Market Power and Technology in US Manufacturing*

Sabien Dobbelaere†, Jordi Jaumandreu‡, and Jacques Mairesse§

March 2025

Abstract

We measure market power in product and labor markets for firms in US manufacturing from 1958 to 2018 using NBER-CES and Compustat data. Measurement is robust to any form of competition and accounts for Hicksian and labor-augmenting productivity to avoid biases in estimation. We estimate the long and short-run elasticities of scale and the wage markdown. These estimates allow us to infer the price-cost markup and evaluate contributions of product market power, labor market power, and technology to short-run profitability. Preliminary results show 36% profitability, with product market power contributing 18 percentage points, technology 12, and labor market power 6.

Keywords: Profitability, price-cost markups, wage markdowns, technology, productivity.

JEL classification: D24, J42, L10.

*We are grateful to Liying Zhang for research assistance.

†Vrije Universiteit Amsterdam. Email: `sabien.dobbelaere@vu.nl`.

‡Boston University. Email: `jordij@bu.edu`.

§ENSAE-CREST, Paris. Email: `jacques.mairesse@ensae.fr`.

1 Introduction

The short-run profitability of a firm with market power in product and labor markets depends on the price that the firm sets for its product and the wage it determines for labor. The output price is set above marginal cost according to the degree of competition in the product market. How much the marginal cost lies above observed average variable costs depends on two factors: the value for the short-run elasticity of scale, shaped by technology, and the firm's monopsony power, which lowers the wage below the marginal productivity of labor. The observed profitability of firms is therefore attributed to three sources: technology, the price-cost markup and the wage markdown. Understanding their relative impact and evolution over time is an important topic of interest.

This paper measures price-marginal cost markups (hereafter markups) and marginal productivity-wage markdowns (hereafter markdowns) in US manufacturing and quantifies the relative contributions of technology, product market power, and labor market power to observed profitability. Building on Azzam et al. (2025), we assume that firms compete in both the product and labor markets in ways unknown to the researcher, choose two variable inputs (labor and materials) to produce the planned output given capital and productivity (which is unobserved to the researcher). From the first-order conditions of cost minimization of the firm, we obtain an expression for the output elasticities of the variable inputs in terms of the short-run scale elasticity, modified by the market power in the labor market, and the shares of variable inputs in variable costs. We then estimate the production function using these elasticities. The estimation of the short-run elasticity of scale and the markdown allows us to estimate the marginal cost from the observed average variable costs up to an uncorrelated error, and hence the markup can be computed up to an error that tends to cancel in any average. The estimation of the markup permits to decompose observed profitability into contributions from technology (marginal cost-average variable cost difference), product market power and labor market power.

Controlling for unobserved productivity is crucial in estimating the production function. We do this in the following way. We assume that unobserved Hicks-neutral productivity follows a linear Markov process, which allows us to control for neutral productivity by differencing the production function model (a generalization of "dynamic panel" estimation). We account for unobserved labor-augmenting productivity by expressing it in terms of the ratio of the variable inputs and the ratio of their prices, following Doraszelski and Jaumandreu (2018) who demonstrate this approach for any production function separable in capital.

Some economists argue that, since 1980, US firms have experienced a sustained increase in profitability. To investigate if this is true and the underlying drivers, we estimate the production function and perform the decomposition using two datasets spanning 1958-2018. The first dataset is the NBER-CES database, which provides industry-level data for 468 six-digit NAICS industries in US manufacturing (excluding a few industries with incomplete data). The second dataset, Compustat, contains cleaned data for approximately 5,600 publicly traded US companies.

Our preliminary estimates based on the NBER-CES database indicate that US manufacturing firms set prices, on average, 18 percentage points above marginal costs, and that these markups have remained relatively stable over time. At the same time, the marginal productivity of labor is estimated to be 20 percentage points higher than the wage paid to workers. Furthermore, technological factors result in a short-run elasticity of scale that pushes marginal costs 19 percentage points above average variable costs. Firms' short-run profitability is on average 36 percentage points. Our estimates of the short-run elasticity of scale, the markup and the markdown imply that 12 percentage points are attributed to technology, 18 to market power in the product market, and 6 to market power in the labor market. Our initial estimates based on Compustat tend to give compatible results, but are still far from being satisfactory. Although we only have preliminary estimates, they have an important potential for analyzing cross-sectional heterogeneity and changes over time. We plan to use this potential to analyze the correlations of measured market power with its determinants.

