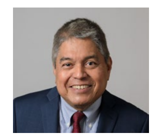
UCONN | College of Agriculture, Health and Natural Resources
Agricultural and Resource Economics

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

Jordi Jaumandreu
Boston University

Rigoberto A. Lopez
University of Connecticut



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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.

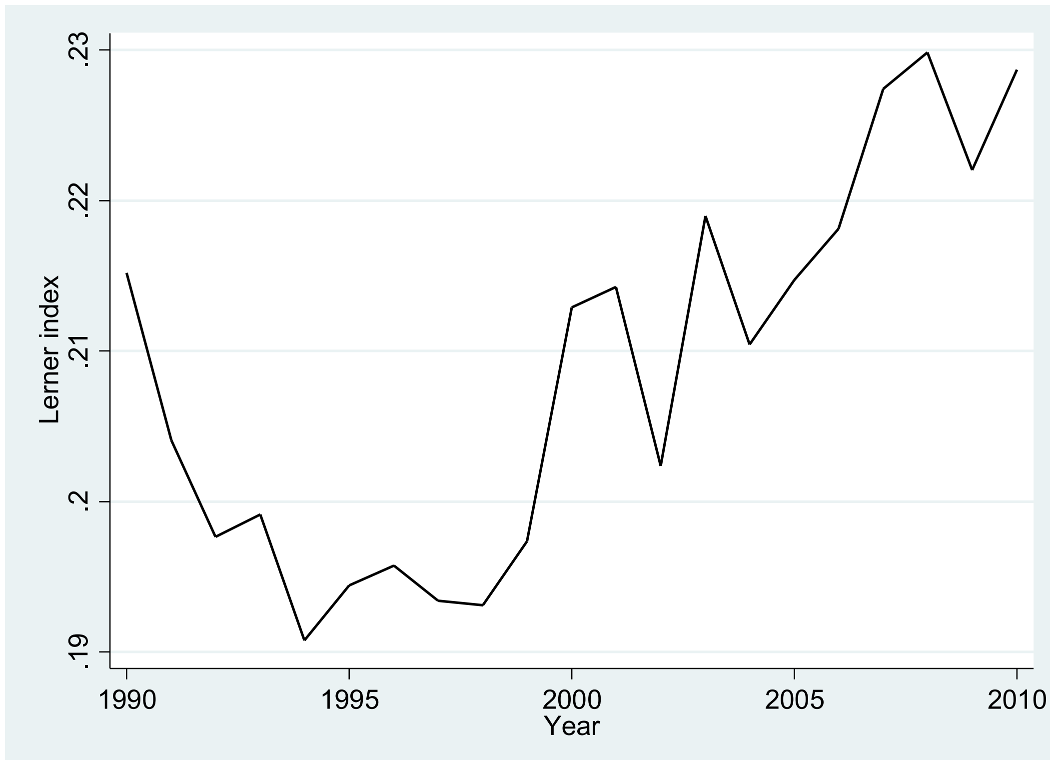
- Lack of recent studies on US food manufacturing productivity: they are dated and often conducted at the aggregate level.
  - Morrison (2001), Celikkol and Stefanou (2004)—meat packing, ReStat, Census report
  - Huang (2003)—US food manufacturing, ERS bulletin
  - Heien (1983)—US food manufacturing 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).
  - Demand-based approaches (>BLP 1995).

  - Recent studies using both approaches point out to rather **high and increasing markups in** food manufacturing and other industries:
    - *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 have become more concentrated and with increasing market markups
    - De Loecker et al. (QJE 2020): markups of 21% in 1980 to 60% now!

An Example from Previous Studies Average Lerner Indexes in US Food Manufacturing, 1990-2010



Lopez, He, Azzam (JAE, 2017), Figure 2.

In this Study

Little is known about the effects of recent technological advances in U.S. food and tobacco manufacturing and the reasons why estimated markups are rising in U.S. food and other industries.

- *In this study:*
- We provide updated estimates of productivity in the U.S. food and tobacco manufacturing using novel models of technological change; and
- We ascertain the implications of productivity for the measurement of markups.
- We provide some possible reasons why estimated markups appear to be increasing.

Data

Data Sources

- **NBER-CES Manufacturing Productivity Database**
  - Public dataset, annual observations 1958-2018
  - Output: Value of Shipments (sales)
  - Inputs: Labor, materials, and capital.
  - Prices: sales deflator, wages, materials deflator, energy deflator, investment deflator (up to 2014).
  - Level of aggregation: 6-digit NAICS codes, resulting in 55 food and beverage manufacturing industries.
  - Total number of observations: 55 industries x 61 years = 3,355 obs.

