

Explaining the Rising Concentration of U.S. Industries: Superstars, Intangibles, Globalization or Barriers to Entry?*

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Abstract

We study the evolution of profits, investment and market shares in US industries over the past 40 years. Globalization explains a large share of the evolution of the manufacturing sector. Foreign competition leads to domestic consolidation and increasing intangible investment. Outside manufacturing we show that two theories account for most of the changes. During the 1990's, and at low levels of initial concentration, we find evidence of efficient concentration driven by tougher price competition, intangible investment, and increasing productivity of leaders. After 2000, however, the evidence suggests inefficient concentration and barriers to entry, as leaders become more entrenched and concentration is associated with lower investment, higher prices and lower productivity growth. We construct statistical proxies to predict if the evolution of an industry is more consistent with efficient or with inefficient concentration.

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Four stylized facts have emerged in recent years regarding the U.S. business sector, summarized in Figure 1. Concentration and Profits have increased (Panels A and B, respectively); while the labor share as well as investment relative to profits and Q have fallen (Panels C and D, respectively). This is true across most U.S. industries as shown by Grullon et al. (2017) (concentration and profits), Autor et al. (2017a) (labor shares) and Gutiérrez and Philippon (2017b) (investment).

While these stylized facts are well established, their interpretation remains controversial. There is little agreement about the causes of these evolutions, and even less about their consequences. At least four prominent explanations have been put forth in the literature:¹

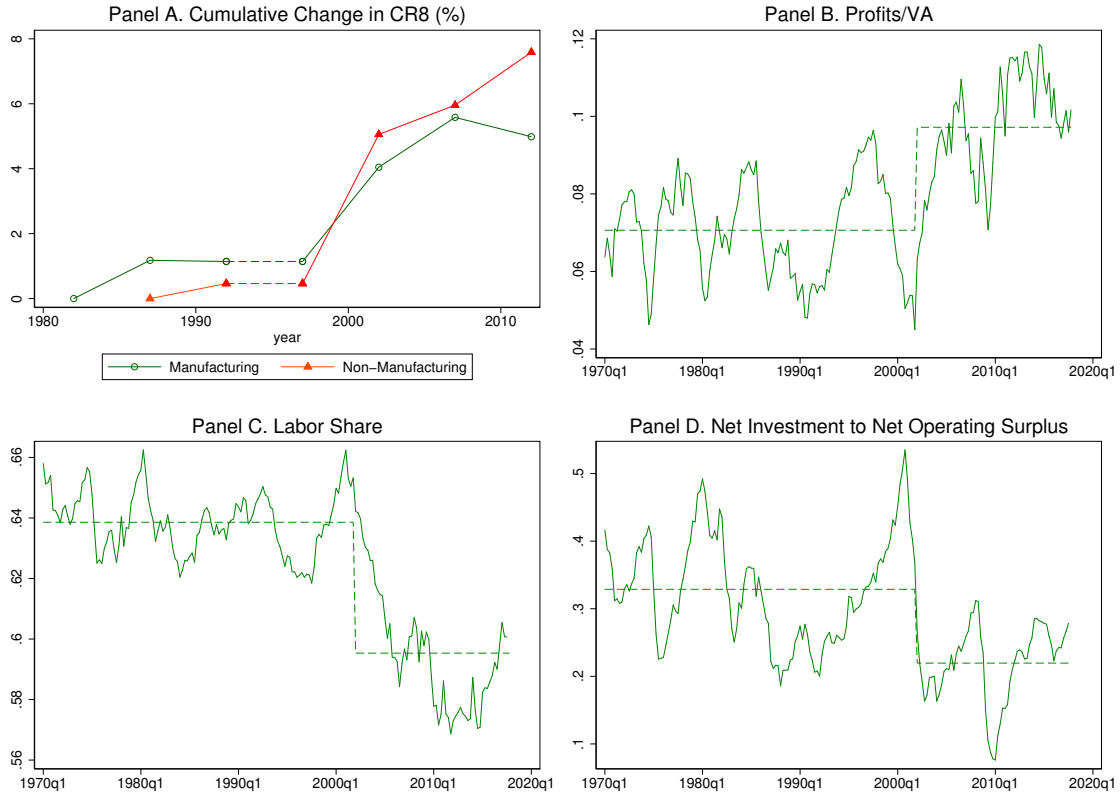
1. **Rising Capital Share** (henceforth α): The evolution of profits could be explained by an increase in the capital share. This would mechanically reduce the labor share while measurement errors could lead to a decrease in (measured) investment. Capital deepening could come from the rise of intangibles as in Alexander and Eberly (2016); Crouzet and Eberly (2018) or automation as in Acemoglu and Restrepo (2017).
2. **Rising Elasticity** (henceforth σ): Autor et al. (2017a) argue that concentration reflects “a winner take most feature” explained by the fact that “consumers have become more sensitive to price and quality due to greater product market competition.” Economic activity shifts towards more productive, higher mark-up, and lower labor share firms.
3. **Increasing Returns to Scale** (henceforth γ): Network effects and increasing differences in the productivity of Information Technology could increase the returns to scale – particularly of top firms. Bessen, 2017 studies the link between IT and Concentration, while Aghion et al. (2018) develop a model where ICT improvements extend the boundary of high-productivity firms, leading to an initial burst followed by a drop in growth.
4. **Rising Barriers to Competition** (henceforth κ): Gutiérrez and Philippon (2018), Jones et al. (2018) and Gutiérrez and Philippon (2019) argue that domestic competition has declined in many U.S. industries because of increasing entry costs, lax antitrust enforcement, and lobbying.

