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Markups in US food manufacturing accounting for non-neutral productivity

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Abstract

We examine the evolution of productivity and markups in US food and beverage manufacturing from 1959 through 2018. We account for non-Hicks-neutral (labour-augmenting) productivity changes and compare markups with those in general manufacturing using the same dataset and model. We also compare our results with those of the increasingly popular De Loecker and Warzynski (2012, American Economic Review, 102, 2437) method, which does not account for non-Hicks-neutral productivity growth. Empirical results show that productivity growth in the food and beverage sector has been relatively slow and driven with equal intensity by Hicks-neutral and labour-augmenting productivity gains. General manufacturing shows higher productivity growth that is mostly labour-augmenting, with markups comparable to those of food manufacturing. We find that accounting for labour-augmenting productivity produces more moderate markup estimates than the De Loecker and Warzynski (2012) method. We also find no evidence of markups rising in either food manufacturing or general manufacturing in the last 20 years, in contrast to much of the recent economic literature.

KEYWORDS

food processing, market power, markups, productivity, technology

JEL CLASSIFICATION

D24, J24, L11, L13, L66

1 | INTRODUCTION

The joint study of productivity and markups in food manufacturing is important for at least two reasons. First, measuring productivity and identifying its drivers permits assessment of the impacts of technology on production performance, which in turn provides the basis for estimation of markups. Second, measuring markups is crucial because of the welfare consequences for consumers and agricultural producers if they depart from allocative efficiency benchmarks.

Given the importance of the productivity of the US food manufacturing sector, the paucity of recent studies is striking. The literature is modest and rather dated (Alpay et al., 2002; Azzam et al., 2004; Heien, 1983; Huang, 2003). A common finding is that food manufacturing productivity growth has been modest. However, this work has not used updated microeconomics models able to deal with firm productivity heterogeneity and distinguish between sources of technical change.

More recent models of productivity analysis than those applied to food manufacturing start with Olley and Pakes (1996), who established a procedure to estimate the distribution of unobserved productivity using investment.[1] Levinsohn and Petrin (2003) extended this method to any variable input. More recently, Ackerberg et al. (2015) added observations about identification and proposed an implementation method that has become standard.

In this study we focus on production-based markups, which start with estimating a production or cost function to derive markups, rather than demand-based approaches that start with demand estimation and then derive markups from pricing assumptions (such as Berry et al., 1995; or Nevo, 2001). Production-based markup approaches have resumed their popularity recently with the De Loecker & Warzynski (De Loecker & Warzynski, 2012; henceforth DLW) method.[2] The DLW method estimates markups by computing the ratio of the estimated elasticity of a variable input to its input share in revenue, adopting the Ackerberg, Caves, and Frazer (ACF) procedure to estimate the elasticity and assuming Hicks-neutral technical change.[3] It has been applied to the French food manufacturing industries to examine the role of exports or imports in markups (Curzi et al., 2021; Jafari et al., 2022). Previous work using the DLW method points to increasing markups as a trend in general manufacturing and other industries (see De Loecker et al., 2020 and the comments in Basu, 2019; Berry et al., 2019; Syverson, 2019; and Dopper et al., 2022). These findings, however, may be partly due to the utilisation of models that lack the flexibility to capture changes linked to labour-augmenting technologies—such as automation, which are empirical facts, thus leading to biased markups (Demirer, 2022; Doraszelski & Jaumandreu, 2021; Raval, 2023).

This article makes three contributions to the literature on productivity and markups. First, it updates productivity growth measures in US food manufacturing. Second, it estimates production-based markups accounting for non-Hicks-neutral technical change, specifically labour-augmenting productivity, without determining the nature of competition and considering the most recent developments in the production approach. To our knowledge, no previous study of US food manufacturing productivity or markups has included non-Hicks-neutral productivity, particularly considering labour-augmenting technical

[1] Melitz and Polanec (2015) explain how to describe this productivity in what they call 'dynamic OP decomposition of productivity'.

[2] Analysis of production integrated with markups in food manufacturing was mainly addressed using the New Empirical Industrial Organisation (NEIO) approach (Bhuyan & Lopez, 1997; Lopez et al., 2002; Lopez et al., 2018; and Koppenberg & Hirsch, 2021; Lee & Van Cayseele, 2022; see Sexton & Lavoie, 2001, and Kaiser & Suzuki, 2006 for a review of earlier NEIO studies).

[3] For an application of the DLW method to input price markdowns, see Rubens (2023).

change. Third, the productivity and markups estimates are compared to those from general manufacturing using the same model and data sources, as well as those generated by the DLW approach.

As in earlier studies, our findings indicate that productivity has been slow in US food manufacturing, with a mean growth of less than 1% per year (that we split evenly between labour-augmenting and Hicks-neutral growth). The estimated average markups are in the range of those from previous studies of US food manufacturing, and both the markups in food and in general manufacturing have been remarkably stable during the last 20 years. This contrasts with recent findings that point to rising markups in the last 20 years, particularly those using the DLW method. Controlling for labour-augmenting productivity, our approach produces more reasonable markups than the DLW approach.

2 | EMPIRICAL FRAMEWORK

2.1 | The setup and alternative procedures

Markups can be computed from the estimation of the production function.[4] This form of estimating markups has been called the 'production approach' because it does not need either the specification and estimation of the demand function or knowledge of firms' pricing behaviour. We introduce non-neutral productivity growth by adding in the production function the possibility of labour-augmenting productivity. Consider the following production function:

$$Q_{jt} = F\left(K_{jt}, \exp\left(\omega_{Ljt}\right)L_{jt}, M_{jt}\right)\exp\left(\omega_{Hjt}\right)\exp\left(\varepsilon_{jt}\right) = Q^*_{jt}\exp\left(\varepsilon_{jt}\right),$$

where K_{jt}, L_{jt} and M_{jt} are capital, labour and materials, ω_{Hjt}, and ω_{Ljt} represent Hicks-neutral and labour-augmenting productivity, respectively, and Q^*_{jt} measures output without the error. Thus, a pure Hicks-neutral technical change is the special case when $\omega_{Ljt} = 0$. The error ε_{jt} is usually assumed not to be autocorrelated and to be uncorrelated with everything.