Empirical Model

- 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

$\beta_{Ljt} = \frac{\partial q_{jt}}{\partial l_{jt}} = \alpha_L + \alpha(m_{jt} - \omega_{Ljt} - l_{jt})$, 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** $\boldsymbol{\omega_{Hjt} = \beta_t + \rho\omega_{Hjt-1}} + \boldsymbol{\xi_{jt}}$ 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 $\gamma_0 = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha}$ -$\rho\,(\alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha})$, and the composite error is $u_{jt} = \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}$.

Empirical Model

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

- We also obtain estimates of economics of size υ.

Empirical Model

- Bain's (1951) markup: $\mu_{jt} = \frac{R_{jt}}{VC_{jt}}$, where R is observed revenue and VC is variable cost.

- Hall's (1988) markup: $\mu_{jt} = \frac{P_{jt}}{MC_{jt}}$.

- Doraszelski and Jaumandreu's (2019) markup:

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

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

Empirical Model

- We estimate the log of the short-run markups as

$$\widehat{\ln \mu} = \ln \frac{R}{VC} + ln\, \hat{v},$$

Where $\hat{v}$ (economies of scale) $= \frac{AVC}{MC}$ so that $MC = v\, AVC$.

- We also compute the user cost of capital uc and calculate a corrected markup as

$$\widehat{ln\mu_C} = \ln \frac{R}{VC} + ln\hat{v} - uc\,\frac{K}{R}$$

Results

Productivity Results for the Food and Beverage Manufacturing Industries

- Production functions parameters (Std. dev.)

time	β_K	υ	α	ρ
0.001	0.293	0.662	0.045	0.944
(0.000)	(0.168)	(0.175)	(0.027)	(0.024)

- Distribution of elasticities (Std. dev.)

	Labor elasticity				
β_K	β_L	Q1	Q2	Q3	Change over time
0.293	0.103	0.039	0.097	0.169	-0.015
-	(0.061)				

- Growth of productivity (Std. dev.)

		1959-2018	1980-2000	2000-2018	2009-2018
Output effect of the growth of, Labor-augmenting prod.,	Mean	**0.003**	0.001	0.002	-0.002
	Std. dev.	(0.064)	(0.063)	(0.048)	(0.036)
Growth of Hick-neutral prod.,	Mean	**0.009**	0.009	0.007	0.003
	Std. dev.	(0.075)	(0.007)	(0.078)	(0.080)

Estimated Markups
For U.S. Food and Beverage Manufacturing Industries

		1980-2000	2000-2018	2009-2018
$\ln \mu = \ln \frac{R}{VC} + \ln \hat{v}$	Mean	**0.009**	**0.106**	**0.089**
	Std. dev.	(0.263)	(0.339)	(0.329)
$\ln \mu_c = ln \frac{R}{VC} + ln\hat{v} - uc\frac{K}{R}$	Mean	-0.047	0.073	0.064
	Std. dev.	(0.268)	(0.341)	(0.329)

