The Dimensions of Productivity Change in the U.S. Food Manufacturing Industries

Rigoberto A. Lopez

Richard DelFavero Professor
University of Connecticut
rigoberto.lopez@uconn.edu

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1. Introduction

U.S. food and beverage manufacturing accounts for approximately one-sixth of the value of shipments, value-added, and employment in all manufacturing. In addition, because agricultural inputs account for most of the cost of food manufacturing, the performance of the food and beverage manufacturing sector is very significant to U.S. agricultural producers as well as to consumers. Given its importance, the paucity of recent studies of the productivity of this sector is striking (e.g., Celikkol and Stefanou, 2004; Huang 2003; Heien, 1983). Measuring productivity and its drivers is important to uncovering the evolving underlying production technology for transforming raw agricultural products into processed ones, which in turn provides a basis for estimation of markups.

The literature on U.S. food manufacturing productivity is modest and rather dated (Heien 1983; Alpay, Kerkvliet, and Buccola, 2002; Huang, 2003; Azzam, Lopez, and Lopez, 2004; Hossain, Jain, and Ramu, 2005). These studies have generally applied either production functions or dual cost function approaches to measure economies of scale , the impacts of technological change on output growth, and the degree of technical substitution between capital, labor, energy, and materials. An underlying finding of the literature on U.S. food manufacturing productivity is that productivity growth has been modest, perhaps due to lack of R&D, and that there are economies of size that support concentration and technical efficiency. Even plant-level studies, by Morrison (2001), using a dual cost function, and Celikkol and Stefanou (2004), who use total factor productivity growth decomposition by quartiles, do not offer much additional insight into assigning such growth to scale and technical change; nor do they address simultaneously within a rigorous microeconomic model of technical and allocative efficiency whether technological change is labor-augmenting and which drivers are behind that change.

More recent models of productivity analysis start with Olley and Pakes (1996), who estimated a production function in the telecommunications industry, using a procedure that allows for estimation of the distribution of unobserved productivity and its changes. Melitz and Polanec (2015) explain and refine the descriptive procedure, calling it "dynamic OP (Olley and Pakes) decomposition of productivity." Levinsohn and Petrin (2003) extended the method for estimating the production function, initially devised for using investment as a proxy for productivity, to any variable input. More recently, Ackerberg, Caves and Frazer (2015) added observations about identification and proposed a method of implementation that has become standard.

Recent studies that use a production function estimation point to an increasing trend in markups in both food processing and other manufacturing industries (see for references Basu, 2019; Berry, Gaynor, and Scott Morton, 2019; or Lopez, He, and Azzam 2018). These findings may be partly due to the utilization of conventional models that lack the flexibility needed to capture important changes in labor-augmenting technologies, automation, and economies of size. Improperly modeling production technology leads to biased estimates not only of productivity but also of ensuing markups under profit-maximizing behavior.

Analysis of productivity integrated with markups has only been, in fact, tangentially addressed in food manufacturing by studies using New Empirical Industrial Organization (NEIO) models grounded in either production or demand theory.[1] NEIO models, which typically estimate

[1] Herein we focus on markups derived from production-based approaches, which start with estimating a production or cost function and derive markups, rather than demand-based approaches that start with demand estimation and then derive markups from pricing assumptions, such as the Berry, Levinsohn, and Pakes (1995) or Nevo (2001) studies.

a cost function with aggregate demand and first-order conditions for profit maximization, include the works of Bhuyan and Lopez (1997), Lopez, Azzam and Lirón-España (2002), and Lopez, He, and Azzam (2018). Earlier NEIO studies of oligopoly and oligopsony power in selected food manufacturing industries are summarized in Sexton and Lavoie (2001) and Kaiser and Suzuki (2006). Studies using standard dual cost functions that do not properly accommodate labor-augmenting technical change find that markups tend to rise over time (Lopez, He, and Azzam, 2018, Table 2).

