Evolution of Productivity and Markups in U.S. Food and General Manufacturing

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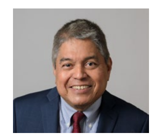

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Introduction

- U.S. food and beverage manufacturing accounts for approximately 1/6 of the value of shipments (sales), value added, and employment of all U.S. manufacturing.

- Because agricultural inputs account for most of the cost of food manufacturing, performance of this sector is important to agricultural producers and consumers alike.

Lack of recent studies on US food manufacturing productivity:

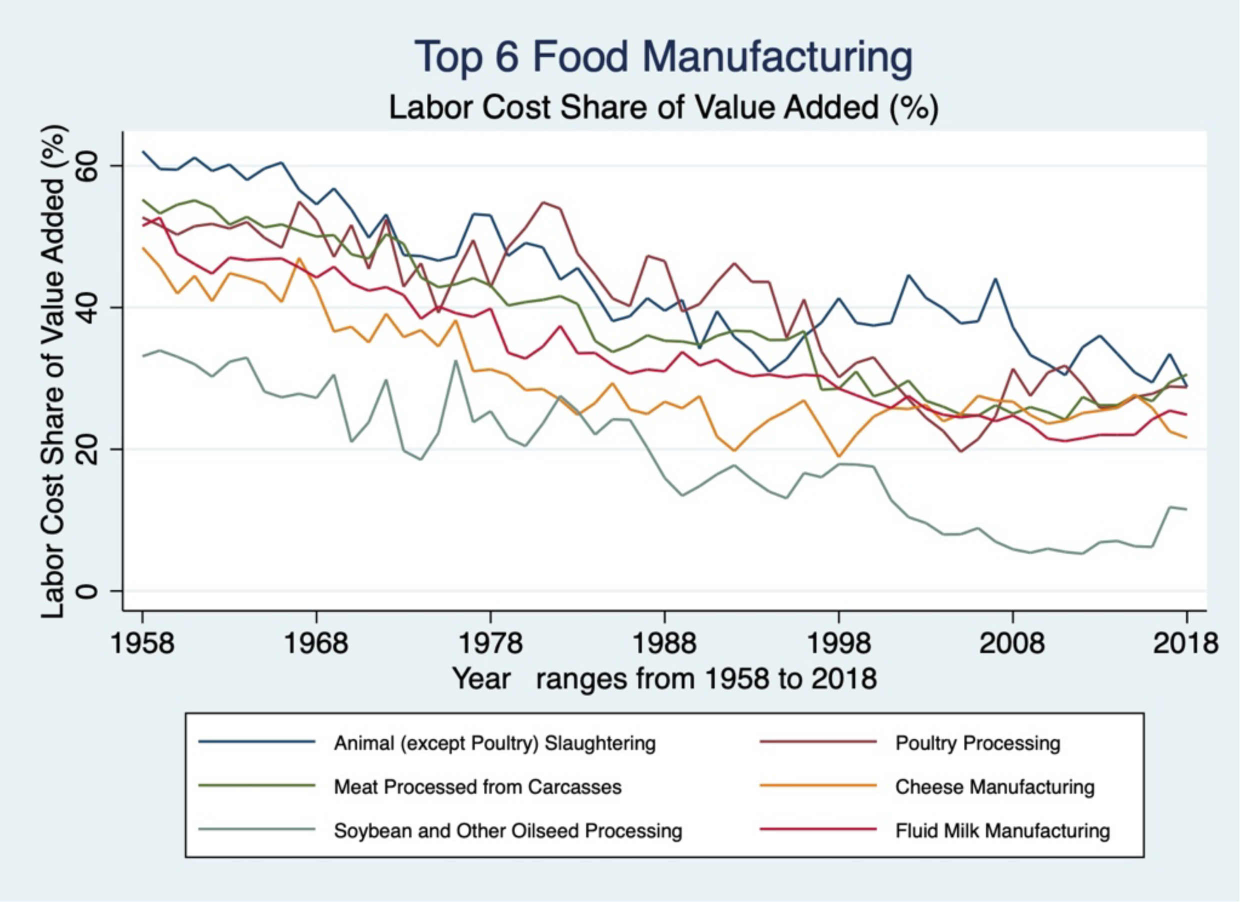
  - Morrison (2001), Celikkol and Stefanou (2004)—meat packing, ReStat, Census report
  - Huang (2003)—US food manufacturing, ERS bulletin
  - Heien (1983)—US food manufacturing and distribution, AJAE
  - Plant level studies in other countries: Germany (Frick et al, 2019; Spain (Kapelko, 2017), Colombia (Shee and Stefanou, 2014).