Our paper relates to the literature on market power estimation using a production function approach as follows. The direct estimation of price-cost margins via production function estimation was used by Hall (1988) and Klette (1999). Their method relied on expressing the output elasticities of the variable inputs in terms of the markup multiplied by their revenue shares. Drawing on this identity, De Loecker and Warzynski (2012) estimate output elasticities in an unrestricted manner and use them to compute markups. This latest method has been widely applied in empirical research, e.g. De Loecker et al. (2016), Brandt et al. (2017), De Loecker and Scott (2016), Autor et al. (2020) and De Loecker et al. (2020). However, recent studies have raised concerns related to data measurement (Traina (2018), Basu (2019), Syverson (2019)), methodology (Doraszelski and Jaumandreu (2019), Demirer (2020), Bond et al. (2021), Doraszelski and Jaumandreu (2021), Hashemi et al. (2022), Raval (2023)) and outcomes (Jaumandreu (2022), Jaumandreu (2024)). Our approach constitutes an alternative measurement for markups by estimating the output elasticities of variable inputs expressed as the short-run elasticity of scale times the share of variable inputs in variable costs. Markups are then derived residually (indirectly) as the difference between observed profitability and the contributions of technology and labor market power to profitability.

The production function approach to estimating simultaneously market power in product and labor markets was first introduced by Dobbelaere and Mairesse (2013) and has been applied in e.g. Dobbelaere and Mairesse (2018), Caselli et al. (2021), Damoah (2021) and Dobbelaere and Wiersma (2025). Their method extended the Hall (1988) and Klette (1999) framework to allow for imperfect competition in labor markets, introducing explicitly the gap between elasticity and share. This has in particular the advantage of being compatible with different models of wage determination, including both employer wage setting and collective bargaining. Building on De Loecker and Warzynski (2012), Yeh et al. (2022) account for monopsonistic employers computing markups and markdowns based on unrestricted output elasticity estimates of variable inputs. Markdowns are calculated as the ratio of the wedge between the output elasticity of labor and the revenue share of labor to the wedge between the output elasticity of materials and the revenue share of materials.

Many papers have recently stressed the importance that biased technical change in the form of labor-augmenting productivity can be having in many observed evolutions of productivity and employment, and expressed concern about how the ignorance of this fact can affect estimation of markups and markdowns. Examples are (Doraszelski and Jaumandreu (2018), Doraszelski and Jaumandreu (2019), Zhang (2019), Raval (2019), Raval (2023), Demirer (2020), Kusaka et al. (2023), Jaumandreu and Mullens (2024) and Azzam et al. (2025)). Azzam et al. (2025) develop a method for simultaneously identifying market power in both input and output markets while accounting for labor-augmenting productivity. The method implies a way to decompose profitability. We extend their framework to a multi-industry setting, decomposing observed profitability into components related to product market power, labor market power, and technology in all US manufacturing industries.

The remainder of the paper is organized as follows. Section 2 introduces the model and profitability decomposition. Section 3 presents the preliminary estimates of markups and markdowns, and the contribution of technology and market power in product and labor markets to profitability.

Section 4 provides some concluding remarks.

2 Model

Let us assume a population of firms. Taking a first-order approximation in logs to the unknown production function $Q = F(K, \exp(\omega_L)L, M)\exp(\omega_H + \varepsilon)$ of a firm gives:

$$q = \beta_0 + \beta_K k + \beta_L(\omega_L + l) + \beta_M m + \omega_H + \varepsilon, \tag{1}$$

where β_X are the elasticities of the inputs K, L and M, representing capital, labor and materials, respectively, ω_L and ω_H are labor-augmenting and Hicks-neutral productivity and ε is a serially uncorrelated error. To refer to the output without error we will use the notation $q = q^* + \varepsilon$.

We remain agnostic about the nature of competition in the product market, allowing the firm to possess any degree of market power. We may assume that the firm maximizes short-run profits by equating marginal revenue to marginal cost, but this is not necessary. We can simply assume that the firm minimizes short-run costs. Similar to the product market, we refrain from specifying the nature of competition in the labor market. We only assume that results in a wage markdown τ that is the percentage gap between the marginal product of labor and the price of labor.