Take the first order condition for cost minimisation of variable factor X (labour or materials), writing MC_{jt} for marginal cost, $\mathrm{MC}_{jt}\frac{\partial Q^*_{jt}}{\partial X_{jt}} = W_{Xjt}$. Multiply both sides by $\frac{X_{jt}}{Q^*_{jt}}$, divide by MC_{jt}, and substitute observed output for Q^*_{jt}, to obtain:

$$\beta_{Xjt} = \mu_{jt}S^R_{Xjt}\exp\left(\varepsilon_{jt}\right), \tag{1}$$

an expression that relates the elasticity for the variable factor β_{Xjt}, the markup μ_{jt}, the observed share of the cost of the variable factor in revenue S^R_{Xjt} and the error of the production function.

De Loecker and Warzynski (2012) solve Expression (1) for μ_{jt} and propose to estimate the markup as:

$$\hat{\mu}_{jt} = \frac{\hat{\beta}_{Xjt}}{S^R_{Xjt}}\exp\left(-\hat{\varepsilon}_{jt}\right), \tag{2}$$

obtaining $\hat{\beta}_{Xjt}$ and $\hat{\varepsilon}_{jt}$ from estimating the production function using the ACF procedure.

[4]Having prices, the production function allows to identify the marginal cost, the other component of markups.

Doraszelski and Jaumandreu (2021) detect that this method, when markups are heterogeneous, generates three biases. The first two are related to the use of the ACF procedure including extra unobservables, and we briefly explain them in Appendix 1. The third, and most important for our context, is caused by neglecting the implications of labour-augmenting productivity for labour elasticity. Many recent papers have confirmed that labour-augmenting productivity is an important empirical fact (Demirer, 2022; Doraszelski & Jaumandreu, 2018; Raval, 2019, 2023; see also Acemoglu & Restrepo, 2018, 2020).

As Hicks (1932) established, with an elasticity of substitution smaller than one, labour-augmenting productivity reduces the share of labour in cost and revenue.[5] Labour elasticity can be written $\beta_{Ljt} = \nu_{jt} S_{Ljt}$, where S_{Ljt} is the share of labour in variable cost and ν_{jt} is the short-run elasticity of scale.[6] The elasticity, therefore, will fall following the fall of the share. It is easy to see that a too rigid specification of labour elasticity in Equation (2) will induce a bias across units and over time.

Doraszelski and Jaumandreu (2019) propose to use the first order conditions (FOCs) for labour and materials. Adding the two expressions, one obtains:

$$\nu_{jt} = \mu_{jt} \frac{\mathrm{VC}_{jt}}{R_{jt}} \exp\left(\varepsilon_{jt}\right),$$

where $\nu_{jt} = \beta_{Ljt} + \beta_{Mjt}$ is the short-run elasticity of scale. Hence, the expression:

$$\frac{R_{jt}}{\mathrm{VC}_{jt}} = \frac{\mu_{jt}}{\nu_{jt}} \exp\left(\varepsilon_{jt}\right) \tag{3}$$

can be used to estimate the markup. Estimating the parameter of scale ν from the production function, the markup can be estimated consistently by taking averages across units of the ratio $\ln \frac{R_{jt}}{\mathrm{VC}_{jt}}$, corrected by $\ln \hat{\nu}_{jt}$. This makes the estimate less sensitive to the estimation of β_{Xjt}, but the production function estimation must have accounted for labour-augmenting productivity and been estimated according to a procedure free of prediction error (e.g., dynamic panel, see Appendix 1).

2.2 | Measurement of non-neutral productivity growth

To simultaneously measure Hicks-neutral and labour-augmenting productivity we follow Doraszelski and Jaumandreu (2019), using a translog production function that is separable in capital and homogeneous of degree ν in the variable inputs labour and materials. A translog production function is a second-order approximation in logs to any arbitrary production function (unlike the Cobb–Douglas [CD] function, which is a first order approximation; see Chambers, 1988). Departing from Cobb–Douglas enables us to find an elasticity of substitution that is different from one and, hence, makes it possible to identify input-augmenting productivity.[7]

[5]See, for example, Jaumandreu (2022) for a precise statement and proof with a production function separable in capital and homogeneity of some degree in the variable factors. In Acemoglu and Restrepo (2018), automation of tasks has the same effect.

[6]To see this, multiply both sides of the FOC for a variable X factor by $\frac{X}{Q^*}$, multiply and divide the right-hand side by AVC, and use the fact that $\frac{\mathrm{AVC}}{\mathrm{MC}} = \nu$ (see Chambers, 1988).

[7]We could have used a constant elasticity of substitution (CES) function, but there is no need or advantage in restricting σ to be constant and thereby greatly complicating the output elasticities of inputs.

Considering the production function to be separable in capital simplifies the treatment considerably, and it is not likely to introduce big differences.[8] Separability in capital, together with the assumption of homogeneity of degree ν in the variable inputs, gives the simplest production function that can deal with the main features we are interested in: an elasticity of substitution that can be different from unity, factor-biased productivity, and, hence, varying shares and elasticities. To this end, consider the following production function:

$$q_{jt} = \alpha_0 + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK} k_{jt}^2 + \alpha_L\left(\omega_{Ljt} + l_{jt}\right) + \frac{1}{2}\alpha_{LL}\left(\omega_{Ljt} + l_{jt}\right)^2 + \alpha_M m_{jt} + \frac{1}{2}\alpha_{MM} m_{jt}^2 + \alpha_{LM}\left(\omega_{Ljt} + l_{jt}\right) m_{jt} + \omega_{Hjt} + \varepsilon_{jt}, \tag{4}$$

where output for firm j at time t (q_{jt}) and inputs (k_{jt} = capital, l_{jt} = labour, and m_{jt} = materials) are expressed in natural log values, and which allows for Hicks-neutral productivity ω_{Hjt} and labour-augmenting productivity ω_{Ljt}. Impose homogeneity of degree$\alpha_L + \alpha_M$ in L_{jt} and M_{jt} by setting $-\alpha_{LL} = -\alpha_{MM} = \alpha_{LM} \equiv \alpha$.[9] The production function becomes:

$$q_{jt} = \alpha_0 + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK} k_{jt}^2 + \alpha_L\left(\omega_{Ljt} + l_{jt}\right) + \alpha_M m_{jt} - \frac{1}{2}\alpha\left(m_{jt} - \omega_{Ljt} - l_{jt}\right)^2 + \omega_{Hjt} + \varepsilon_{jt.} \tag{5}$$

The elasticities of output with respect to variable inputs L_{jt} and M_{jt} are[10]:

$$\begin{aligned} \beta_{Ljt} &= \frac{\partial q_{jt}}{\partial l_{jt}} = \alpha_L + \alpha\left(m_{jt} - \omega_{Ljt} - l_{jt}\right), \text{and} \\ \beta_{Mjt} &= \frac{\partial q_{jt}}{\partial m_{jt}} = \alpha_M - \alpha\left(m_{jt} - \omega_{Ljt} - l_{jt}\right), \end{aligned} \tag{6}$$

and the short-run elasticity of scale is given by $\nu = \beta_{Ljt} + \beta_{Mjt} = \alpha_L + \alpha_M$.