Despite explaining a common set of (baseline) facts, these explanations have widely different implications for welfare. According to σ , for example, concentration is good news: it leads more productive firms to expand, while product market competition increases. According to κ , concentration is bad news: it leads to an increase in economic rents and a decline in innovation. The goal of this paper is to determine which of these explanations is consistent with aggregate and sector-level trends.

Let us make three comments before discussing our approach and results. First, these hypotheses are not mutually exclusive. Leaders can become more efficient and more entrenched at the same time – which can explain their growth, but also create rising barriers to entry (Crouzet and Eberly, 2018). Indeed, a combination of all these explanations is often heard in the discussion of internet giants Google, Amazon, Facebook or Apple. Second, intangibles can play a role in all of these explanations. They may lead to

¹One could entertain other hypotheses – such as weak demand or credit constraints – but previous research has shown that they do not fit the facts. See Gutiérrez and Philippon (2017b) for detailed discussions and references.

Figure 1: Evolution of U.S. Concentration, Profits, Labor Shares and Investment



Notes: Panel A based on the cumulated sales-weighted average change in 8-firm Concentration Ratio (CR8). Data from the U.S. Economic Census based on SIC-4 codes before 1992 and NAICS-6 codes after 1997. We include only those industries that are consistently defined over each 5-year period, so that no change is measured from 1992 to 1997. When multiple tax groups are reported, only taxable firms are included. CR8 equals the market share (by sales) of the 8 largest firms in each industry. Panels B, C and D based on quarterly data for the Non-Financial Corporate sector from the Financial Accounts of the United States, via FRED. Profit rate defined as the ratio of After Tax Corporate Profits with IVA and CCA_{adj} to Value Added (series W328RC1A027NBEA and NCBGVAA027S, respectively). Labor Share defined as the ratio of compensation of employees (NCBCEPQ027S) to gross value added (NCBGVAQ027S). NI/OS defined as the ratio of net investment (gross fixed capital formation minus consumption of fixed capital, series NCBGFCFA027N minus NCBFCFA027N) to net operating surplus (series NCBOSNQ027S). Dotted lines show the average of the corresponding series before and after 2002.

