Increasing Returns to Scale and Markups

Olga Shanks

George Mason University

ostaradu@gmu.edu

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Motivation

- Increasing Returns to Scale can explain
    - Rising industry concentration
    - Decreasing share of labor in total output
    - Rising markups

  Yet economists use the assumption of constant returns
    - Autor et al. (2020) use CRS and require a change in consumer price sensitivity
    - Karabarbounis and Neiman (2014) use CRS and require the capital-labor elasticity of substitution to be greater than one
    - De Loecker et al. (2020) argue that markups cause industry concentration

- Estimation of Markups
    - De Loecker et al. (2020) argue that the aggregate markup of U.S. firms rose from 1.2 to 1.6 since 1980 to 2016
    - Inconsistent with profitability trends
    - Treatment of variable and fixed costs
    - Long vs. short horizons

Data

- Compustat Fundamentals Annual database
- Publicly traded companies in the U.S. from 1980 to 2019

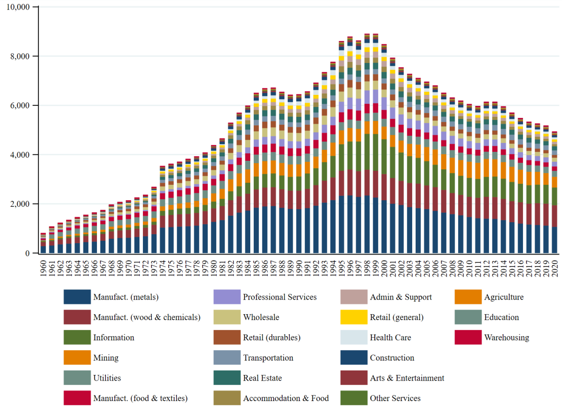
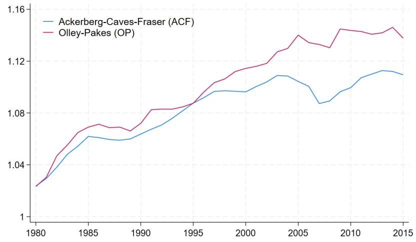


Figure: Number of firms in Compustat by year by industry

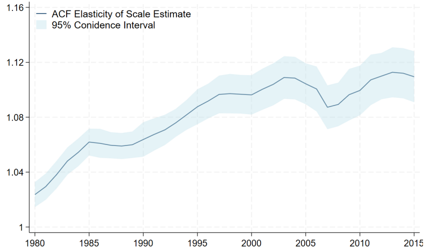
Data (cont.)

- Variable costs: Cost of Goods Sold (COGS) + Selling, General and Administrative (SG&A)
- Capital costs: Property, Plant and Equipment (PPE) $\times$ user cost of capital
- User cost of capital is estimated: $r_t = i_t - \pi_t + \delta_t$
  i_t: the Federal Funds rate
  π_t: FRED reported inflation rate, and
  $\delta_t = 12\%$ for depreciation and risk premium
- Revenues and costs deflated by BEA chain-type price indexes by industry (2- or 3-digit NAICS level)
- Excluded Finance sector (NAICS code 52)
- 5-year rolling periods, e.g. 1980-1984, 1981-1985, etc.

Results: Aggregate Returns to Scale



(a)



(b)

- Elasticity of scale is above 1
- Divergence after the Internet revolution
- OLS and Syverson's methods are biased
- Focus on ACF because:
    - Most conservative estimate
    - Allows estimation of standard errors
    - Variable costs are dynamic like capital