Note that we need to control for two unobservable heterogeneous productivities, ω_{Hjt} and ω_{Ljt}, which makes the problem non-trivial. We use the traditional dynamic panel approximation to control for Hicksian productivity ω_{Hjt}, assuming that it follows a linear inhomogeneous Markov process, $\omega_{Hjt} = \beta_t + \rho\omega_{Hjt-1} + \xi_{jt}$. We first explain how we use the FOCs of the variable factors to derive an expression in terms of observables to control for labour-augmenting productivity ω_{Ljt}.

Taking the FOCs for the two variable inputs and dividing one by the other (see Appendix 2) yields:

$$\omega_{Ljt} = \left(m_{jt} - l_{jt}\right) + \frac{\alpha_L}{\alpha} - \frac{\alpha_L + \alpha_M}{\alpha} S_{Ljt}, \tag{7}$$

where S_{Ljt} is the share of labour cost in variable cost. Using this expression to replace unobservable labour-augmenting productivity ω_{Ljt} in the production function results in the new expression:

$$q_{jt} = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK} k_{jt}^2 + \left(\alpha_L + \alpha_M\right) m_{jt} - \frac{1}{2}\frac{\left(\alpha_L + \alpha_M\right)^2}{\alpha} S_{Ljt}^2 + \omega_{Hjt} + \varepsilon_{jt}, \tag{8}$$

[8]The production function is separable in capital because we can write F(.) as $F\left(K, H\left(\exp\left(\omega_L\right)L, M\right)\right)$. This implies that the relative marginal productivities of labour and materials are independent from capital. In Equation (5), this is reflected by the absence of interaction terms with capital.

[9]Homogeneity of degree ν implies that if we multiply the variable inputs by λ, output is multiplied by λ^{ν}. Notice that multiplying the variable inputs in (5) by λ (adding $\ln\lambda$ to each variable log-input) and simplifying under the parameter equality restrictions is the same as multiplying the output by λ^{ν}(i.e., we get the additional term $\nu\ln\lambda$).

[10]The elasticity with respect to observed labour L_{jt} is the same as the elasticity with respect to exp (ω_{Ljt}) L_{jt}, since $\frac{\partial q_{jt}}{\partial l_{jt}} = \frac{\partial q_{jt}}{\partial\left(\omega_{Ljt} + l_{jt}\right)}\frac{\partial\left(\omega_{Ljt} + l_{jt}\right)}{\partial l_{jt}} = \frac{\partial q_{jt}}{\partial\left(\omega_{Ljt} + l_{jt}\right)} = \beta_{Ljt}$.

in which only the unobservable Hicks-neutral productivity ω_{Hjt} is left.

Subtracting the same equation lagged one period and multiplied by ρ (the autoregressive parameter of ω_{Hjt}), one can write:

$$q_{jt} = \gamma_0 + \beta'_t + \rho q_{jt-1} + \alpha_K \left(k_{jt} - \rho k_{jt-1}\right) + \frac{1}{2}\alpha_{KK}\left(k_{jt}^2 - \rho k_{jt-1}^2\right) + \left(\alpha_L + \alpha_M\right)\left(m_{jt} - \rho m_{jt-1}\right) - \frac{1}{2}\frac{\left(\alpha_L + \alpha_M\right)^2}{\alpha}\left(S_{Ljt}^2 - \rho S_{Ljt-1}^2\right) + u_{jt}, \tag{9}$$

where $\gamma_0 = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} - \rho\left(\alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha}\right)$, $\beta'_t = \beta_t - \rho\beta_{t-1}$, and the composite error is $_{jt} = \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}$. This approach, called dynamic panel estimation, controls unobserved Hicks-neutral productivity through pseudo-differencing the variables. We proceed to estimate Equation (9) by non-linear GMM. Once we obtain the parameter estimates, we can obtain estimates for ω_{Ljt} and ω_{Hjt} for every industry and year, and hence detailed productivity growth.

2.3 | Measurement of markups

We estimate ν from the input elasticities in Equation (9) and compute the log of the short-run markup as follows[11]:

$$\ln\hat{\mu}_{jt} = \ln\frac{R_{jt}}{VC_{jt}} + \ln\hat{\nu}_{jt}. \tag{10}$$

Of course this means that our individual estimates have an error:

$$\ln\hat{\mu}_{jt} = \ln\mu_{jt} + \left(\ln\hat{\nu}_{jt} - \ln\nu_{jt}\right) + \varepsilon_{jt},$$

but we expect this error to cancel when we take averages across industries and time. Formally, if $\hat{\nu}$ is consistent, then $E\left(\ln\hat{\mu}_{jt}\right) = \ln\mu$. We apply Equation (10) to estimate markups for the food and general manufacturing across industries over time using the data described below.

3 | DATA AND ESTIMATION

The main data source for production, revenues, prices, and variable cost is the NBER-CES Manufacturing Productivity Database (Becker et al., 2021), which has been recently updated to 2018.[12] The data is available at the six-digit North American Industrial Classification System (NAICS) code level for 1958–2018. This public dataset contains yearly observations on value of shipments (sales) and expenses on inputs (labour, material, energy, capital) as well as price deflators for the value of shipments, materials, energy and investment. We divide the inputs into three categories: labour, materials, and capital.[13] Capital is measured with nominal values

[11]Without the correction for the ratio of average variable cost to marginal cost, our measure can be taken as an approximation of gross economic profitability, $\ln\frac{R}{\mathrm{VC}} = \ln\frac{1}{1-\pi} \simeq \pi$, where $\pi = \frac{R - \mathrm{VC}}{R}$.

[12]Like its predecessor, the updated NBER-CES database aggregates results from the Annual Survey of Manufactures and the quintennial Census of Manufactures, bridging the inter-Census years with the Annual Survey of Manufactures data. An advantage of using this database is that it has concatenated various definitions of sectors over time, and it has been widely used, allowing for comparison of results. In 2018, the Census of Manufactures covered approximately 650,000 establishments, of which about 48,000 were in food manufacturing.