This article offers two contributions to the literature on productivity and markups in the U.S. food manufacturing industries. First, it updates measures of productivity growth in U.S. food and beverage manufacturing industries while accounting for labor-augmenting technical change. To our knowledge, no previous study of food manufacturing productivity or markups has properly accounted for labor-augmenting technical change that can lead to more reasonable markups than those found in the NEIO literature, where markups typically range between 25 and 45 percent. Our findings with labor-augmenting productivity and taking unobserved productivity shocks into consideration indicate that productivity has been sluggish in this sector in the last 20 years, particularly when compared to the general manufacturing productivity. Secondly, considering that our empirical approach does not require detailed specification of the nature of competition and technology, we also find, unlike previous food manufacturing studies, that the markups have been remarkably stable, at around 10 percent, in the last 20 years

2. Empirical framework

2.1) Measurement of labor-augmenting and Hicks-neutral productivity

To measure productivity, we use the translog production function (separable in capital input) proposed by Doraszelski and Jaumandreu (2019):

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

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

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

The elasticities of the variable inputs L_{jt} and M_{jt} are [2]

$\beta_{Ljt} = \frac{\partial q_{jt}}{\partial l_{jt}} = \alpha_L + \alpha(m_{jt} - \omega_{Ljt} - l_{jt})$, and

$\beta_{Mjt} = \frac{\partial q_{jt}}{\partial m_{jt}} = \alpha_m - \alpha(m_{jt} - \omega_{Ljt} - l_{jt})$,

(3)

where the short-run elasticity of scale is given by $v = \beta_{Ljt} + \beta_{Mjt} = \alpha_L + \alpha_M$. Taking the FOCs for the two variable inputs and dividing one by the other yields the expression

$$\omega_{Ljt} = (m_{jt} - l_{jt}) + \frac{\alpha_L}{\alpha} - \frac{\alpha_L + \alpha_M}{\alpha} S_{Ljt}, \quad (4)$$

where $S_{Ljt} = \frac{W_{jt}L_{jt}}{W_{jt}L_{jt} + P_{Mjt}M_{jt}}$ is the share of labor cost in variable cost. Using this expression to replace the unobservable labor-augmenting productivity ω_{Ljt} in the production function results in the new expression

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

$q_{jt} = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK}k_{jt}^2 + (\alpha_L + \alpha_M)M_{jt} - \frac{1}{2} + \frac{(\alpha_L+\alpha_M)^2}{\alpha} S_{Ljt}^2 + \omega_{Hjt} + \varepsilon_{jt}$, (5)

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

To deal with Hicksian productivity ω_{Hjt} we assume that it follows the linear in the homogeneous Markov process $\omega_{Hjt} = \beta_t + \rho\omega_{Hjt-1} + \xi_{jt}$. Take equation (5) lagged one period, multiply it by ρ, and subtract it from expression (5) with ω_{Hjt} replaced. Then we can express it as

$$q_{jt} = \gamma_0 + \beta_t + \rho q_{jt-1} + \alpha_K (k_{jt} - \rho k_{jt-1}) + \frac{1}{2}\alpha_{KK}(k_{jt}^2 - \rho k_{jt-1}^2)$$

$$+(\alpha_L+\alpha_M)(m_{jt} - \rho m_{jt-1}) - \frac{1}{2}\frac{(\alpha_L+\alpha_M)^2}{\alpha}(S_{Ljt}^2 - \rho S_{Ljt-1}^2) + u_{jt}, \qquad (6)$$

where $\gamma_0 = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} - \rho\,(\alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha})$, and the composite error is $u_{jt} = \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}$. This estimation approach is called a dynamic panel.

In sum, we control for ω_L, replacing it with the expression obtained using the ratio of first order conditions (FOC) for cost minimization. We estimate by nonlinear GMM and recover estimates $\widehat{\omega_L}$ and $\widehat{\omega_H}$ for every industry and year to estimate productivity growth.

2.2) Measurement of markups

We start the analysis of markups with some conventional measurements, such as the ratio revenue to variable costs, following Bain (1951) , $\frac{R_{jt}}{VC_{jt}}$, or De Loecker and Warzynski's (DLW) (2012) proposal to compute the ratio of an input elasticity to the (corrected) share of the input in revenue. DLW estimate the markup $\mu_{jt} = \frac{P_{jt}}{MC_{jt}}$ by reordering the FOC of cost minimization for input $X_{jt,}$ $MC_{jt}\frac{\partial Q_{jt}^*}{\partial X_{jt}} = W_{Xjt}$, as $\frac{P_{jt}}{MC_{jt}} = \frac{\partial Q_{jt}^*}{\partial X_{jt}} / \frac{W_{Xjt}}{P_{jt}}$. Completing the numerator and denominator conveniently and replacing the variable input elasticity $\beta_{Xjt} = \frac{X_{jt}}{Q_{jt}^*}\frac{\partial Q_{jt}^*}{\partial X_{jt}}$ and the disturbance ε_{jt} with estimates, we obtain

$\hat{\mu}_{jt}= \frac{\widehat{\beta}_{Xjt}}{S^R_{Xjt}}$ exp (-$\hat{\epsilon}_{jt}$), where $S^R_{Xjt} = \frac{W_{Xjt}X_{jt}}{P_{jt}Q_{jt}}$ is the input share in revenue. Note that S^R_{Xjt} is based on actual output Q_{jt}, and this is the reason why the correction $\hat{\varepsilon}_{jt}$ is needed.