Cost minimization of the inputs L and M implies:

$$\begin{aligned} MC\frac{\partial F}{\partial L^*} &= (1+\tau)W/\exp(\omega_L), \\ MC\frac{\partial F}{\partial M} &= P_M, \end{aligned}$$

where τ is the degree of monopsony power in the labor market.

Define $\nu = \beta_L + \beta_M$, the sum of the elasticities of the variable inputs, as the short-run elasticity of scale, and S_X as the share of the input X in variable cost. The sum of the first-order conditions, duly multiplied by the quantities of the inputs over the output Q^*, gives $\nu = \frac{AVC}{MC}(1 + S_L\tau)$ and we can write $\frac{AVC}{MC} = \nu/(1 + S_L\tau)$. This is the usual relationship between marginal cost and average variable cost (see, e.g. Chambers (1988)), corrected for labor market power. Using this relationship and notation, cost minimization implies the following expressions for the elasticities:

$$\begin{aligned}\beta_L &= \frac{(1+\tau)}{(1+S_L\tau)}\nu S_L,\\ \beta_M &= \frac{1}{(1+S_L\tau)}\nu S_M.\end{aligned}$$

We can write the approximation (1) to the production function in terms of the parameters to be estimated. We do this by rewriting the production function in terms of the long-run elasticity to scale $\lambda = \beta_K + \beta_L + \beta_M$ and the short-run elasticity of scale ν. In our baseline model we take both parameters of scale λ and ν as constants, but note that this could be generalized and, in particular, the individual elasticities β_L and β_M are not necessarily constant. The approximation to the production function becomes:

$$\begin{aligned}q &= \beta_0 + \lambda k + \beta_L(\omega_L + l - m) + \nu(m-k) + \omega_H + \varepsilon,\\ &= \beta_0 + \lambda k + \nu(m-k) + \nu\frac{(1+\tau)}{(1+S_L\tau)}S_L(\omega_L + l - m) + \omega_H + \varepsilon,\end{aligned} \tag{1}$$

where the parameters to estimate are λ, ν and τ.

We need to control for the two unobservables ω_L and ω_H. We can control for labor-augmenting productivity approximating by the ratio $\omega_L + l - m$ using the equation that Doraszelski and Jaumandreu (2018)obtain for functions separable in capital,

$$m - l = -\sigma(p_M - w) + (1-\sigma)\omega_L,$$

where σ is the elasticity of substitution between the two variable inputs. Adapting this equation to our expression and the situation with possible monopsony power we get:

$$\omega_L + l - m = -\frac{\sigma}{1-\sigma}(\ln\frac{S_L}{1-S_L} + \ln(1+\tau)).$$

Plugging the last expression in the production function we have:

$$q = \beta_0 + \lambda k + v(m-k) - \nu(1+\tau)\frac{\sigma}{1-\sigma}S_L(\ln\frac{S_L}{1-S_L} + \ln(1+\tau))/(1+S_L\tau) + \omega_H + \varepsilon.$$

To simplify notation and gain clarity let us write $x = S_L(\ln\frac{S_L}{1-S_L} + \ln(1+\tau))/(1+S_L\tau)$ and use time subindices for the lagged variables. If we assume that ω_H follows the Markov process $\omega_H = \rho\omega_{H,-1} + \xi$, Hicks neutral productivity can be controlled by the dynamic panel procedure of differentiating the equation. With sample notation (using firm and time subindices) we have:

$$\begin{aligned} q_{jt} = \quad & \beta_0' + \rho q_{jt-1} + \lambda(k_{jt} - \rho k_{jt-1}) + v(m_{jt} - k_{jt} - \rho(m_{jt-1} - k_{jt-1})) \\ & -\nu(1+\tau)\frac{\sigma}{1-\sigma}(x_{jt} - \rho x_{jt-1}) + \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}. \end{aligned} \tag{4}$$

Now the parameters to estimate are $\rho, \lambda, \nu, \sigma$ and τ. Eq. (4) can be estimated by a nonlinear procedure such as the nonlinear GMM that we will employ.