Table 1: Summary of Test Measures and Predictions

		Data	Theories			
			α	σ	γ	κ
Basic Measures						
0. Basic Measures	Domestic Concentration	+	?	+	+	+
	Measured Profits	+	+	+	+	+
	Labor share	-	-	-	-	-
	Investment gap	+	+	?	+	+
Additional Measures						
1. International Evidence	Common global trends in basic measures	-	+	+	+	-
2. Entry, Exit and Turnover	Leader turnover	-	?	+	-	-
	Elasticity of Entry to Q	-	?	+	+	-
	Exit Rate	-	?	+	+	-
3. Joint evolution of CR , TFP and prices	Corr($\Delta CR, \Delta TFP$)	+..-	?	+	+	-
	Corr($\Delta CR, \Delta P$)	-..+	?	-	-	+
4. Investment & profits by leaders	Aggregate investment rate	-	+	?	?	-
	Leader investment rate	-	-	+	+	-
	Leader profit margins	+	?	?	+	+
5. Returns to Scale	Estimated RS*	0+	0	-	+	?

capital deepening (e.g., replacing workers with computers and software); may increase the elasticity of substitution (e.g., through online price comparison) or the returns to scale (e.g., organizational capital); and may create barriers to entry (e.g., through patents and/or the compilation of Big Data). Finally trade and globalization can explain some of the same facts (Feenstra and Weinstein, 2017; Impullitti et al., 2017). Foreign competition can lead to an increase in domestic concentration and a decoupling of firm value from the localization of investment. It is therefore important to control for imports in our analyses. That said, foreign competition is significant for about 3/4 of the manufacturing sector, or about 10% of the private economy – so it cannot explain the aggregate trends.

Model. We present a simple model to clarify these theories., and derive a broad set of predictions for each hypothesis. These predictions include the joint evolution of competition, concentration, productivity and prices. Some of these predictions have been studied by the literature. We contribute new facts/results for each of them and, perhaps more importantly, bring them together to better differentiate among our alternate hypotheses.

Aggregate Results. Table 1 summarizes our main results. It contrasts the theoretical prediction of each hypothesis against the empirical behavior of each measure.² Predictions colored in green are consistent with the data. Predictions colored in red are not.

²The empirical behavior of each measure is established using a wide range of aggregate-, industry- and firm-level data, as described below. The data appendix describes our data sources and definitions.

Table 1 shows that different theories can have similar predictions. The most obvious example is concentration. Rising concentration can come from increasing competition (SIGMA) or from rising barriers to entry (KAPPA). This explains why IO economists are uncomfortable when people use concentration to think about competition. This is why we need to consider several measures.

Globalization plays an important role in manufacturing, particularly for the industries most affected by Chinese competition. We find that foreign competition forces laggards to shrink or exit, while leaders respond by increasing investment – particularly in intangible assets. Domestic concentration increases but import-adjusted concentration (i.e., properly accounting for foreign firms selling in the U.S.) remains flat. The response of US firms to the China shock seems to invalidate standard measures of markups based on cost of goods sold (De-Loecker et al., 2019). The endogenous response of intangible expenses leads to an increase in COGS-based measures of markups. On the other hand, exit and profit margins correctly signal the increase in foreign competition.

The σ theory says that consumers have become more price elastic. Competition in the form of low search can clearly increase concentration. For instance, Syverson (2004) studies the concrete market and finds that “When producers are densely clustered in a market, it is easier for consumers to switch between suppliers (making the market in a certain sense more competitive).” In addition, tough competition truncates the left tail of the productivity distribution as inefficient producers cannot compete. This then leads to higher productivity. If the economy transitions from a low sigma to a high sigma, we should observe: (i) concentration driven by exit; (ii) more volatility of market shares since demand responds more strongly to cost shocks; (iii) concentration associated with lower prices and higher productivity. We already know that this hypothesis describes well the evolution of the retail industry from 1990 to 2005 (Basu et al., 2003; Blanchard, 2003). Hortacsu and Syverson (2015) argue that two factors explain higher retail productivity: superstores and e-commerce. We also know that inefficient retailers exit. After 2000, however, we find that these 3 predictions are rejected by the data in most industries. Market shares become more persistent, exit rates remain stable, and the correlation between productivity growth and concentration becomes negative.