A look at the Cost Side For U.S. Food and Beverage Manufacturing Industries

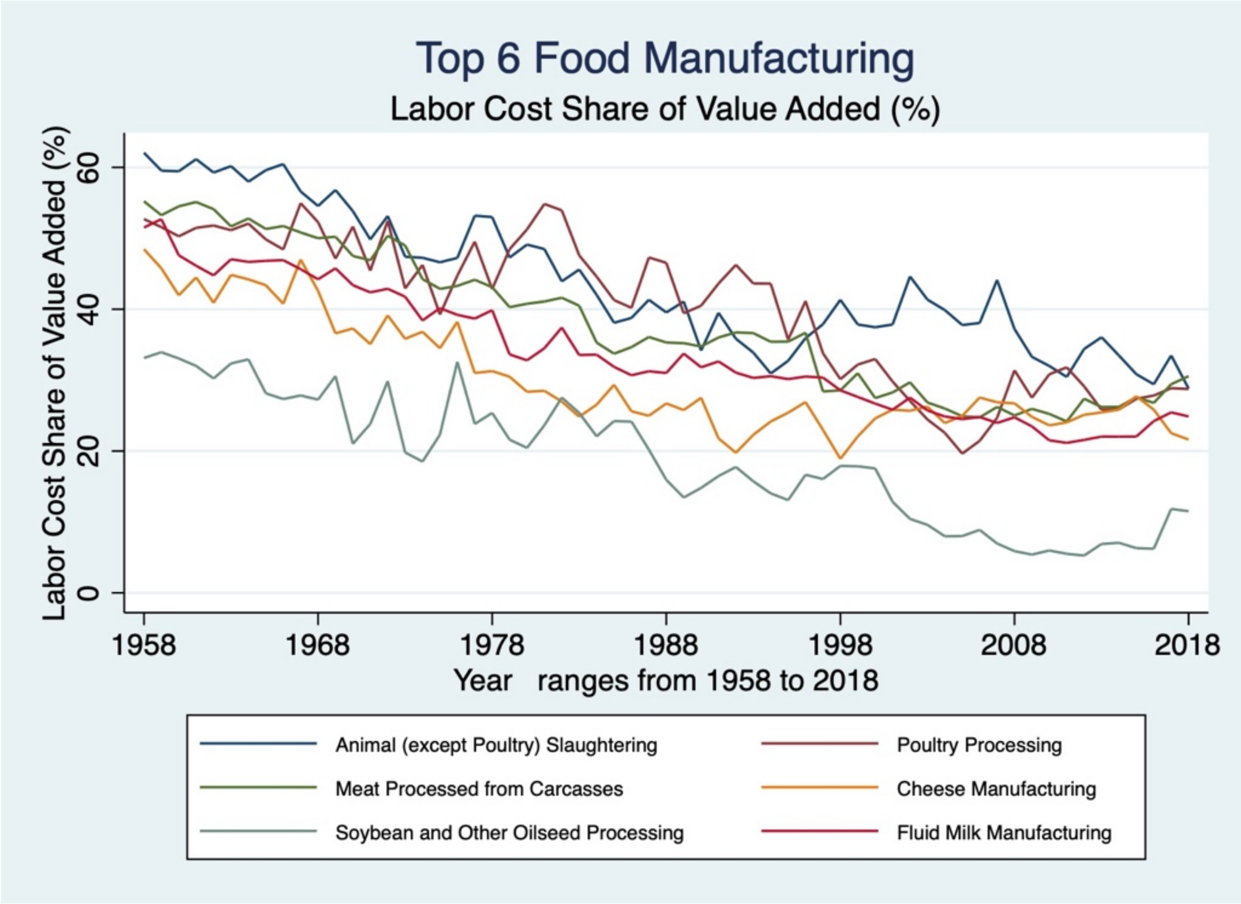
- Variable Cost over Revenue (Std. dev.)

	1959-2018	1980-2000	2000-2018	2009-2018
Mean	0.691	0.762	0.624	0.633
Std. dev.	(0.153)	(0.111)	(0.164)	(0.162)