[13]Energy costs were excluded from variable costs as they accounted for less than 2% of average total variable cost expenses.

of fixed assets, which include machinery and equipment, and then deflated by the investment price deflator. For labour, we compute average wages by dividing labour expenses by the number of employees. We deflate the value of shipments and materials by their respective price deflators.

For our purposes, we include NAICS codes for 55 food manufacturing sectors (49 under NAICS = 311, food; and 6 under NAICS = 312, beverages) for which data was observable for 61 years (1958–2018). As we drop the first observation for each industry to use the lags of the variables, this results in 3300 observations. In addition, for comparison of productivity rates and markups, we also apply the model to all 468 US manufacturing sectors with continuous data from 1958–2018 (28,080 observations).[14]

Table 1 shows descriptive statistics for food and beverage manufacturing. Revenue, capital and employment growth seem to have slowed down since the 1958–1980 period. The labour share of variable cost declined by a bit over two percentage points, in part because of its late recovering (see Figure 1). This is in contrast with the fall of nearly eight percentage points for all manufacturing (not shown here). This will have consequences for our estimates. An important caveat is that our analysis proceeds with data aggregated at the industry level, although our model is intrinsically a firm-level model.[15]

We estimate our baseline model using a translog production function that accounts for both Hicksian and labour-augmenting productivity, using pseudo-differences and non-linear GMM. The results are shown in Table 2. From the ν_{jt} estimates of the production function we estimate markups as in Equation (10). Instruments are detailed in the footnotes of the table. For comparison, we estimate the DLW model. We apply the ACF procedure, regressing (log) output on inputs (k = capital, l = labour, and m = materials) and the prices of labour and materials scaled by the price of output using a complete polynomial of order five in the variables. In the second stage, we fit in turn a Cobb–Douglas and a translog production function. We then compute the log of the markup estimated according to Equation (2) applied to labour, as in DLW and papers that have followed it. Results are reported in Table 4 (the instruments used in estimation are detailed in the table notes). The empirical production and markup results are presented below.

4 | RESULTS AND DISCUSSION

4.1 | Elasticities and productivity results

Table 2 displays estimates of the translog production function with labour-augmenting productivity for the food and all manufacturing industries. Both estimates look similar. The estimated short-run elasticity of scale, or sum of the elasticities of labour and materials, for the food and beverage industries is 0.886. The elasticity with respect to capital is imprecisely estimated at 0.088. The sum of these two elasticities implies a long-run production function with approximately constant returns to scale. The large variance in the elasticity

[14]The data is available in two versions: SIC (Standard Industrial Classification) codes prior to 1997, which contained 459 industries in 1987, and NAICS codes, which contained 473 industries in 1997 (NBER-CES Manufacturing Industry Database, 2021). We worked with 468 NAICS codes that had complete data because some industries' observations are missing from 1958–1996, as new industries emerged or were reclassified under the 1997 NAICS codes.

[15]By necessity, we use industry data at the six-digit NAICS level. Our estimation would only be equivalent if each industry consisted of a representative firm replicated as many times as the number of firms. For a given industry, the ratio of revenue to variable cost can be written as a sum of individual ratios weighted by variable cost weights. Any parameter estimates and computation done with the industry magnitudes ignores changes that may happen in the distribution of the ratios and the weights. There is no reason, however, to expect large biases because of this. Nevertheless, inappropriate use of individual data, such as weighting the estimated markups by revenue that have not been controlled by labour-augmenting productivity, is likely to produce acute biases (see, for example, Jaumandreu, 2022).

TABLE 1 Descriptive statistics for food and beverage manufacturing.[a]

Variable	Unit	1959–2018	1959–1980	1980–2000	2000–2018	2009–2018
		Mean[b] (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
		(1)	(2)	(3)	(4)	(5)
Revenue	Growth[c]	0.047 (0.101)	0.070 (0.115)	0.038 (0.089)	0.033 (0.091)	0.023 (0.076)
Output price	Growth	0.029 (0.087)	0.044 (0.107)	0.022 (0.072)	0.020 (0.077)	0.009 (0.083)
Capital	Growth	0.026 (0.050)	0.044 (0.049)	0.018 (0.033)	0.013 (0.058)	0.010 (0.070)
Employment	Level, thousands	29,018 (39,941)	30,700 (42,495)	28,109 (36,625)	28,113 (40,297)	27,785 (39,020)
	Growth	−0.002 (0.071)	−0.001 (0.068)	−0.006 (0.069)	0.003 (0.075)	0.010 (0.065)
Labour cost share in VC	Level	0.158 (0.093)	0.167 (0.283)	0.155 (0.085)	0.149 (0.086)	0.138 (0.083)
$\ln \frac{R}{VC}$	Level	0.402 (0.276)	0.103 (0.154)	0.421 (0.263)	0.519 (0.339)	0.502 (0.329)
Wage	Growth	0.042 (0.044)	0.058 (0.047)	0.041 (0.042)	0.025 (0.045)	0.022 (0.041)
Price of materials	Growth	0.030 (0.085)	0.039 (0.096)	0.018 (0.081)	0.026 (0.072)	0.013 (0.083)

[a] Census of Manufactures/Annual Survey of Manufacturers as aggregated in NBER-CES database at the 6-digit NAICS codes for industries in NAICS 311 and 312. Total: 55 industries per year.

[b] Mean across the 55 industries over the indicated time periods.

[c] Log rates.

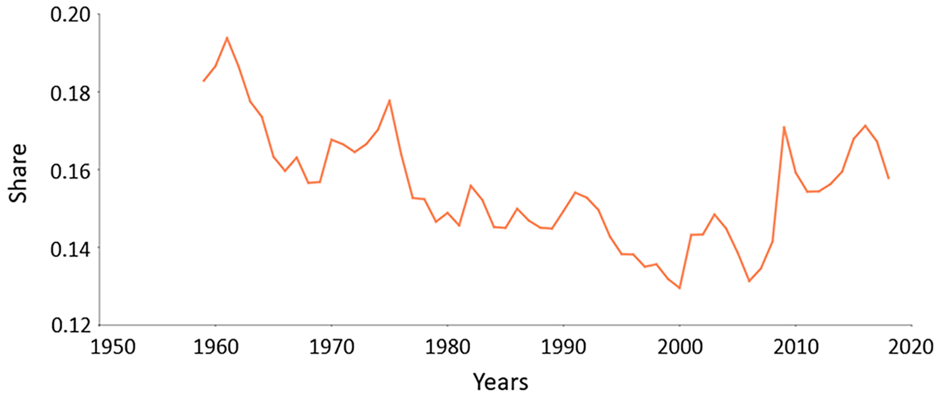

FIGURE 1 The share of food and beverage shipments in total manufacturing. [Colour figure can be viewed at wileyonlinelibrary.com]

of capital is likely due to the estimates of capital for the first 20 years of the sample. The starting NBER-CES values of the stock of capital seem somewhat small, and the growth of capital during this period becomes huge. However, the mean values of the estimated parameters seem reasonable. The average implicit elasticities of substitution are 0.558 and 0.706 for food and beverage and all manufacturing, respectively. These sensible estimates support the use of the translog function. The relative elasticities of labour and materials, 0.138/0.886 = 0.156 and 0.748 / 0.886 = 0.844, respectively, show a lower and greater weight of the inputs labour and materials for food and beverage manufacturing than for all manufacturing. However, labour elasticity dispersion across industries, shown in quartiles, mirrors that of the entire manufacturing sector.