Decomposition of profitability Eq. (4) does not estimate directly the markup. However, the value of the markup is implicit as it is a decomposition of the gross profitability observed to the firm. To see both things, write the ratio of revenue to variable costs as:

$$\frac{R}{VC} = \frac{PQ}{AVCQ^*} = \frac{1}{\frac{AVC}{MC}}\frac{P}{MC}\exp(\varepsilon) = \frac{1}{\nu}(1+S_L\tau)\mu\exp(\varepsilon).$$

Having estimated ν and τ, the markup μ can be residually estimated as

$$\ln\mu = \ln\frac{R}{VC} + \ln\nu - \ln(1+S_L\tau) - \varepsilon,$$

where ε tends to cancel if we take an average of enough firms.

Knowing $\ln\mu$, observable gross profitability, defined as $\ln\frac{R}{VC}$ (that is readable as a profit percentage), can be decomposed into the parts due to technology and the market power of the firm in the product and labor markets:

$$\ln \frac{R}{VC} = -\ln \nu + \ln \mu + \ln(1 + S_L \tau) + \varepsilon. \tag{5}$$

3 Profitability of product and labor market power and technology

We estimate our empirical production function (Eq. (4)) over the period 1959-2018 with a constant and a full set of dummies (59). We use nonlinear optimization of a GMM quadratic form with the consistent weight $\left(N^{-1} \sum_j Z_j' Z_j\right)^{-1}$, where Z_j is the matrix of instruments (with T_j rows) for every industry/firm j. We present first-stage estimates, compute analytical asymptotic robust standard errors, and use the delta method to approximate the standard errors of the elasticities, evaluated at the means of the observed variables. The instruments include, in addition of the constant and the time dummies, the following variables expressed in logarithms and their transformations: capital and capital lagged, materials lagged, powers of the lagged share of labor, the wage and index of price of materials, both linearly and squared. We use a moderate number of overidentifying restrictions (5 and 6). Appendix A provides detailed information on the two datasets used for estimation: the NBER-CES database and the Compustat dataset.

Table1 presents the preliminary results for the estimation of Eq. (4). Column (2) reports the reports the estimated parameters and output elasticities based on the NBER-CES sample of 468 industries. The elasticities of labor (β_L), materials (β_M) and capital (β_K) are estimated to be 0.25, 0.63 and 0.04, respectively. The autoregressive parameter (ρ) is quite close to one, indicating that Hicks-neutral productivity follows a random walk. Hence, the production function estimation is nearly equivalent to estimating in first differences. The long-run elasticity of scale (ρ) is estimated to be 0.93, which, although somewhat low, is acceptable given that we are modeling 60 years of growth. The short-run elasticity of scale (ν) is estimated to be 0.89.

The elasticity of substitution between labor and materials (σ) is very well estimated at 0.77, despite the crudity of the approximation. Since σ is clearly below unity, labor-augmenting productivity is responsible for reducing the share of labor in variable costs (Hicks (1932)).[1] The underlying intuition is that, while an increase in labor-augmenting productivity displaces labor by its percent-

[1] See Appendix 1 of Jaumandreu and Mullens (2024) for a derivation.

age amount, it lowers the cost of efficient labor with a substitution effect that is smaller because the elasticity of substitution is less than unity. With no change in the nominal wage, the labor share is going to decrease (Jaumandreu and Mullens (2024)). It is worth noting that in obtaining these preliminary results, the production function specification implicitly estimates the entire distribution of Hicks-neutral and labor-augmenting productivity, both across industries and over time.

We get a plausible estimate of the proportional wage markdown (τ) of 20%, indicating that a firm's marginal revenue product of labor is, on average, 20% higher than the wage it pays to its workers. This estimate is significantly lower than the 54% reported by Yeh et al. (2022). Alternatively, taking the reciprocal of the markdown ($1\backslash(1+\tau)$), this implies that workers are paid 83 cents for every marginal dollar they generate. The markdown is imprecisely estimated, indicating that it is quite unrealistic to attribute a uniform value to all manufacturing industries. In subsequent steps, we will model the model the markdown based on its determinants to better understand how it varies with industry conditions.