We then apply Doraszelski and Jaumandreu's (2019) method of starting with the expression for the ratio revenue over variable cost, or price-average variable cost ratio, in terms of the markup:

$$\frac{R_{jt}}{VC_{jt}} = \frac{\mu_{jt}}{v_{jt}} \exp(\varepsilon_{jt}), \tag{7}$$

where v_{jt} is the short-run scale and ε_{jt} is the observation-specific deviation.[3] We denote the elasticity of scale as time-variable to cover the most general case, but in practice we use a constant v. We estimate ν econometrically from equation (6) and compute the log of the short-run markup in the following way:

$$\widehat{\ln \mu_{jt}} = \ln \frac{R_{jt}}{VC_{jt}} + ln\ \widehat{v_{jt}}, \tag{8}$$

We expect the error ε of our measurement to tend to cancel the averages across industries and time, and, hence, we expect our means to be accurate. Formally, if $\hat{\nu}$ is consistent $E\,(\widehat{\ln \mu}) = ln\mu$. We consider short-run (average and marginal) costs.[4] It is important to consider the possibility that part of this markup can be attributed to the cost of capital. To do this, no matter how roughly, we compute by industries and user cost of capital uc and calculate a corrected markup as

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[3] Dividing numerator and denominator of $\frac{R}{VC}$ by quantity Q and assuming that the relationship between Q and the cost relevant quantity Q^* is $\frac{Q}{Q^*} = \exp(\varepsilon)$, we have $\frac{R}{VC} = \frac{P}{AVC} \exp(\varepsilon)$. In a cost minimizing firm, the elasticity of scale ν equals AVC/MC. See, for an extended discussion, Doraszelski and Jaumandreu (2019).

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

$$\widehat{\ln \mu_{Jt}} = \ln \frac{R_{jt}}{VC_{jt}} + ln\ \widehat{v_{Jt}} - uc_{jt} \frac{k_{jt}}{R_{jt}}, \quad (9)$$

where uc_{jt} denotes the user cost of capital for firm or industry *j* in year *t*. Thus, we apply equations (8) and (9) to estimate markups for the food manufacturing and non-food manufacturing industries over time and across industries using the data described below.

3.) Data and estimation

The main data source for production, revenues, and variable cost is the CES-NBER Manufacturing Productivity database (Becker, Gray, and Markalov, 2021), which has been recently updated to 2018.[5] It a public dataset that contains yearly observations on the value of shipments (sales), expenditures on inputs (labor, material, energy, capital), and price deflators for value of shipments, materials, energy, and investment. We divide the inputs into three categories: labor, materials, and capital. For labor, we compute average wages by dividing labor expenses by the number of employees. The data is available at the 6-digit NAICS codes for 1958-2018.

For our purposes, we include NAIC codes for 55 food manufacturing sectors (49 under NAICS=311, food manufacturing; and 6 under NAICS=312, beverages). In addition, for comparison of productivity rates and markups, we also apply the model to 468 U.S. manufacturing sectors with data from 1958-2018.[6]

The CES-NBER database provides annual data on the nominal values of fixed assets, which includes machinery and equipment. However, it lacks information on depreciation rates,

[5] Like its predecessor, the updated CES-NBER database aggregates results from the Annual Survey of Manufacturers and the quintennial Census of Manufacturers, bridging the inter-Census years with the Annual Survey of Manufacturers 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 Manufacturers covered approximately 650,000 establishments, of which, about 48,000 were in food manufacturing.

[6] The data is available in two versions: SIC (Standard Industrial Classification) codes prior to 1997 which contained 459 industries in 1987 and NAICS (North American Industrial Classification System) codes which contained 473 industries in 1997 (NBER-CES Manufacturing Industry Database, 2021). We work with 468 NAICS codes that have complete basic data.

which can, notwithstanding, be computed implicitly. With respect to price capital*,* we compute a user cost of capital services as a general interest rate plus the depreciation rate at the 6-digit NAICS level minus the inflation rate as measured by the variation of the price deflator of the value of fixed assets.