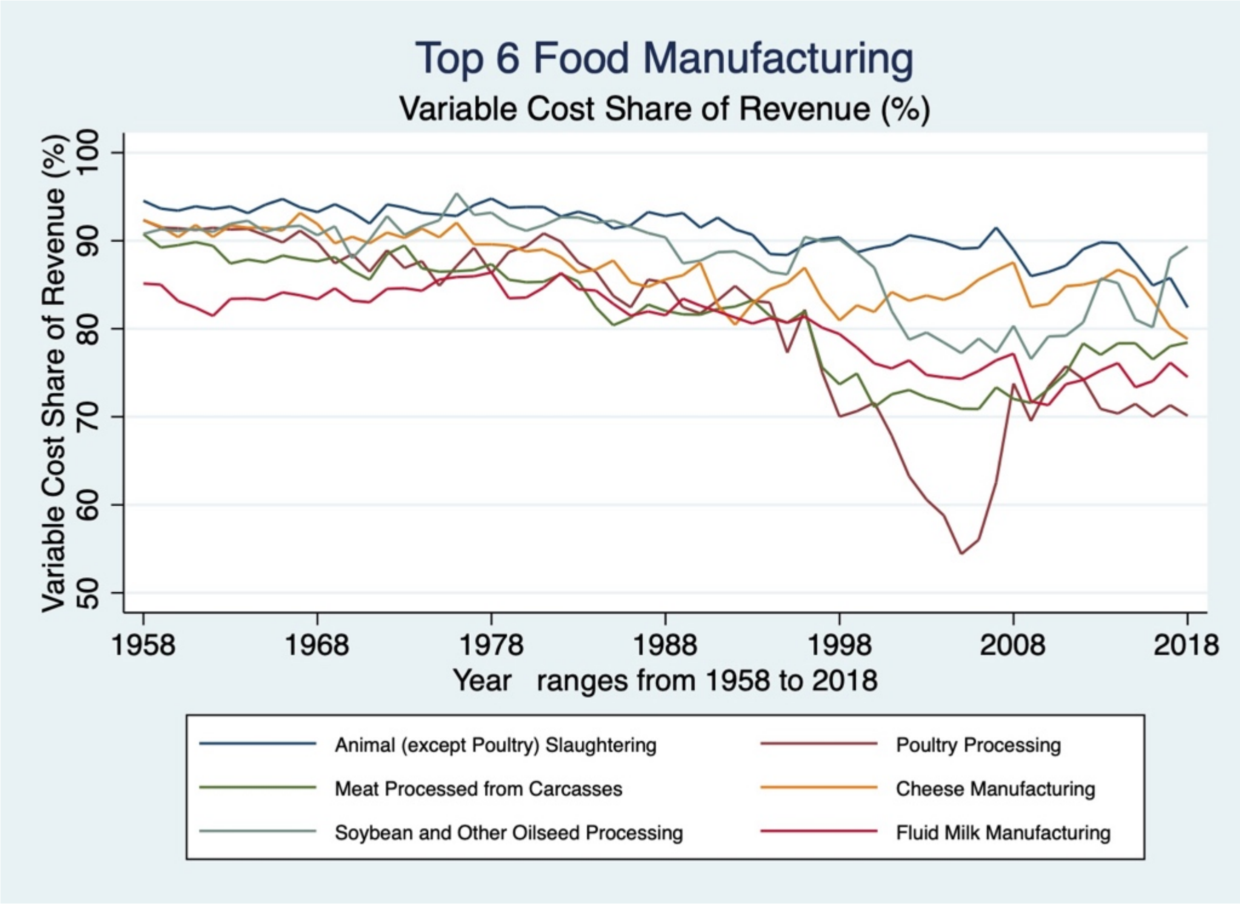
- Labor Share of Variable Cost (Std. dev.)

	1959-2018	1980-2000	2000-2018	2009-2018
Mean	0.158	0.167	0.149	0.138
Std. dev.	(0.094)	(0.103)	(0.086)	(0.083)

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



Top 6 Food Manufacturing Industries, Variable Cost share of Revenue



Food Industry vs. US Manufacturing

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

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

0.662 vs. 0.907.

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

Overall, lower growth in productivity in the food industry vs the manufacturing industry

Hick-neutral productivity: More important in the food industries than in US manufacturing:

2/3 of overall output productivity growth vs 1/3 in US manufacturing

That is, l**abor- augmenting productivity in** the food industry account for only 1/3 of output growth vs. 2/3 in US manufacturing.

- **C) Markups**

Significantly higher markups in US manufacturing than in food manufacturing

Food manufacturing: around 10% and stable in the last 20 years.

US manufacturing: around 26%, also stable in the last 20 years.

Rising Markups?

Possible explanations:

1. **Accounting data problems**.
    1. Missing inputs: services and contracts
    2. Outsourcing of jobs may result in fake “observed” saving of labor and materials=missing inputs in the variable cost computation.
2. **Inadequate elasticity of scale.**
    1. From equation (1), appropriate estimation of v is necessary for proper estimation of markups.
    2. If we over-estimate v or ignore v when v<1, we over-estimate markups.
3. **Aggregate vs. firm-level based measurement**

    Not considering firm heterogeneity. For example, firms with stronger efficiency gains through L-augmenting productivity will get smaller labor elasticity (smaller labor shares in cost) and greater revenue shares (Kerigh, 2021).

Takeaways

- Productivity growth in the U.S. food manufacturing industries has been slow since 1959.
  1. Food manufacturing labor augmenting productivity is much lower and less important than labor augmenting productivity growth in all US food manufacturing.
  2. In general, food manufacturing productivity growth has been lagging behind US manufacturing productivity.
- Markups in U.S. food industries have been rather low when compared to previous studies and general manufacturing
  1. We find markups in the 10% range. Previous studies: 20-35%.
  2. We also find markups in US manufacturing at 26% (2.6X those in food manufacturing).
- We do not find evidence of markups rising in either US food manufacturing or general manufacturing in the last 20 years.

Thank you!