Labour-augmenting productivity is described by its output effect: that is, the effect of the increase in labour efficiency on output, which equals the value of the growth of labour-augmenting productivity multiplied by the elasticity of labour. Mean annual total productivity growth is low at 0.004 + 0.004 = 0.008, less than one percentage point. It is, however, evenly split between labour-augmenting and Hicks-neutral productivity in food and beverage manufacturing, which also trails productivity in general manufacturing, mostly due to slower labour-augmenting productivity growth. The evolution of both productivities is depicted in Figure 2. Figure 3 depicts their variation across industries.

Our estimated 0.8% annual growth aligns with prior research, reflecting the historically low productivity growth. For instance, Heien (1983) estimates a total factor productivity growth rate of 0.7% per year for US food manufacturing and distribution for 1950–77, close to our average estimate of 0.8%. The NBER-CES estimates that total factor productivity growth, using accounting methods, grew 0.9% per year, on average, between 1959 and 2018.[16] Hossain et al. (2005) estimate an annual productivity growth rate of 0.9%, and Chan-Kang et al. (1999) estimate it at 0.7%, while Morrison (1997) estimates it at 0.5% in these industries. On the high end, Alpay et al. (2002) estimate annual productivity growth between 1971 and 1994 at 1.54%. However, none of the earlier studies decompose productivity to account for labour-augmenting productivity.

4.2 | Markup results

The markups, computed as the log of revenue over variable cost plus the estimated elasticity of scale, are reported in Table 3. For food manufacturing, average markups from 1959 to 2018 are

[16]Note that the results are for 1959–2018 as they used 1958 observations as lagged variables in the estimations.

TABLE 2 Estimated translog production functions with labour-augmenting and Hicksian productivity, 1958–2018.[a]

Production function parameters (SD)					Distribution of elasticities (SE)						Dispersion and growth of productivity (SD)			
					Labour elasticity						Output effect $\beta_L \omega_L$		ω_H	
Time	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	Mean growth	Cross-s. std.dev	Mean growth
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Food manufacturing[b,c]														
0.000	0.088	0.886	0.078	0.926	0.088	0.138	0.052	0.130	0.226	−0.020	0.488	0.004	0.277	0.004
(0.000)	(0.142)	(0.155)	(0.029)	(0.046)	—	(0.081)						(0.070)		(0.079)
All manufacturing[d,e]														
	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)

[a]NBER-CES database at 6-digit NAICS, 55 industries for food manufacturing and 468 industries for all US manufacturing.

[b]Instruments: constant, time trend, and third-degree polynomials in k, $m - l$ and $s_{L,-1}$. Parameters to estimate are six (constant, trend, ρ and three elasticities), so degrees of freedom are five.

[c]Cross-section standard deviation is computed across the 55 industries in 2018. The time trend accounts for almost nothing.

[d]Instruments: constant, time dummies (59), a third-degree polynomial in k, $m - l$ and lagged k, m, l and real input prices (wage and materials). Parameters to estimate are 64 (constant, dummies, ρ and 3 elasticities), so degrees of freedom are four.

[e]Cross-section standard deviation is computed across 368 industries in 2018. Time dummies account for about 0.235 and −0.184, respectively, which can be considered to add 0.004 and −0.003 to the mean growth of productivity, respectively.

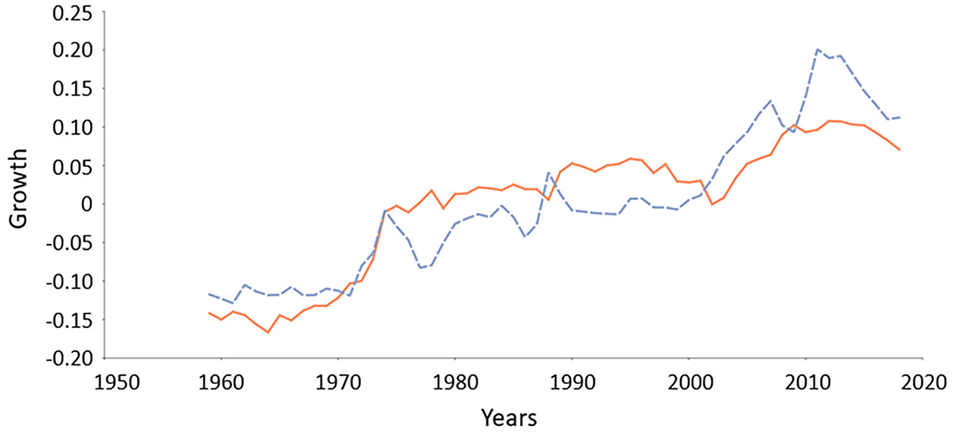

FIGURE 2 Labour-augmenting and Hicks-neutral productivity growth, 1959–2018, in food and beverage manufacturing. Solid line: Output effect of labour-augmenting productivity. Dashed line: Hicks-neutral productivity. [Colour figure can be viewed at wileyonlinelibrary.com]