Drawing on Becker, Gray, and Markalov (2021), who updated the CES-NBER database, we estimate the depreciation rate for each industry by backing it out from the perpetual inventory equation $K_{jt} = (1 - d_{jt})K_{jt-1} + INV_{jt}$, where d is the depreciate rate, *K* the value of fixed assets, and *INV* is investment. The rate of depreciation is $d_{jt} = (INV_{jt} / K_{jt-1}) - \left(K_{jt} - K_{K_{jt-1}jt-1}\right) / K_{jt-1.}$ Becker, Gray, and Markalov (2021) take INV from the Federal Reserve Board reports.[7] We use the 10-year interest rate (Bhuyan and Lopez, 1997).

The mean input cost shares for the 55 industries in the sample are listed in Table 1.[8] As expected, the share of the cost of material is dominant, seconded by the cost of labor, and then capital expenditures, and the energy cost share which is minimal in this sector. Therefore, the energy input was merged into materials.

The NBER-CES data was used with equation (6) to estimate Hicks-neutral and labor-augmenting productivity for food manufacturing as well as all U.S. manufacturing (468) for comparative purposes. The models are estimated using pseudo-differences and nonlinear GMM. The instruments used in food manufacturing are a constant, time trend, the variable $(m - l)$, and third-degree polynomials in k, $s_{L,t-1}$and $p_{M,t-1} - p_{t-1}$ (6 degrees of freedom).

Using the ν estimate of the production function and data, we estimate the markups according to equation (8) for U.S. and all manufacturing industries. In addition, we estimate the

[7] More specifically, they were obtained from https://www.federalreserve.gov/releases/g17/related_data/manuf_invest_capital.htm.

[8] Capital expenses were estimated by multiplying the value of fixed assets times the user cost of capital.

markups corrected for variable capital cost given by equation (9). The empirical results for the production function parameters and the markups are presented below.

4) Results and discussion

4.1) Productivity results

Table 2 displays the parameter estimates of the production function for the food and beverage manufacturing industries and for the whole manufacturing sector. The degree of short-run economies of scale v is estimated for food manufacturing at 0.662. This low elasticity implies decreasing economies of scale, which is consistent with the fact that capital adjustments are more easily made in the long-run and that these industries may face capacity constraints in the short-run. When compared to the results for all manufacturing, the food manufacturing industries have a significantly lower degree of short-run economies of scale (0.662 vs. 0.884). These values imply that marginal cost is about 51 percent above the average variable cost in food manufacturing but only 10 percent above the average variable cost in manufacturing in general It can be said that food manufacturing shows lower economies of scale.[9] Moreover, the output elasticity with respect to capital is 0.293, so results point to a long-run elasticity of scale that is close to constant economies of scale (0.955).

The output elasticity with respect to materials is estimated at 0.103 and the elasticity for materials at 0.559 (v - β_L=0.662-0.103). Thus, output is much more responsive to materials than to variations in labor. When we compare the results for the whole manufacturing sector, food manufacturing industries turn out to have not only a significantly lower degree of short-run economies of scale (0.662 vs. 0.884) but also a significantly lower role of labor elasticity in these

[9] It can be shown that v=AVC/MC=1/((Q/VC)(δVC/δQ)), so the inverse of the short-run economies of scale equals in equilibrium the elasticity of variable cost with respect to output (a cost concept).

indicators: 0.103/0.662=0.156 vs. 0253/0.884=0.286. Output in manufacturing is more responsive to variations in labor while a little less responsive to increases in materials (0.631/0.884=0.714 vs. 0.559/0.662=0.844). The distribution of the labor elasticities reveals that the spread in food manufacturing is, in fact, only slightly greater than in the whole manufacturing sector. The ratio of the third to first quartile of the data give 0.169/0.039=4.3 vs. 0.403/0.118=3.4.

What do the results say with respect to productivity growth? First, the average productivity growth for the whole period is modest, and somewhat more modest for food manufacturing industries. The sum of the output effect of labor-augmenting productivity (productivity growth multiplied by the elasticity of output with respect to labor) and Hicksian or neutral productivity, is 1.5 percentage points for the whole sector and 1.2 percentage points for food manufacturing. Second, the composition of this growth in productivity is different. While labor-augmenting productivity doubles Hicksian productivity in the whole manufacturing sector (1 percent versus 0.5 percent), Hicksian productivity is much more important than labor-augmenting productivity in food manufacturing (0.9 percent versus 0.3 percent). This is reflected in the low pace at which the elasticity of labor in food manufacturing is decreasing over time (1.5 percent during the whole period versus 7.5 percent in the whole manufacturing sector). Notice that this also shows that the decrease in the labor share has been insignificant.