The γ theory says that returns to scale have increased and explain the rise in concentration. We estimate returns to scale as in (Basu et al., 2006) and we find a small increase. Many industries around the world use the same technologies as in the US but do not experience the same concentration. Estimates of return-to-scale in manufacturing have remained stable or decreased (Ho and Ruzic, 2017). Returns to scale thus cannot explain the broad trends that we document, even though they probably matter in some industries.

The κ theory emerges as the most relevant explanation over the past 15 years. It correctly predicts the evolution of profits, entry, exit, turnover, prices, productivity and investment in most industries.

To conclude the paper, we propose a systematic classification of the drivers of industry-level changes. We perform a Principal Components Analysis on a wide range of measures covering all the predictions in Table 1. We find that the first principal component, PC1, captures γ and σ theories of efficient concentration while the second principal component, PC2, captures barriers of entry and merger-driven concentration. This distinction is quite stark and allows us to show which industries are more heavily affected by these two main drivers.

Related Literature. We provide a partial review of the literature. We discuss individual papers in more details in the relevant sections below. There is a growing literature studying trends on competition, concentration, and entry. [Davis et al. \(2006\)](#) find a secular decline in job flows. They also show that much of the rise in publicly traded firm volatility during the 1990's is a consequence of the boom in IPOs, both because young firms are more volatile, and because they challenge incumbents. [Haltiwanger et al. \(2011\)](#) find that “job creation and destruction both exhibit a downward trend over the past few decades”. [Decker et al. \(2015\)](#) argue that, whereas in the 1980's and 1990's declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000's, including the traditionally high-growth information technology sector. [Furman \(2015\)](#) shows that “the distribution of returns to capital has grown increasingly skewed and the high returns increasingly persistent” and argues that it “potentially reflects the rising influence of economic rents and barriers to competition”³. [CEA \(2016\)](#) and [Grullon et al. \(ming\)](#) are the first papers to extensively document the broad increases in profits and concentration. [Grullon et al. \(ming\)](#) also show that firms in concentrating industries experience positive abnormal stock returns and more profitable M&A deals. [Blonigen and Pierce \(2016\)](#) find that M&As are associated with increases in average markups. [Dottling et al. \(2017\)](#) find that concentration has increased in the U.S. while it has remained stable (or decreased) in Europe. [Faccio and Zingales \(2017\)](#) show that competition in the mobile telecommunication industry is heavily influenced by political factors, and that, in recent years, many countries have adopted more competition-friendly policies than the US. [Autor et al. \(2017a\)](#) study the link between concentration and the labor share. An important issue in the literature is the measurement of markups and excess profits. The macroeconomic literature focuses on the cyclical behavior of markups ([Rotemberg and Woodford, 1999](#); [Nekarda and Ramey, 2013](#)). Over long horizons, however, it is difficult to separate excess profits from changes in the capital share. [De-Loecker et al. \(2019\)](#) estimate markups using the ratio of sales to costs of goods sold, but in the long run this ratio depends on the share of intangible expenses, and the resulting markup does not directly provide a measure of market power. [Barkai \(2017\)](#), on the other hand, estimates directly the required return on capital and finds a significant increase in excess profits.

The weakness of investment has been discussed in the context of weak overall growth ([IMF, 2014](#); [Furman, 2015](#); [Hall, 2015](#); [Fernald et al., 2017](#)). [Alexander and Eberly \(2016\)](#) emphasize the role of intangible investment. [Gutiérrez and Philippon \(2017b\)](#) show that the recent weakness of investment relative to Tobin's Q is not explained by low expected productivity growth, low expected demand, or financial frictions. Consistent with our emphasis on market power, [Lee et al. \(2016\)](#) find that capital stopped flowing to high Q industries in the late 1990's. A large literature, surveyed by [Gilbert \(2006\)](#), studies the relationship between competition, innovation and investment. [Comin and Philippon \(2005\)](#) find that “firm volatility increases after deregulation [and] is linked to research and development spending.” [Aghion et al. \(2009\)](#) study how foreign firm entry affects investment and innovation incentives of incumbent firms. [Varela \(2017\)](#) studies the feedback effects on investment from relaxing laggards' financial constraints. She finds that improving laggards' access to funding not only increases their own investment, but also pushes leaders to invest more to remain competitive. [Corhay et al. \(2017\)](#) study the link between (risky) markups and expected excess