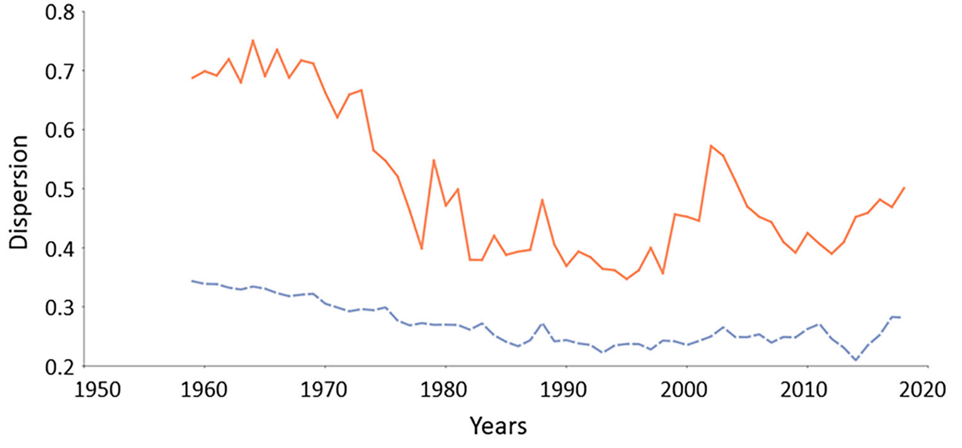

FIGURE 3 Dispersion of labour-augmenting and Hicks-neutral productivity, 1959–2018, in food and beverage manufacturing. Solid line: Standard deviation across industries of the output effect of labour-augmenting productivity. Dashed line: Standard deviation across industries of Hick-neutral productivity. [Colour figure can be viewed at wileyonlinelibrary.com]

estimated at approximately 28% over marginal cost. Figure 4 depicts the evolution of average markup. The elasticity of scale indicates that marginal cost exceeds average variable cost by around 12 percentage points ($\ln 0.886 \simeq -0.12$) and is thus responsible for decreasing the value of $\ln \frac{R}{VC}$ from 40 to 28 percentage points, which stands up well when compared with other studies that estimated markups calculated from the NBER-CES census data. In fact, it is almost identical to the average value computed for the entire manufacturing sector.[17]

The evolution of markups in the food and beverage industries is quite peculiar—different from the evolution of markups in the entire manufacturing sector. Average markup increases a

[17]The margins $\ln\frac{R}{VC}$ computed with Compustat data, which are derived from the financial data of the Standard and Poor's (S&P) companies, are about 15 percentage points lower than those computed with NBER-CES census data, which we attribute to side-stepping accounting factors when dealing with non-manufacturing establishments. From this perspective, our average markup of food and beverage manufacturing would have been 13 percentage points, which seems reasonable. If, in addition, firms have been outsourcing variable costs (e.g., repairs and maintenance, logistics, storage, transportation, contract labour) to non-manufacturing establishments (see Fort et al., 2018), this could increase the census-based markups.

TABLE 3 Estimated means and distribution of markups, 1959–2018.

	1959–2018	1959–1980	1980–2000	2000–2018	2009–2018	1959–2018	1959–1980	1980–2000	2000–2018	2009–2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Food manufacturing					**All manufacturing**				
Markup[a]	0.281	0.162	0.300	0.398	0.381	0.278	0.218	0.286	0.337	0.336
	(0.276)	(0.154)	(0.263)	(0.339)	(0.329)	(0.159)	(0.118)	(0.152)	(0.181)	(0.178)
Mean of industry changes[b]	0.256	0.063	0.192	0.002	−0.034	0.146	0.039	0.086	0.021	0.002
	(0.302)	(0.086)	(0.232)	(0.275)	(0.190)	(0.174)	(0.095)	(0.135)	(0.160)	(0.138)
Prop. of negative changes	0.091	0.218	0.073	0.509	0.618	0.130	0.252	0.218	0.404	0.479
Q3 of changes	0.311	0.126	0.229	0.054	0.028	0.229	0.093	0.132	0.096	0.069
Q2 of changes	0.100	0.054	0.135	−0.015	−0.044	0.141	0.046	0.078	0.021	0.006
Q1 of changes	0.099	0.013	0.056	−0.102	−0.125	0.050	0.009	0.013	−0.051	−0.064

[a] $\ln\mu = \ln\frac{R}{VC} + \ln\hat{\nu}$. For food manufacturing, $\hat{\nu} = 0.886$ and for all manufacturing, $\hat{\nu} = 0.924$, as given by the estimates in Table 2.
[b] As changes are time differences and the panel is balanced, the means of period changes equal the change in the means.

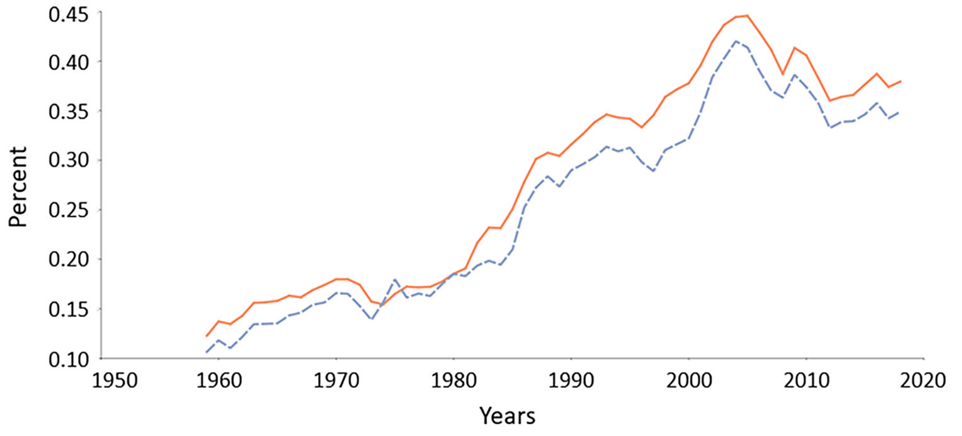

FIGURE 4 Percent markup and markup corrected for the cost of capital, 1959–2018, in food and beverage manufacturing. Solid line: Log of (revenue/variable cost) + scale elasticity. Dashed line: Log of (revenue/variable cost) + scale elasticity – user cost *(capital/revenue). [Colour figure can be viewed at wileyonlinelibrary.com]

little from the beginning of the study period until 1975 and steadily from 1975 to 2005, at which point it falls and becomes stagnant at a value of around 33 percentage points. For example, the steady increase is from 0.165 to 0.446, which implies almost 30 percentage points in 30 years. This corresponds to a decrease in the ratio $\frac{VC}{R}$ to three-quarters of its starting value during this period, which goes far beyond what happens in all manufacturing, where $\frac{VC}{R}$ decreases only to 90% of its initial value during the same time span. This suggests that the forces at work in manufacturing (see footnote 17) may have been operating with special intensity in food manufacturing.