Results: Industry-specific Elasticity of Scale

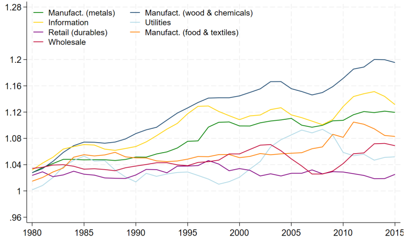


Figure: Top 7 industries

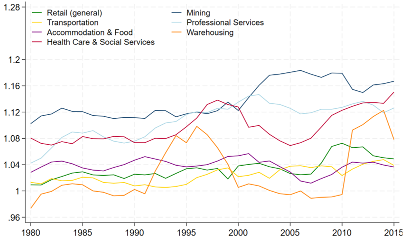


Figure: Middle 7 industries

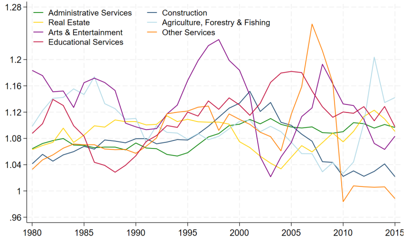


Figure: Bottom 7 industries

- Highest elasticity of scale
  - Manufacturing of wood and chemicals
  - Mining
  - Information
- Lowest elasticity of scale
  - Retail
  - Accommodation and Food
  - Transportation
- High volatility in the bottom 7 industries, likely due to the small number of observations

Markup Estimation

- Cost-minimizing firm:
  $L(V, K, \lambda) = P^V V + rK - \lambda(Q(\Omega, V, K) - \overline{Q})$

- Derive from FOCs:

$$\mu = e_V \frac{PQ}{P^V V}, \tag{1}$$

where μ is markup and e_V is output elasticity of the variable input

- According to Varian (1992), Syverson (2019) and others,

$$\mu = \frac{P}{MC} = \frac{P}{MC}\frac{AC}{AC}\frac{Q}{Q} = \frac{AC}{MC}\frac{PQ}{AC \times Q} = e_{scale}\frac{PQ}{TC} \tag{2}$$

- De Loecker et al. (2020) use e_V: $\mu = e_{COGS}\frac{Sales}{COGS}$
  Traina (2018) uses e_V: $\mu = e_{COGS+SG\&A}\frac{Sales}{COGS+SG\&A}$
  Present research uses e_{scale}: $\mu = e_{COGS+SG\&A+capex}\frac{Sales}{COGS+SG\&A+capex}$

Variable Costs

Variable costs: COGS vs. COGS + SG&A?

- COGS typically include:
  - raw materials
  - direct labor
  - manufacturing overhead
  - freight in
- SG&A typically include:
  - wages of sales and office staff
  - shipping of finished goods
  - rent & utilities
  - R&D
- COGS have been going down, while SG&A have been trending up: firms have been shifting costs from COGS to SG&A
- Firms have the incentive to improve Gross Margin (i.e. Revenues - COGS)
- Firms in the same industry may "decide" whether to record certain costs as COGS vs. SG&A
- Based on above: Variable costs = COGS + SG&A
  Traina (2018)'s $\mu = 1.2$ vs. De Loecker et al. (2020)'s $\mu = 1.6$

Choice of Markup Formula

Markup formula: $\mu = e_V \frac{PQ}{P^V V}$ or $\mu = e_{scale} \frac{PQ}{TC}$?

- $\mu = e_V \frac{PQ}{P^V V}$ reflects a short-term view, where firms cannot adjust capital
- $\mu = e_{scale} \frac{PQ}{TC}$ reflects a long-term view, where all costs can change
- Long-term view is more appropriate for looking at data from 1980 to 2019
- Long-term view is more appropriate for large firms (most publicly traded firms)
- hardware refresh cycles have been shrinking from 10 to 5 to 3 years with fast-changing technology
- Renting vs. owning real estate will result in different classifications of costs for firms in the same industry (SG&A for renting and capital for owning)
- Based on above: $\mu = e_{scale} \frac{PQ}{TC}$

Results: Decomposition of the Aggregate Markup

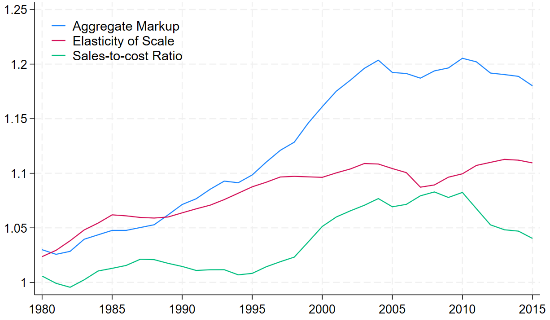
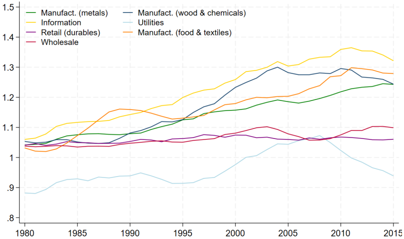


Figure: Decomposition of the Aggregate Markup into Elasticity of Scale and Sales-to-cost Ratio.