Introduction

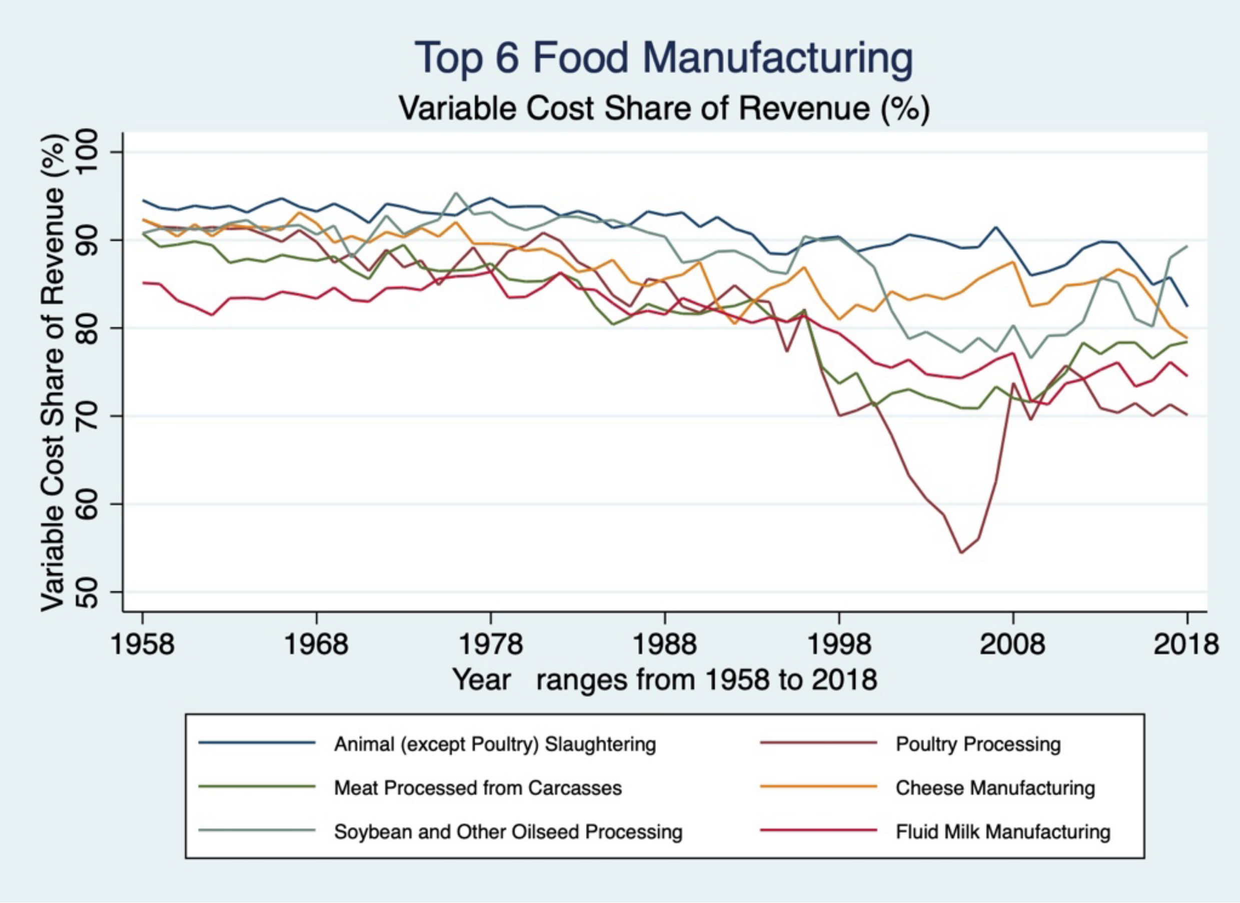
- Markups computed via
  - **Production-based** approaches (> Hall 1988; NEIO, Appelbaum, 1982). The most popular recently: DeLoecker and Warzinsky (2012, here in DLW).
  - **Demand-based** approaches (>BLP 1995).