³[Furman \(2015\)](#) also emphasizes emphasizes the weakness of corporate fixed investment and points out that low investment has coincided with high private returns to capital, implying an increase in the payout rate (dividends and shares buyback).

returns. [Davis and Haltiwanger \(2019\)](#) emphasize the role of the housing market.

Last, our paper is related to the effect of foreign competition – particularly from China (see [Bernard et al. \(2012\)](#) for a review). [Bernard et al. \(2006\)](#) show that capital-intensive plants and industries are more likely to survive and grow in the wake of import competition. [Bloom et al. \(2015\)](#) argue that Chinese import competition leads to increased technical change within firms and a reallocation of employment towards more technologically advanced firms. [Frésard and Valta \(2015\)](#) find that tariff reductions lead to declines in investment in markets with competition in strategic substitutes and low costs of entry. Within-industry, they find that investment declines primarily at financially constrained firms. The decline in investment is negligible for financially stable firms and firms in markets featuring competition in strategic complements. [Hombert and Matray \(2015\)](#) show that R&D-intensive firms were better able to cope with Chinese competition than low-R&D firms. They explain this result based on product differentiation, using the [Hoberg and Phillips \(2017\)](#) product similarity index. [Autor et al. \(2013\)](#); [Pierce and Schott \(2016\)](#); [Autor et al. \(2016\)](#); [Feenstra et al. \(2017\)](#) study the effects of Chinese import exposure on U.S. manufacturing employment. [Feenstra and Weinstein \(2017\)](#) estimate the impact of globalization on mark-ups, and conclude that mark-ups decreased in industries affected by foreign competition. Some of these papers find a reduction in investment for the ‘average’ firm, which is consistent with our results and highlights the importance of considering industry leaders and laggards separately. Estimates of return-to-scale in manufacturing have remained stable or decreased ([Ho and Ruzic, 2017](#)).

The remainder of this paper is organized as follows. Section 1 derives theoretical predictions. Section 2 compares the US to other countries. Section 3 discusses empirical proxies for competition in the context of the globalization and the China shock. Section 4 discusses turnover of industry leaders. Section 5 focuses on prices and productivity. Section 6 focuses on investment. Section 7 present estimates of return to scales. Finally, section 8 concludes with a proposal to attribute theories to industries.

1 Theory

In this section we use a sequence of simple models to derive testable predictions for the various hypotheses.⁴ The timing of the models follows the classic model of [Hopenhayn \(1992\)](#): (i) there is a sunk entry cost κ ; (ii) firms draw their productivities a (and/or idiosyncratic demand shocks); (iii) they either produce with a fixed operating cost ϕ or they exit early.

1.1 Good Concentration, Bad Concentration.

Consider an industry with N identical firms with productivity $a_i = A$ for all $i \in [0, N]$, and industry demand Y . Suppose the game among the N firms leads to a markup μ over marginal cost. Firms set the price

$$p = \frac{1 + \mu}{A}$$

⁴Hypothesis α is that there has been an increase in the capital share of firms’ production function $y = ak^\alpha n^{1-\alpha}$. The increase in α coincides with a shift from tangible to intangible capital. We will look directly at the evolution of the stock of intangible capital in Section 6.

and firm i 's profits are

$$\pi_i = \left(p - \frac{1}{A} \right) y_i - \phi = \frac{\mu}{1 + \mu} p y_i - \phi$$