The estimate of the price-cost markup (μ), which we infer residually by expressing this parameter in terms of observable gross profitability and the short-run elasticity of scale adjusted for labor market power, is 1.20. This implies that manufacturing firms set prices, on average, 20% above marginal costs. Appendix Figure B1 illustrates that markups remained relatively stable over time, initially declining until the early 1990s before experiencing a slight increase within narrow margins. Unlike De Loecker et al. (2020), the model estimates that the markup increased by only two percentage points from the early 1990s to 2018. Column (3) of Table 1 presents preliminary parameter estimates based on the Compustat database. While these estimates tend to go in the same direction as those based on the NBER-CES database, obtaining plausible values for this much more heterogeneous sample of firms requires modeling unobserved heterogeneity in the next steps.

Table 2 reports the decomposition of profitability into technological factors, product market power and labor market power corresponding to the production function estimates of Table2 based on the NBER-CES sample of industries. The gross economic rate of profitability is estimated to be 36%, which is somewhat large and can be attributed to the nature of the data. The NBER-CES data aggregates the Census data on manufacturing establishments, and hence can be excluding many firm outlays that are consigned in headquarters and warehouses not included in manufacturing.[2] The decomposition looks very reasonable and shows that the largest contributor to the 36% profitability is market power in the product market: the fact that US manufacturing firms charge prices that are, on average, 20% above marginal costs implies a contribution to profitability of 18 percentage points. The contribution of technology to profitability amounts to 12 percentage points, originating from marginal costs being 19% above average variable costs. The fact that a firm's marginal revenue product of labor is on average 20% higher than the wage it pays to its workers implies a contribution of market power in the labor market to profitability of 6 percentage points.

4 Concluding remarks

Some economists have attributed to US corporate profits a sustained rise relative to sales since 1980. The possibility of persistent supranormal profits to the detriment of social welfare has raised concerns about business dynamism and economic inequality arising from rents. In this paper, we assess the contribution of technology, and market power in product and labor markets to firms' profitability in US manufacturing. In doing so, our study expands upon Azzam et al. (2025), which focuses on the US meatpacking industry, by extending it to a multi-industry setting.

We measure markups and markdowns relying on the production function approach without specifying the demand for the firm's product or the its labor supply and and placing no restriction on the nature of competition in these markets. To avoid bias in the marginal productivity of labor arising from labor-augmenting productivity, we control for Hicksian and labor-augmenting productivity. We estimate the long and short-run elasticities of scale and the wage markdown. These estimates allow us to infer the price-cost markup and evaluate the contributions of technology, markups and markdowns to short-run profitability. We want to perform the decomposition using two datasets spanning 1958-2018. The first is the NBER-CES database, which provides industry-level data for 468 six-digit NAICS industries in US manufacturing, treating industries as representative firms and the second is Compustat, which contains cleaned data for approximately 5,600 publicly traded US companies.

[2]Although this may imply a problem for the assessment of the level of the markup since an exaggeration in the level of short-run profitability would be by construction bias up the value for the markup, it should be less for the variation in the markup over time.

Preliminary results show that average profitability over 1958-2018 period is about 36%. The largest contributor to this profitability is market power in the product market, price-cost markups, which have remained relatively stable over time, contribute 18 percentage points. The contribution of technology to profitability amounts to 12 percentage points, originating from marginal costs being 19% above average variable costs in equilibrium. The fact that a firm's marginal revenue product of labor is on average 20% higher than the wage it pays to its workers implies a contribution of wage markdowns to profitability of 6 percentage points. Repeating the analysis using Compustat firm-level data tends to give compatible results, further investigation is needed.

While our estimates are still preliminary, they reveal a great potential for analyzing cross-sectional heterogeneity and changes over time. In addition, our production function specification is implicitly estimating simultaneously the entire distribution of Hicks-neutral and labor-augmenting productivity across both dimensions. The next steps involve finalizing the estimations and decomposing profitability, including observable determinants of monopsony power to better explain the observed heterogeneity.