  - Recent studies using both approaches point out to **increasing markups in** food manufacturing and other industries:
    - *U.S. Food industries*:
    - Lopez, He, and Azzam (2018)-JAE, markups increasing and in the 30% range.
    - Bhuyan and Lopez (1997): AJAE, markups in the 30-40% range.
    - *U.S. Manufacturing*:
    - Basu (AEP 2019): markups rising in the U.S. with production-based approaches
    - Berry et al. (AEP 2019): markups rising in the U.S. with demand-based approaches
    - Grullon et al. (RF 2019): 75% of industries rising markups
    - De Loecker et al. (QJE 2020): markups of 21% in 1980 to 60% now!
    - *French Food Manufacturing Industries*:
    - Curzi et al. (AJAE 2021): Using DLW, 30% average markup in 2001-2013.
    - Jafari et al. (AJAE 2022): Using DLW, 80% median markup in 2011-2019.

Top 6 Food Manufacturing Industries, Labor Cost Share of Value Added



Top 6 Food Manufacturing Industries, Variable Cost share of Revenue



In this Study

Little is known about the effects of recent technological advances in U.S. food and tobacco manufacturing, particularly labor-saving technology, and how they impact estimates of productivity and markups.

- We provide **updated estimates of productivity** in the U.S. food manufacturing allowing for labor-augmenting productivity; and
- We ascertain the **implications** of non-neutral productivity growth for the **measurement of markups**.
- We **compare our baseline results** with labor-augmenting productivity **to** results using the popular **DLW approach**.

Data

Data Sources

- **<u>NBER-CES Manufacturing Productivity Database</u>**
  - Public dataset, annual observations 1958-2018
  - **Level of aggregation**: 6-digit NAICS codes, resulting in 55 food and beverage manufacturing industries, 486 general manufacturing industries.
  - **Total number of observations**: 55 industries x 61 years = 3,355 for manufacturing, and 486 x 61 years= 29,646 for general manufacturing.

  - **<u>Key Variables</u>**:
  - **Output**: Value of Shipments (sales)
  - **Inputs**: Labor, materials, and capital.
  - **Prices**: sales deflator, wages, materials deflator, investment deflator (up to 2014).

Empirical Model

Estimating markups based on production function estimates:

- Take the first order condition for cost minimization of a generic X variable factor

$$MC_{jt}\frac{\partial Q_{jt}^{*}}{\partial X_{jt}} = W_{Xjt},$$

- After re-arranging the previous expression, De Loecker and Warzynski (2012) propose the markup estimator based on one input (typically labor):

$$\hat{\mu}_{jt}= \frac{\widehat{\beta}_{Xjt}}{S_{Xjt}^{R}}\ \exp\left(-\hat{\varepsilon}_{jt}\right), \tag{1}$$

where $\hat{\beta}_{Xjt}$ and $\hat{\varepsilon}_{jt}$ are obtained by estimating the production function, and S_{Xjt}^{R} is the share of the cost of the input in the firm's revenue.

- Doraszelski and Jaumandreu's (2019) using FOC for labor and materials (not only one input), obtains the following markup estimator:

$$\mu_{jt}\exp\left(\varepsilon_{jt}\right) = \frac{R_{jt}}{VC_{jt}}\,v_{jt}, \tag{2}$$

- v_{jt} is the short run elasticity of scale, ε_{jt} is assumed to be uncorrelated over time and industries.

Empirical Model

<u>Empirical production function:</u>

- Following Doraszelki and Jaumandreu (JPE 2018), we allow use a translog production function that is:
  - Separable in capital input
  - Allows for Hick-neutral and labor-augmenting productivity technical change
  - Expressing output and inputs in log terms

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

- ω_{Hjt} is Hicks neutral technical change
- ω_{Ljt} is labor-augmenting technical change

Empirical Model

- To simplify, 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 elasticities of output w.r.t. variable inputs L_{jt} and M_{jt} are

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

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

where the **short-run economies of scale** is given by $\boldsymbol{v_{Ljt}} = \beta_{Ljt} + \beta_{Mjt} = \alpha_L + \alpha_M$.

Empirical Model

We use dynamic panel estimation to control for unobserved productivity:

1. Take the FOCs for the two variable inputs and divide one by the other obtain an expression for ω_{Ljt} that is observable.

2. Substitute the expression for ω_{Ljt} in the production function to obtain an expression in which only the unobservable Hicks-neutral productivity ω_{Hjt} is left.