The conclusion is thus that Hicks-neutral technical change has played a relatively more important role in food manufacturing than in the general manufacturing sector. Thus, food manufacturing is trending more slowly towards using less labor to maintain their output than other manufacturing industries. This may indicate that, relative to general manufacturing, the food manufacturing industries have been slow in introducing new technology to replace labor, such as robots for automatic tasks. Only more recently, during the COVID pandemic, have labor issues arisen related to worker shortages and health, particularly in industries such as meatpacking that are labor intensive when compared to other food and non-food industries.

4.2) Markup results

The results for the estimated markups in the food manufacturing industries are presented in Table 3. The results for food manufacturing can be compared with the results for the whole manufacturing industry reported in Table 4. The markups for food manufacturing in the first part of the sample seem to be impacted by some problems in the measurement of capital, so we will temporarily focus on the period after 2000. The mean markups (price over marginal cost) for the post-2000 years are estimated at around 10 percent. These markups indicate a significantly lower degree of market power than in previous studies, in which these markups were estimated to be above 25 percent. For instance, for the same industries Lopez, He, and Azzam estimated them at around 25 percent and Bhuyan and Lopez at around 35-40 percent. As indicated below, part of the reason for this is that previous studies do not correct for the degree of decreasing economies of scale ($v<1$). Moreover, markups in food manufacturing have been about a third of the estimated markups in general manufacturing in the last 20 years (0.10 versus 0.31). Thus, our results suggest that food manufacturing is more competitive than was found in previous studies and more competitive than other U.S. manufacturing industries.

The results with markups corrected for capital intensity are of the same magnitude and direction as our benchmark results discussed above. Thus, including the variable cost of capital does not change our main conclusions with respect to markups in food manufacturing or in general U.S. manufacturing. In fact, the estimates of the user cost of capital after 2000 for food manufacturing and the whole manufacturing sector are very similar.

4.3) Explanations for previous high and increasing markups

Table 3 highlights another important and noteworthy finding: markups seem to be remarkably stable in the last 20 years in both food and general manufacturing. Thus, we do not find evidence of increasing markups in these industries, in contrast to recent findings or assertions of increasing markups in U.S. manufacturing (Berry, Gaynor, and Scott Morton, 2019; Basu, 2019). In fact, in the entire manufacturing sector, markups were also quite stable pre-2000, increasing to a new value of approximately five additional percentage points by 2000. We offer several possible explanations for other studies that find rising markups.

First is the use of inadequate elasticity of scale or lack of adjustment for it. From equation (8), v is necessary for the proper estimation of markups, unless v=1. If v<1 (decreasing short-run economies of scale), then we over-estimate markups if we ignore v. This may explain the high markups found in the food manufacturing industries in previous studies. In addition, in terms of trends, the decreasing output elasticities with respect to labor will result in increasing markups if the method by De Loecker and Warzynski (2012) to measure markups is employed.

Second, accounting data problems can result in higher and even increasing markups, in part because the data, such as that from Compustat and Census, represents basic accounting information and not economic data. Several input categories may be classified differently due to missing inputs, such as services (Berry, Gaynor, and Scott Morton, 2019) and outsourcing. For instance, outsourcing of transportation or tasks previously done internally may result in a contrived reduction of labor reported because the labor is now embodied or hidden in contracts with third parties and not reported as employees or in wages.

A third potential reason may be due to the intricacies of aggregation. Aggregate and disaggregated data have different strengths and weaknesses. Our analysis is based on industry rather than firm heterogeneity, which can introduce systematic errors neglecting individual heterogeneity. But disaggregated data can exacerbate the problem of confusing efficiency and market power increases. For example, firms with strong efficiency gains through labor-augmenting productivity will get lower labor elasticities (smaller labor shares in cost) and greater revenue shares (Kehrig and Vincent, 2017, 2020). The gains in efficiency can determine biases in the markup aggregates. However, the NBER-CES dataset only captures industry averages, which avoid this problem.

5) Conclusion

This article provides updates on productivity growth and markups for 55 U.S. food and beverage industries in the post-1958 period and compares these results to general manufacturing industries. We find that productivity growth in U.S. food and beverage manufacturing has been more strongly driven by Hicks-neutral technical change than by labor-augmenting productivity. However, in general manufacturing, the results are the opposite: productivity is being driven by labor-augmenting productivity growth rather than Hicks-neutral technical change. This suggests that output growth in food manufacturing has been less strongly driven by labor-oriented technical change. Moreover, we find that productivity growth has been lagging that of general U.S. manufacturing.