The estimate of an average markup of 28 percentage points is in any case within range of previous estimates for food manufacturing. For instance, using stochastic frontier estimation, Lopez et al. (2018) estimate the average markups to be approximately 21% in US food manufacturing between 1990 and 2010. Bhuyan and Lopez (1997) estimate the average markup at 34% in US food manufacturing between 1972 and 1987. The result also agrees with the estimates for market power reported in Table 1 of the summary by Sheldon and Sperling (2003). Using DLW, Curzi et al. (2021) estimate average markups to be approximately 30% for a sample of French food companies between 2001 and 2013. On the other hand, our average estimate is well below Jafari et al.'s (2022) median markup of 84% above marginal cost for French manufacturing companies between 2011 and 2019.

It is worth noting that estimated food manufacturing markups have been stable during the last 20 years, around 38 percentage points above marginal cost. The same stability pattern holds for general manufacturing, with 34% markups over marginal cost in the same period. This contrasts with the dominant idea in many recent studies that markups have been rising in the general economy for at least 20 years (see De Loecker et al., 2020 and the papers listed in the introduction).[18]

4.3 | Comparison with DLW markups

Table 4 compares the markups estimated with labour-augmenting productivity with the markups estimated using the DLW method (applied with the ACF estimation procedure).

[18]Various alternative possibilities have been offered beyond the obvious idea that market power is indeed increasing, from increases in outsourcing of inputs and labour services (Basu, 2019), to greater product differentiation (Dopper et al., 2022), to increasing importance of fixed costs and intangible capital (Berry et al., 2019; Dopper et al., 2022), and to aggregation biases (Kehrig & Vincent, 2021). Here we offer another reason for biased calculations.

TABLE 4 Comparison of mean markups computed with labour-augmenting productivity and DLW.

	Mean markup across industries and subperiods			
	1959–1980	**1980–2000**	**2000–2018**	**2009–2018**
Procedure of estimation	**(1)**	**(2)**	**(3)**	**(4)**
Food manufacturing				
Own procedure: Translog and LAP	0.162	0.300	0.398	0.381
ACF-DLW with CD[a]	1.022	1.182	1.300	1.350
ACF-DLW with Translog[b]	0.879	1.093	1.243	1.299
Manufacturing				
Own procedure: Translog and LAP	0.218	0.286	0.337	0.336
ACF-DLW with CD[c]	0.487	0.643	0.812	0.847
ACF-DLW with Translog[d]	0.249	0.353	0.462	0.491

[a]Instruments: constant, dummies, polynomial in variable $\boldsymbol{k}$ and lagged $\boldsymbol{k}$, $\boldsymbol{l}$ and $\boldsymbol{m}$. Parameters to estimate are 64 (constant, dummies, $\boldsymbol{\rho}$ and three elasticities), so there are two degrees of freedom.

[b]Instruments: constant, time dummies, third degree polynomial in lagged variables $\boldsymbol{l}$ and $\boldsymbol{m}$ (nine terms), variables$(\boldsymbol{m}-\boldsymbol{l})$ and $(\boldsymbol{m}-\boldsymbol{l})^2$, and lagged variables in real input prices. Parameters to estimate are 65 (constant, dummies, $\boldsymbol{\rho}$, three elasticities and $\boldsymbol{\alpha}$), so there are eight degrees of freedom.

[c]Instruments: constant, time dummies, variable $\boldsymbol{k}$ and lagged variables $\boldsymbol{k}$, $\boldsymbol{l}$ and $\boldsymbol{m}$. Parameters to estimate are 64 (constant, dummies, $\boldsymbol{\rho}$, and three elasticities), so the equation is exactly identified.

[d]Instruments: constant, time dummies, third degree polynomial in $\boldsymbol{k}$, variables$(\boldsymbol{m}-\boldsymbol{l})$ and $(\boldsymbol{m}-\boldsymbol{l})^2$, lagged variables $\boldsymbol{k}$, $\boldsymbol{l}$, $\boldsymbol{l}^2$, $\boldsymbol{m}$, $\boldsymbol{m}^2$. Parameters to estimate are 65 (constant, dummies, $\boldsymbol{\rho}$, three elasticities and $\boldsymbol{\alpha}$), so there are five degrees of freedom.

For pedagogical reasons, and because researchers have often applied the DLW method with a CD function, we compute margins using both a CD and a translog production function. Each production function is also separable in capital and homogeneous in the variable inputs. With a CD function, the elasticity of labour is constant and we expect the markup to be driven cross-section and over time almost exclusively by the labour shares (see Equation 2). With the translog we expect the estimates to improve because the elasticity changes with the ratio of materials to labour. However, in contrast with our procedure, nothing controls for labour-augmenting productivity, so this variation is based on the observed labour as opposed to the 'efficient' labour. If labour augmenting productivity is important, this should still bias the results.

When CD/ACF/DLW is used, markups show an upward bias and increase all the time. The upward bias hinges on an estimated elasticity of labour (0.338 for manufacturing and 0.281 for food manufacturing) that broadly exceeds the labour shares. The upward trend comes from the division of the constant labour elasticity by the labour share. The markups in food manufacturing are particularly huge because the ACF procedure does not provide reasonable estimates of the elasticity of capital versus the elasticity of labour.

When the translog/ACF/DLW is used, markup estimates not only tend to move significantly downward relative to the CD/ACF/DLW, but also show a moderate trend upwards in the last 20 years in either food or general manufacturing. However, this comes at the price of other biases in the estimation: while the translog for food manufacturing shows a reasonable elasticity of substitution of 0.678, the translog for manufacturing flips the sign of a key parameter and the elasticity of substitution becomes 1.384. This would induce biases in the computation of productivity, if this estimate is used. In any case, not controlling for labour-augmenting productivity disables the DLW translog in getting the correct levels and trends in markups.

TABLE 5 Labour-augmenting and Hicksian productivity across food manufacturing industries, 2000–2018.

Relative output effect		Relative ω_H level		ω_L growth[a]		Output effect of ω_L		ω_H growth[a]	
Industries	**Value**	**Industries**	**Growth**	**Industries**	**Value**	**Industries**	**Growth**	**Industries**	**Growth**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Animal food	0.238	Seafood	0.018	Seafood	0.015	Bakeries	0.005	Beverages	0.004
Dairy	0.209	Milling	−0.004	Bakeries	0.015	Meat	0.002	Sugar	0.003
Milling	0.208	Animal food	−0.005	Meat	0.009	Seafood	0.002	Meat	0.002
Meat	0.134	Dairy	−0.024	Animal food	0.008	Sugar	0.001	Dairy	0.002
Seafood	0.090	Beverage	−0.024	Milling	0.007	Fruit and vegetables	0.000	Milling	0.002
Fruit and vegetables	0.077	Bakeries	−0.066	Sugar	0.006	Milling	0.000	Animal food	0.001
Sugar	0.048	Fruit and vegetables	−0.068	Fruit and vegetables	0.003	Animal food	0.000	Bakeries	0.001
Bakeries	−0.328	Sugar	−0.087	Dairy	0.002	Dairy	0.000	Fruit and vegetables	0.000
Beverages	−0.589	Meat	−0.122	Beverages	−0.008	Beverages	−0.003	Seafood	−0.004

[a]Per year.