3. Let Hicksian productivity follow a Markov process $\boldsymbol{\omega_{Hjt}} = \boldsymbol{\beta_t} + \boldsymbol{\rho\omega_{Hjt-1}} + \boldsymbol{\xi_{jt}}$ and utilize the lagged production function inverted to obtain the following production function expression to be estimated:

$$q_{jt} = \gamma_0 + \beta_t + \rho q_{jt-1} + \alpha_K\,(k_{jt} - pk_{jt-1}) + \frac{1}{2}\alpha_{KK}(k_{jt}^2 - \rho k_{jt-1}^2)$$
$$+(\alpha_L + \alpha_M)\big(m_{jt} - \rho m_{jt-1}\big) - \frac{1}{2}\frac{(\alpha_L+\alpha_M)^2}{\alpha}(S_{Ljt}^2 - \rho S_{Ljt-1}^2) + u_{jt},$$

where $\gamma_0 = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha}$ -ρ $(\alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha})$, and the composite error is $u_{jt} = \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}$.

Empirical Model

- We then recover estimates $\widehat{\omega_L}$ and $\widehat{\omega_H}$ for every industry and year as measures of productivity.

- We then obtain estimates of economics of size $\boldsymbol{v}$ (= $\frac{AVC}{MC}$), and estimate markups as
  - $\widehat{\ln \mu} = \ln \frac{R}{VC} + ln\, \hat{v}$,

We also estimate:

- The model with adjustment for variable capital cost.

- the DLW-ACF model with the same data.

Results

Productivity Results for the Food Manufacturing Industries

- Production functions parameters (Std. dev.)

time	β_K	υ	α	ρ
0.000	0.088	**0.886**	0.078	0.926
(0.000)	(0.155)	(0.155)	(0.029)	(0.046)

- Distribution of elasticities (Std. dev.)

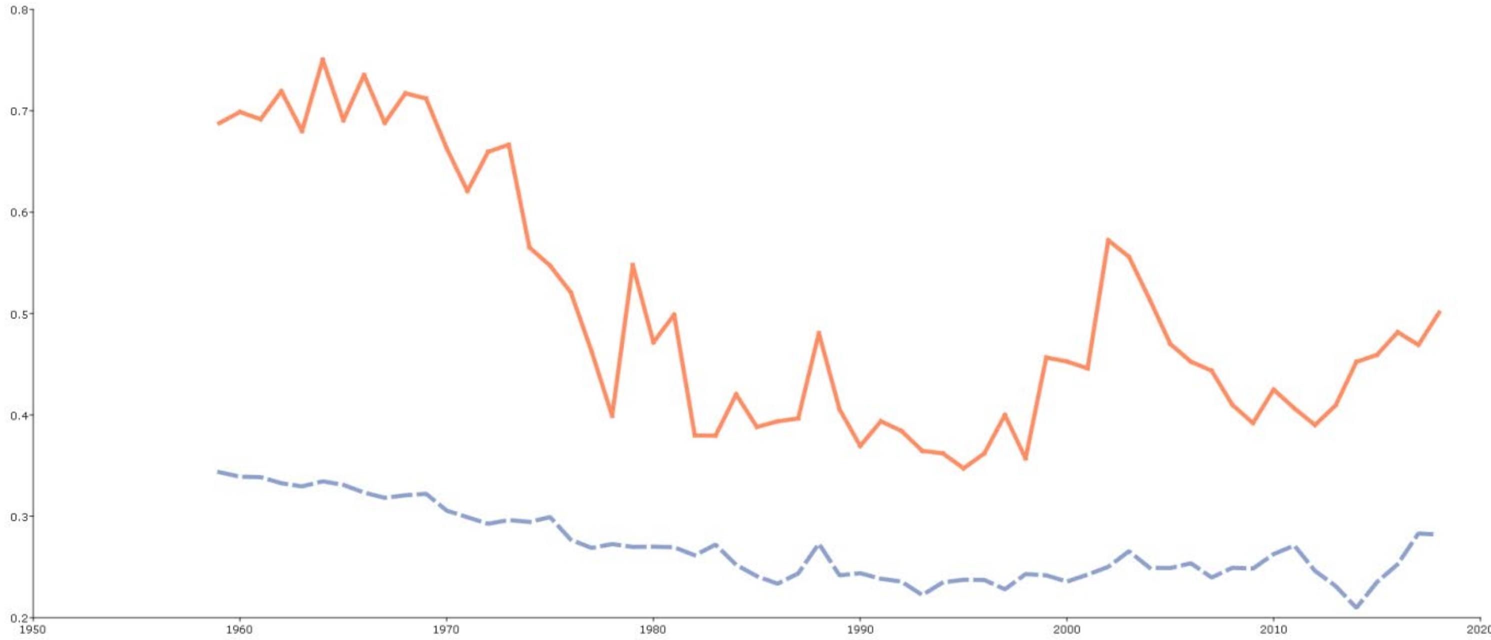
	Labor elasticity				
β_K	β_L	Q1	Q2	Q3	Change over time
0.088	**0.138**	0.052	0.130	0.226	-0.020
-	(0.081)				