We also find that markups in the U.S. food and beverage industries have been rather low when compared to the findings of previous studies. More precisely, we estimate that markups of price over marginal cost have been in the vicinity of 10 percent in the last 20 years, and they have been rather stable in these industries. The immediate implication is that food and beverage manufacturing industries are more competitive than previously found and that stable markups do not support the broader literature claiming that markups are increasing in U.S. manufacturing. Markups in U.S. manufacturing are 2.5 times the markups in food manufacturing, lending support to the idea that U.S. food manufacturing is more competitive than other manufacturing sectors of the economy.

However, we also do not find evidence of markups rising in general manufacturing in the last 20 years. We attribute the large magnitudes and upward trend in markups over time found in previous studies to inadequate specification or omission of the elasticity of scale in the markup estimation, missing inputs that are increasingly becoming part of services to third parties (such as contractual work), and biases introduced by the methods of computation. In future work with firm-level data, unlike the data used in this article, we plan to focus and shed light on firm heterogeneity, trying to deal systematically with these sources of bias in productivity and markup measures.

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Table 1. Variable Cost shares

NAICS	Sector	Labor	Capital	Mat.
311111	Dog and Cat Food Manufacturing	0.09	0.05	0.86
311119	Other Animal Food Manufacturing	0.06	0.03	0.91
311211	Flour Milling	0.07	0.03	0.90
311212	Rice Milling	0.07	0.03	0.90
311213	Malt Manufacturing	0.07	0.07	0.85
311221	Wet Corn Milling	0.07	0.09	0.83
311222	Soybean Processing	0.02	0.02	0.96
311223	Other Oilseed Processing	0.05	0.05	0.90
311225	Fats and Oils Refining and Blending	0.05	0.03	0.92
311230	Breakfast Cereal Manufacturing	0.17	0.09	0.73
311311	Sugarcane Mills	0.13	0.08	0.78
311312	Cane Sugar Refining	0.07	0.05	0.88
311313	Beet Sugar Manufacturing	0.12	0.07	0.81
311320	Chocolate and Confectionery from Cacao Beans	0.12	0.05	0.83
311330	Confectionery from Purchased Chocolate	0.20	0.06	0.74
311340	Nonchocolate Confectionery Manufacturing	0.22	0.07	0.71
311411	Frozen Fruit, Juice, and Vegetable Manufacturing	0.16	0.06	0.78
311412	Frozen Specialty Food Manufacturing	0.17	0.05	0.78
311421	Fruit and Vegetable Canning	0.14	0.06	0.80
311422	Specialty Canning	0.14	0.06	0.80
311423	Dried and Dehydrated Food Manufacturing	0.15	0.06	0.79
311511	Fluid Milk Manufacturing	0.11	0.04	0.86
311512	Creamery Butter Manufacturing	0.04	0.02	0.94
311513	Cheese Manufacturing	0.06	0.02	0.92
311514	Dry, Condensed, and Evaporated Dairy Product	0.08	0.04	0.88
311520	Ice Cream and Frozen Dessert Manufacturing	0.15	0.05	0.80
311611	Animal (except Poultry) Slaughtering	0.07	0.02	0.92
311612	Meat Processed from Carcasses	0.12	0.03	0.85
311613	Rendering and Meat Byproduct Processing	0.16	0.07	0.78
311615	Poultry Processing	0.16	0.03	0.81
311711	Seafood Canning	0.13	0.05	0.82
311712	Fresh and Frozen Seafood Processing	0.14	0.03	0.83
311812	Commercial Bakeries	0.34	0.07	0.59
311813	Frozen Cakes, Pies, and Other Pastries Manufacturing	0.21	0.05	0.74
311821	Cookie and Cracker Manufacturing	0.24	0.07	0.69
311822	Flour Mixes and Dough from Purchased Flour	0.15	0.05	0.80
311823	Dry Pasta Manufacturing	0.14	0.06	0.79
311830	Tortilla Manufacturing	0.26	0.04	0.69

