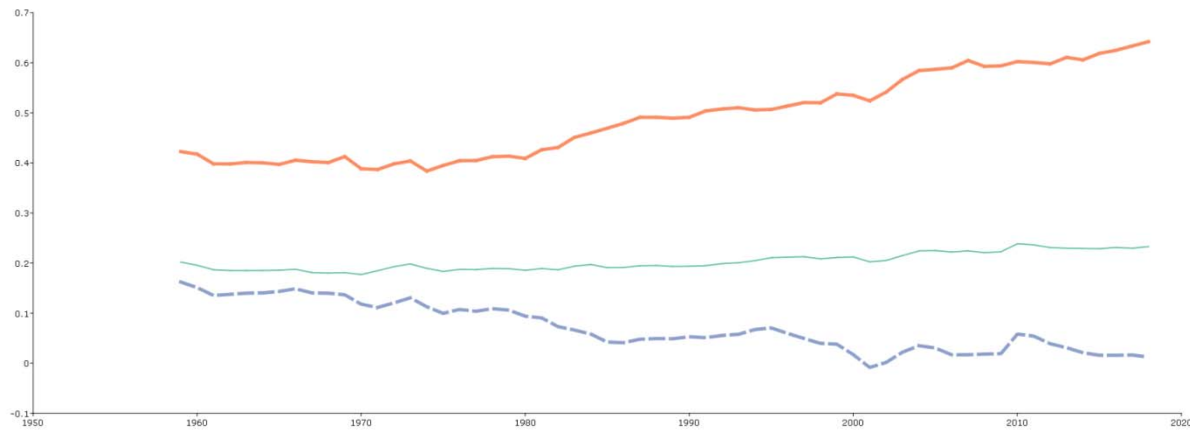


Figure A4: Evolution of Compustat Margins, ln (R/VC).[a]



Solid line: VC=*cogs*
Dashed line: VC=*cogs+xsga*
Thin solid line: VC=*cogs+(xsga-rd-adv)*
[a] Winsorized at the 0.05 and 0.95 quantiles.