TABLE 6 Correlations of labour-augmenting and Hicksian productivity.

	ω_L	ω_H	$\Delta\omega_L$	$\Delta\omega_H$
ω_L		0.091		
$\Delta\omega_H$			−0.219	
Capital intensity, $k - l$	0.580	0.210		
Rate of investment, $\frac{I}{K}$	−0.163	−0.017		
Proportion blue collars, $\frac{L_{BC}}{L}$	0.144	0.048		
Wage, W	0.305	0.331		
Output growth, Δq			0.244	0.451

4.4 | Heterogeneity results

Table 5 shows productivity levels and growth from 2000 through 2018 for nine food and beverage manufacturing sectors.[19] Labour-augmenting productivity levels (note that we refer to the output effect of this efficiency) differ significantly, with a 75% maximum gap, while differences in Hicksian productivity growth barely reach 15%. There is, however, some correlation in the ranking of industries that present the highest and lowest productivities. Animal food, dairy, and milling consistently outperform average productivity across industries, while fruits and vegetables, sugar, and bakeries lag the most.

The range of growth rates is very narrow both for the output effect of labour-augmenting productivity and for Hicks-neutral productivity. Average growth stays less than one percentage point, mostly non-negative. Interestingly, industries with below-average productivity tend to show higher labour-augmenting productivity growth, while above-average ones exhibit more Hicks-neutral productivity growth. This suggests a process of convergence in the levels of labour-augmenting productivity that may be consciously stimulated through investments to enhance the productivity of labour. In this regard, Frick et al. (2019) point to strong positive effects of innovation on labour productivity for European food manufacturing firms.

Table 6 reports correlations that provide hints into the drivers of productivity in food and beverage manufacturing. Labour-augmenting and Hicksian productivity growths are weakly correlated. However, labour-augmenting productivity strongly correlates with (the log of) the capital/labour ratio; that is, more capital per worker is associated with a higher productivity of labour. The absence of a significant positive correlation between the labour-augmenting productivity and the rate of investment suggests that this may be more of a long-run relationship. Both productivity types are also positively correlated to labour compensation and demand growth, possibly reflecting compensation for labour skills, and the procyclical character of productivity.

5 | CONCLUSION

Our estimates of productivity growth in US food manufacturing indicate that this has been slow over the years, with nearly equal contributions by labour-augmenting and Hicksian productivity growth. The finding of slow productivity growth is consistent with previous studies that have overlooked labour-augmenting productivity. In contrast, productivity growth

[19]We report for 9 two-digit NAICS industries from the total of 11 as we dropped Miscellaneous and Tobacco and employ abbreviated names.

in general manufacturing has been significantly higher, particularly labour-augmenting productivity.

Our average markup estimates are in the range of previous estimates for food manufacturing. The popular DLW method for estimating markups leads to exaggerated markups, especially in food manufacturing, and markups that tend to increase as the labour share decreases.

By accounting for labour-augmenting productivity, our approach leads to more moderate estimates in the range of 16% to 38% for food manufacturing and 22% to 34% in general manufacturing, and in both cases stable in the last 20 years. In contrast to much of the recent economic literature, we find no evidence of markups rising in either food manufacturing or general manufacturing in the last 20 years and can safely conclude that our methodology provides good estimates of the levels and evolution of productivity and markups in this period.

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CONFLICT OF INTEREST STATEMENT

We declare that we do not have any actual, potential, or perceived financial or other similar interests associated with the content of this journal article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available from the National Bureau of Economic Research at https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

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APPENDIX 1

The ACF procedure contains an error of 'prediction' when markups are heterogeneous and the FOCs used to account for ω_H contain unobservables. For example, cost minimisation formulas contain the unobservable MC (which depends on the heterogeneity of demand), and unobservable labour-augmenting productivity, if it exists, is present modifying measured labour. The error of prediction biases the estimation of the elasticity $\widehat{\beta}_{Xjt}$ and the error $\widehat{\varepsilon}_{jt}$.

The mechanism is the following: The procedure estimates the production function parameters and errors in two stages. The first stage splits q into parts: $\phi(z)$ and ε. The vector of variables z stands for the combination of the arguments of the production function and the 'proxy' function used to account for ω_H. Under the above conditions the split only obtains $q = \widetilde{\phi}(z) + \zeta + \varepsilon$. The error of 'prediction' ζ shows up because not all the variables of the proxy function can be observed. The second stage then obtains the parameter estimates using the estimated $\widetilde{\phi}(z)$ and the markup is corrected with $\widetilde{\varepsilon} = \zeta + \varepsilon$. This generates the biases.

APPENDIX 2

The FOCs for the two variable inputs L_{jt} and M_{jt} are:

$$\mathrm{MC}_{jt}\frac{Q_{jt}}{L_{jt}}\frac{\partial q_{jt}}{\partial l_{jt}} = \mathrm{MC}_{jt}\frac{Q_{jt}}{L_{jt}}\left(\alpha_L + \alpha\left(m_{jt} - \omega_{Ljt} - l_{jt}\right)\right) = W_{jt}$$

and

$$\mathrm{MC}_{jt}\frac{Q_{jt}}{M_{jt}}\frac{\partial q_{jt}}{\partial m_{jt}} = \mathrm{MC}_{jt}\frac{Q_{jt}}{M_{jt}}\left(\alpha_M - \alpha\left(m_{jt} - \omega_{Ljt} - l_{jt}\right)\right) = P_{Mjt}.$$

Related by quotient they give $\frac{\alpha_L + \alpha(m_{jt} - \omega_{Ljt} - l_{jt})}{\alpha_M - \alpha(m_{jt} - \omega_{Ljt} - l_{jt})} = \frac{W_{jt}L_{jt}}{P_{Mjt}M_{jt}} = \frac{S_{Ljt}}{1 - S_{Ljt}}$. Cross-multiplying the terms and rearranging, we obtain $\omega_{Ljt} = \left(m_{jt} - l_{jt}\right) + \frac{\alpha_L}{\alpha} - \frac{\alpha_L + \alpha_M}{\alpha} S_{Ljt}.$