Results: Industry-specific Markups



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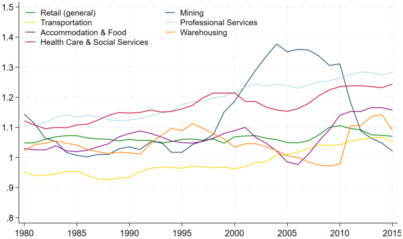

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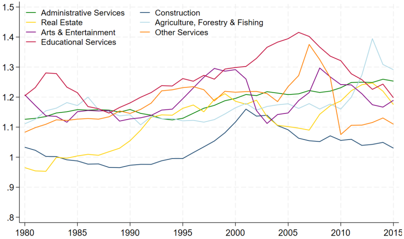

Figure: Bottom 7 industries

- Highest markups
  - Information
  - Manufacturing of wood and chemicals
  - Manufacturing of food and textiles
- Lowest elasticity of scale
  - Utilities
  - Transportation
  - Construction
- High volatility in the bottom 7 industries, likely due to the small number of observations

Macroeconomic Implications

Constant Returns to Scale

$Y_i = z_i K^\alpha L^{1-\alpha}$

Firms with higher z_i are more productive and get bigger

Implications: break up a big firm $\Rightarrow$ same high z_i across many small firms $\Rightarrow$ increased competition and efficiency

Increasing Returns to Scale

$Y_i = z_i L^\alpha K^\beta,\ \alpha + \beta > 1$

Firms of bigger size are more productive

Implications: break up a big firm $\Rightarrow$ same high z_i across many small firms $\Rightarrow$ increased competition, but destroys productivity

Appendix

Estimation Methods: OLS and Syverson's method

- OLS

$$Y = AK^{\alpha}V^{\beta} \tag{3}$$

$$y_{it} = a + \alpha k_{it} + \beta v_{it} + u_{it}, \tag{4}$$

so $\alpha + \beta$ measures the elasticity of scale

- Syverson's method

$$Y = A(K^{\alpha}V^{1-\alpha})^{\gamma} \tag{5}$$

$$y_{it} = a + \gamma \ln\left(K_{it}^{\alpha}V_{it}^{1-\alpha}\right), \tag{6}$$

where α is the share of capital in total costs, and γ is the elasticity of scale

Note: all regressions are run on data within 5-year rolling periods and include year fixed effects and sub-industry fixed effects

Issues with Estimation: Omitted Price Bias

- Simple OLS in logs as a starting point: $y_{it} = \beta_0 + \beta_k k_{it} + \beta_v v_{it} + u_{it}$
- Klette and Griliches (1996): output price is correlated with input choices
- Bond et al. (2021): deflating prices does not resolve the bias in the presence of market power and heterogeneous markups

$$r_{it} = y_{it} + p_{it} = \beta_0 + \beta_k k_{it} + \beta_v v_{it} + p_{it} + u_{it}, \tag{7}$$

where, in logs, r_{it} is revenue, y_{it} is output, p_{it} is price, k_{it} is capital, v_{it} is variable inputs, and u_{it} is the error term.