- Growth of productivity (Std. dev.)

		1959-2018
Output effect of the growth of, Labor-augmenting prod.,	Mean	**0.004**
	Std. dev.	(0.070)
Output effect of the growth of Hick-neutral prod.,	Mean	**0.004**
	Std. dev.	(0.079)

Growth of productivity, all manufacturing, 1959-2018

- Labor: solid line, Hicks: dashed line



Food Industry vs. US Manufacturing Productivity Results

- **A) Economies of scale** $\hat{\nu} = \frac{AVC}{MC}$

Higher short-run elasticities of scale in U.S. manufacturing than in food manufacturing:

0.886 vs. 0.907.

- **B) Productivity growth estimates:** $\widehat{\omega_L}$ and $\widehat{\omega_H}$

Overall, lower productivity growth in the food industry vs all US manufacturing.

- **Hick-neutral productivity:** More important in the food industries than in US manufacturing.
  - 1/2 of overall output productivity growth vs 1/3 in US manufacturing
- **Labor-augmenting productivity:** Less important in the food industries than in US manufacturing.
  - 1/2 of overall output productivity growth vs 2/3 in US manufacturing

Markups Estimates: Our Approach and the DLW Approach

	Mean markup across industries and subperiods			
Procedure of estimation	1959-1980	1980-2000	2000-2018	2009-2018
	(1)	(2)	(3)	(4)
Food Manufacturing				
Own procedure	0.162	0.300	0.398	0.381
ACF-DLW procedure	0.688	0.712	0.736	0.803
Manufacturing				
Own procedure	0.218	0.286	0.337	0.336
ACF-DLW procedure	0.271	0.359	0.478	0.513

Food Industry vs. US Manufacturing Markups

Average markups for 1959-2018 are similar in both food and US manufacturing at around 25%, but they do have remarkable different evolutions.

- **Food manufacturing:** increase steadily, around 30 percentage points, from 1975-2005 and then fall and become stable during the last 20 years (40%).

- **US manufacturing**: increase gradually but to a significant lesser extent than food manufacturing, around 15 percentage points, also stable in the last 20 years (34%).

Markup and markup corrected with the variable cost of capital, all manufacturing, 1959-2018

- Markup: solid line, corrected: dashed line

Our Estimates vs. DLW Markups

- The DLW method results in
  - Markups that are 1.5-2X larger than our estimates and also above the preponderant estimates in the literature
  - The markups are increasing over time, in line with recent literature, particularly using the DLW method

- Doraszelki and Jaumandreu (2023) detect 3 biases generated by the DLW (2012) method)
  - The ACF procedure contains an error of "prediction" when markups are heterogeneous
  - This approach biases the estimation of β_{Xjt} and ε_{jt}, and hence the markups.
  - If there is labor augmenting productivity, the downward trend in the elasticity of labor will be missed, biasing the estimated markups.

Takeaways

- Productivity growth in the U.S. food manufacturing industries has been slow since 1959.
    1. Productivity growth in food manufacturing has been lagging behind US manufacturing productivity.
    2. Labor augmenting productivity is lower and less important in food manufacturing than in all US manufacturing.
- Markups in U.S. food industries are in line with general manufacturing for 1959-2018, but with a remarkable different evolution.
    - Ignoring labor-augmenting productivity biases estimates of productivity growth and production-based markups.
- In contrast to the DLW-ACF results,
    - we do not find evidence of markups rising in either US food manufacturing or general manufacturing in the last 20 years
    - DLW markup estimates are 1.5 to 2X larger than our estimates and are unreasonable given the preponderant literature.

Thank you!