311911	Roasted Nuts and Peanut Butter Manufacturing	0.09	0.03	0.88
311919	Other Snack Food Manufacturing	0.19	0.07	0.74
311920	Coffee and Tea Manufacturing	0.09	0.05	0.86
311930	Flavoring Syrup and Concentrate Manufacturing	0.12	0.06	0.82
311941	Mayonnaise, Dressing, and Other Prepared Sauce	0.13	0.05	0.82
311942	Spice and Extract Manufacturing	0.17	0.04	0.78
311991	Perishable Prepared Food Manufacturing	0.19	0.04	0.77
311999	All Other Miscellaneous Food Manufacturing	0.15	0.05	0.80
312111	Soft Drink Manufacturing	0.11	0.06	0.83
312112	Bottled Water Manufacturing	0.19	0.08	0.73
312113	Ice Manufacturing	0.46	0.13	0.41
312120	Breweries	0.16	0.12	0.72
312130	Wineries	0.18	0.08	0.74
312140	Distilleries	0.13	0.06	0.81
312210	Tobacco Stemming and Redrying	0.05	0.03	0.92
312221	Cigarette Manufacturing	0.15	0.07	0.77
312229	Other Tobacco Product Manufacturing	0.21	0.04	0.75
	Arithmetic Mean	0.14	0.05	0.81
	Weighted Average	0.12	0.04	0.84

Notes: Cost shares on the 6-digit NAICS sector level averaged over 1959-2018. Total cost equals the sum of labor cost, capital cost, and material cost. Labor cost is the total payroll. We use the total real capital stock to multiply the deflator of total capital expenditure to proxy nominal capital stock. Then, we develop nominal capital cost by nominal capital stock and user cost of capital.

Table 2: Parameter Estimates of the Translog Production Function with Labor-augmenting and Hicksian Productivity, 1958-2018

Production function params. (Std. dev.)

Food manufacturing					All manufacturing			
time	β_K	υ	α	ρ	β_K	υ	α	ρ
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0.001	0.293	0.662	0.045	0.944	0.047	0.907	0.089	0.975
(0.000)	(0.168)	(0.175)	(0.027)	(0.024)	(0.013)	(0.023)	(0.009)	(0.003)
					0.078	0.884	0.083	0.975
					(0.019)	(0.021)	(0.008)	(0.003)

Distribution of elasticities (Std. dev.)

Food manufacturing						All manufacturing					
	Labor elasticity						Labor elasticity				
β_K	β_L	$Q_{0.1}$	$Q_{0.5}$	$Q_{0.09}$	Change over time	β_K	β_L	Q_1	Q_2	Q_3	Change over time
(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
0.293	0.103	0.039	0.097	0.169	-0.015	0.047	0.260	0.118	0.257	0.403	-0.075
-	(0.061)					-	(0.111)				
						0.078	0.253	0.115	0.251	0.392	-0.073
						(0.035)	(0.108)				

Dispersion and growth of productivity (Std. dev.)

Food manufacturing				All manufacturing			
Output effect $\beta_L\ \omega_L$		ω_H		Output effect $\beta_L\ \omega_L$		ω_H	
Cross-s. std. dev.	Mean growth	Cross-s. std. dev.	Mean growth	Cross-s. std. dev.	Mean growth	Cross-s. std. dev.	Mean growth[f]
(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
0.436	0.003	0.268	0.009	0.404	0.010	0.317	0.005
	(0.063)		(0.075)		(0.124)		(0.069)
				0.406	0.010	0.467	0.005

	(0.125)	(0.070)

Note: Food Manufacturing and all manufacturing data are at the 6-digit NAICS level in the Survey of Manufactures/Census of Manufactures as defined in the NBER-CES Manufacturing Database (2021). The sample for food manufacturing includes 55 industries and for all manufacturing 486 industries using the 2017 NAICS definition throughout the sample period.

[e] The time trend accounts for about 0.06 during the whole period.

[f] Time dummies account for about 0.234 and 0.198, respectively, during the whole period, which can be considered adding 0.004 and 0.003 to these means.

Table 3: Markups in US Food Manufacturing 1959-2018

		1959-2018	1959-1980	1980-2000	2000-2018	2009-2018
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Markup [a]	Mean	-0.010	-0.129	0.009	0.106	0.089
	Std. dev.	(0.276)	(0.154)	(0.263)	(0.339)	(0.329)
	Mean of period changes [b]	0.256	0.063	0.192	0.002	-0.034
	Std. dev.	(0.302)	(0.086)	(0.232)	(0.275)	(0.190)
	Prop. of negative changes	0.091	0.218	0.073	0.509	0.618
	Q3 of changes	0.311	0.126	0.229	0.054	0.028
	Q2 of changes	0.100	0.054	0.135	-0.015	-0.044
	Q1 of changes	0.099	0.013	0.056	-0.102	-0.125
Corrected markup [c]	Mean	-0.085	-0.258	-0.047	0.073	0.064
	Std. dev.	(0.331)	(0.292)	(0.268)	(0.341)	(0.329)
User cost of capital [d]	Mean	0.074	0.028	0.095	0.105	0.104
	Std. dev.	(0.055)	(0.047)	(0.031)	(0.049)	(0.055)

[a] $\ln \mu = \ln \frac{R}{VC} + \ln \hat{v}$, $\hat{v} = 0.662$, as given by the estimate in Table 2.