After deflating:

$$r_{it}^d = \beta_0 + \beta_k k_{it} + \beta_v v_{it} + (p_{it} - p_{t\_index}) + u_{it} \tag{8}$$

- Potential solution
  - add a proxy variable for $(p_{it} - p_{t\_index})$
  - share in total industry costs, s
  - s reflects relative firm size; size affects the firm's residual demand, which in turn affects the price differential

Issues with Estimation: Simultaneity and Selection

$$r_{it}^{d} = \beta_0 + \beta_k k_{it} + \beta_v v_{it} + s_{it} + u_{it} \tag{9}$$

- Simultaneity
  - u_{it} contains productivity shock Ω_{it}
  - Productivity shock affects inputs
  - Productivity shock is observed by the firm but unobserved by the econometrician
- Selection
  - Firms may respond to a negative productivity shock by exiting the market altogether
- Olley and Pakes (1996) and Ackerberg et al. (2015) resolve these biases

Estimation Methods: Olley-Pakes

$$inv_{it} = inv_t(\Omega_{it}, k_{it}, s_{it}) \tag{10}$$
$$\Omega_{it} = h_t(inv_{it}, k_{it}, s_{it}) \tag{11}$$
$$r^d_{it} = \beta_0 + \beta_v v_{it} + \beta_k k_{it} + \beta_s s_{it} + h_t(inv_{it}, k_{it}, s_{it}) + e_{it} \tag{12}$$
$$\phi_{it} = \beta_k k_{it} + \beta_s s_{it} + h_t(inv_{it}, k_{it}, s_{it}) \tag{13}$$

- estimate (6) with OLS using a second-order polynomial for ϕ_{it}

$$\Omega_{it} = g_t(\Omega_{it-1}, P_{it}) + \varepsilon_{it} \tag{14}$$
$$P_{it} = p_t(inv_{it-1}, k_{it-1}, s_{it-1}) \tag{15}$$
$$r^d_{it} - \hat{\beta}_v v_{it} = \beta_0 + \beta_k k_{it} + \beta_s s_{it} + g_t(\hat{\phi}_{it-1} - \beta_k k_{it-1} - \beta_s s_{it-1}, \hat{P}_{it}) + \varepsilon_{it} + e_{it} \tag{16}$$

- estimate (9) with probit using a second-order polynomial for p_t
- estimate (10) with nonlinear least squares using a second-order polynomial for g_t
- all regressions are run on data within 5-year rolling periods and include year fixed effects and sub-industry fixed effects

Estimation Methods: Ackerberg-Caves-Frazer

$$\Omega_{it} = h_t(inv_{it}, v_{it}, k_{it}, s_{it}) \quad (17)$$

$$r^d_{it} = \beta_0 + \beta_v v_{it} + \beta_k k_{it} + \beta_s s_{it} + h_t(inv_{it}, v_{it}, k_{it}, s_{it}) + e_{it} \quad (18)$$

$$\phi_{it} = \beta_v v_{it} + \beta_k k_{it} + \beta_s s_{it} + h_t(inv_{it}, v_{it}, k_{it}, s_{it}) \quad (19)$$

- estimate (12) with OLS using a second-order polynomial for ϕ_{it}

$$E\left[y_{it} - \beta_0 - \beta_v v_{it} - \beta_k k_{it} - \beta_s s_{it} + g_t(\hat{\phi}_{it-1} - \beta_v v_{it-1} - \beta_k k_{it-1} - \beta_s s_{it-1}, \hat{P}_{it}) \otimes \begin{pmatrix} v_{it} \\ k_{it} \\ s_{it-1} \\ \hat{P}_{it} \\ \hat{\phi}_{it-1} \end{pmatrix} \right] = 0 \quad (20)$$

- estimate (14) with generalized method of moments using a second-order polynomial for g_t
- all regressions are run on data within 5-year rolling periods and include year fixed effects and sub-industry fixed effects

Results: Markups Using Different Cost Categories

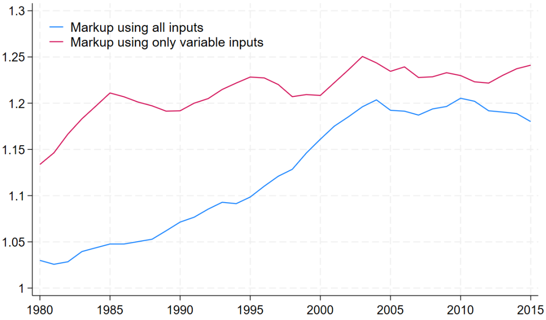

Figure: Markups Using Different Cost Categories

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