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Table 1: Production function estimation 1959-2018

Parameters and Elasticities	NBER-CES Industries[a]	Compustat Firms[b]
Autoregressive (ρ)	0.975	0.987
(s.e.)	(0.003)	(0.003)
Long-run scale (λ)	0.926	0.702
(s.e.)	(0.023)	(0.041)
Short-run scale (ν)	0.886	0.514
(s.e.)	(0.030)	(0.053)
Elasticity of substitution (σ)	0.772	0.459
(s.e.)	(0.079)	(0.905)
Wage markdown (τ)	0.199	0.895
(s.e.)	(0.163)	(5.524)
Elasticity of capital (β_K)	0.040	–
(s.e.)	(0.013)	–
Elasticity of labor (β_L)	0.254	–
(s.e.)	(0.009)	–
Elasticity of materials (β_M)	0.633	–
(s.e.)	(0.021)	–
Industries/Firms	468	5,621
Observations	28,080	65,006

[a]: Instruments are constant, time dummies, $k, k_{-1}, m_{-1}, \ln(s_{L,-1})^2, w_{-1}, w_{-1}^2, p_{M,-1}, p_{M,-1}^2, p_{-1}, p_{-1}^2$.
[b]: Instruments are constant, time dummies, $k, k_{-1}, k_{-1}^2, m_{-1}, \ln(s_{L,-1}), \ln(s_{L,-1})^2, \ln(s_{L,-1})^3, w_{-1}, w_{-1}^2, p_{M,-1}, p_{M,-1}^2$.

Table 2: Decomposition of Profitability 1959-2018 (%)

Sample	Gross Profit ($\ln \frac{R}{VC}$)	Technology ($-\ln \nu$)	Product Market Power ($\ln \mu$)	Labor Market Power ($\ln(1+S_L\tau)$)
NBER-CES Industries	0.357	0.121	0.181	0.055
Compustat Firms	–	–	–	–

A Data Appendix

A.1 NBER-CES data

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 et al. (2013)).

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 28,548 observations. We use the variables *EMP*(employment), *PAY* (payroll), *VSHIP* (shipments), *MATCOST* (cost of materials), *CAP* (real capital) and the deflators *PISHIP* (shipments), *PIMAT* (materials), and *PIINV* (investment). ll 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 an 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 matching with Compustat (where firms are assigned to SIC codes).

A.2 Compustat data

We downloaded the Compustat data from Wharton Research Data Service (WRDS) on September 15, 2021. We use all available firms classified (SIC codes) as manufacturing in the Fundamentals Annual North America Compustat Data from 1958 to 2018. 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 for more details, seeJaumandreu and Mullens (2024)).

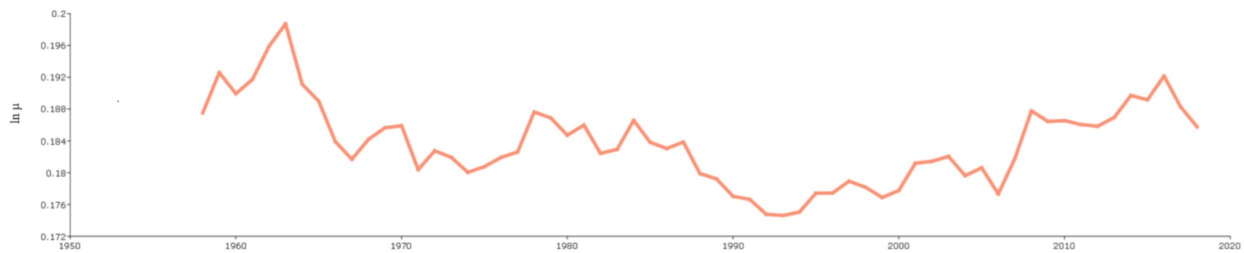
To employ an identical sample throughout the different measurements we keep a firm-year if it is not missing (or zero or negative value) any of the variables measuring sales, employment, variable costs and assets (*sale*, *emp*, *cogs*, *xsga*, *ppent* and *ppegt*). It turns out there are no years left 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.[3] 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 sample with available information follows the same pattern as the original over time. However, the effect of missing information tends to grow somewhat over time. Additionally, only a subset of firms in the Compustat sample report the key variable of the wage bill. To address this limitation, we use the subsample of wage-reporting firms and the NBER-CES data simultaneously to impute average wages and hence wage bills to the remaining firms. This process is facilitated by the similarity of wage data across both sources. As a result of this imputation and the exclusion of firms with particularly negative margins, the number of firms or sequences in the regression differs slightly.

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

B Additional Results

Appendix Figure B1: Markup evolution from 1959-2018



Note: This figure shows the evolution of the estimated price-cost markup ($ln\mu$) over the 1959-2018 period based on the NBER-CES database.