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

[c] $\ln \mu_c = \ln \frac{R}{VC} + \ln \hat{v} + uc\frac{K}{R}$, $\hat{v} = 0.662$, as given by the estimate in Table 2.

[d] $uc = (r - d + \Delta p_I)$, r is the weighted-average effective loan rate of all commercial and industry loans (Federal Reserve Bank of Saint Louis), and d and Δp_I is implicit in the capital, investment, and investment price in the NBER-CES database.

Table 4: All manufacturing: Markups 1959-2018

		1959-2018	1980-2000	2000-2018	2009-2018
(1)	(2)	(3)	(5)	(6)	(7)
Markup [a]	Mean	0.259	0.268	0.319	0.318
	Std. dev.	(0.159)	(0.152)	(0.181)	(0.187)
	Mean of period changes [b]	0.145	0.085	0.021	0.001
	Std. dev.	(0.174)	(0.135)	(0.160)	(0.138)
	Prop. of negative changes	0.130	0.218	0.404	0.479
	Q3 of changes	0.229	0.132	0.096	0.069
	Q2 of changes	0.141	0.078	0.021	0.006
	Q1 of changes	0.050	0.013	-0.051	-0.064
Corrected markup [c]	Mean	0.176	0.205	0.272	0.277
	Std. dev.	(0.234)	(0.160)	(0.195)	(0.202)
User cost of capital [d]	Mean	0.079	0.103	0.104	0.099
	Std. dev.	(0.063)	(0.036)	(0.079)	(0.101)

[a] $\ln \mu = \ln \frac{R}{VC} + \ln \hat{\nu}$, $\hat{\nu} = 0.662$, as given by the estimate in Table 2.

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

[c] $\ln \mu_c = \ln \frac{R}{VC} + \ln \hat{\nu} + uc\frac{K}{R}$, $\hat{\nu} = 0.662$, as given by the estimate in Table 2.

[d] $uc = (r - d + \Delta p_I)$, r is the weighted-average effective loan rate of all commercial and industry loans (Federal Reserve Bank of Saint Louis), and d and Δp_I is implicit in the capital, investment, and investment price of the NBER-CES database.

Table 5: A Look at the Cost Side of Food Manufacturing

	1959-2018	1959-1980	1980-2000	2000-2018	2009-2018
	(1)	(2)	(3)	(4)	(5)
Variable Cost over Revenue, $\frac{VC}{R}$					
Mean	0.691	0.762	0.676	0.624	0.633
Std. dev.	(0.153)	(0.111)	(0.150)	(0.164)	(0.162)
Labor share in Variables Cost, $S_L = \frac{WL}{VC}$					
Mean	0.158	0.167	0.155	0.149	0.138
Std. dev.	(0.093)	(0.103)	(0.085)	(0.086)	(0.083)
Mean of period changes [a]	-0.023	-0.028	0.020	-0.015	0.008
Std. dev.	(0.082)	(0.059)	(0.034)	(0.045)	(0.035)
Prop. of negative changes	0.618	0.691	0.182	0.655	0.436
Output effect of the growth of Labor-augmenting prod., $\beta_L \Delta\omega_L$					
Mean	0.003	0.006	0.001	0.002	-0.002
Std. dev.	(0.064)	(0.077)	(0.063)	(0.048)	(0.036)
Growth of Hicks-neutral prod., $\Delta\omega_H$					
Mean	0.009	0.011	0.009	0.007	0.003
Std. dev.	(0.075)	(0.0073)	(0.0073)	(0.078)	(0.080)
Dispersion of Labor-augmenting prod., $\beta_L \Delta\omega_L$					
Std. dev.	0.465	0.571	0.358	0.412	0.393
Dispersion of Hicks-neutral prod., $\Delta\omega_H$					
Std. dev.	0.360	0.372	0.274	0.251	0.246

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