In a symmetric equilibrium with identical firms, all firms produce

$$y = \frac{Y}{N}$$

So profits are

$$\pi = \frac{\mu}{1 + \mu} \frac{pY}{N} - \phi$$

Under free entry, we have

$$\frac{E[\pi]}{r + \delta} \leq \kappa$$

where r is the discount rate, δ is the exogenous exit rate, and κ is the sunk entry cost. The free entry condition is then

$$N \geq \frac{\mu}{1 + \mu} \frac{pY}{(r + \delta) \kappa + \phi}$$

A simple case is when industry demand is unit elastic (Cobb Douglas). In that case $Y(p) = \bar{Y}/p$ and we have $N \geq \frac{\mu}{1 + \mu} \frac{\bar{Y}}{(r + \delta) \kappa + \phi}$. Then, we have the following proposition

Proposition 1. *In response to shocks to ex-post markups μ , concentration is positively related to competition. In response to shocks to κ , concentration is negatively related to competition.*

This proposition summarizes the fundamental issue with using concentration to shed light on competition. Concentration is endogenous and can signal either increasing or decreasing degrees of competition. In other words, when looking at concentration measures, it is crucial to take a stand on why concentration is changing, in particular to see if it is driven by shrinking margins or by higher barriers to entry.

Corollary 1. *Concentration is a valid measure of market power only when concentration is driven by barriers to entry or by mergers.*

Note that it is straightforward to extend the analysis to the case where μ depends on the number of firms. We can write $\frac{\mu}{1 + \mu} = \bar{l} N^{-\theta}$ where \bar{l} is the baseline Lerner index (when the mass of entrants is normalized to 1) and θ is the elasticity of the markup to concentration. We would then write the free entry condition as $N^{1 + \theta} \geq \frac{\bar{l} \bar{Y}}{(r + \delta) \kappa + \phi}$. In a standard CES-monopolistic competition model, for instance, we have $\theta = 0$ and $\bar{l} = 1/\sigma$.

1.2 Selection and Ex-Post Profits

Consider now a model with CES and heterogenous marginal costs.

- Each entrant pays κ for the right to produce one variety $i \in [0, \hat{N}]$;
- After entry, each firm draws productivity a_i , and decides whether to produce with fixed operating cost ϕ and markup μ_i .

Let $N \leq \hat{N}$ be the number of active producers and by convention we order the varieties so that $i \in [0, N]$ are active while $i \in (N, \hat{N}]$ exit early. The demand system is

$$Y^{\frac{\sigma-1}{\sigma}} = \int_0^N y_i^{\frac{\sigma-1}{\sigma}} di$$

where $\sigma > 1$ is the elasticity between different firms in the industry. This demand structure implies that there exists an industry price index $P^{1-\sigma} \equiv \int_0^N p_i^{1-\sigma} di$ such that the demand for variety i is

$$y_i = Y \left(\frac{p_i}{P} \right)^{-\sigma}$$

The firm sets a price $p_i = \frac{1+\mu_i}{a_i}$ and the profits of firm i are now given by $\pi_i = \frac{\mu_i}{(1+\mu_i)^\sigma} a_i^{\sigma-1} P^\sigma Y - \phi$. If we assume monopolistic competition, the optimal markup $\mu^m = \frac{1}{\sigma-1}$ maximizes $\frac{\mu_i}{(1+\mu_i)^\sigma}$. But we do not need to consider only this case. We could assume limit pricing at some markup $\mu < \frac{1}{\sigma-1}$, strategic interactions among firms, and so on. For now we simply keep μ as a parameter.

Firms with productivity $a < a^*$ do not produce, so the active producers are $N = (1 - F(a^*)) \hat{N}$ where \hat{N} is the number of firms that pay the entry cost. Similarly, the density of producers's productivity is $dF^*(a) = \frac{dF(a)}{1-F(a^*)}$. Since all the firms draw from the same distribution of productivity, we have

$$P = \frac{1 + \mu}{A^* N^{\frac{1}{\sigma-1}}}$$

where $A^* \equiv \left(\int a^{\sigma-1} dF^*(a) \right)^{\frac{1}{\sigma-1}}$. Profits are then

$$\pi(a_i; a^*, PY, N) = \frac{\mu}{1 + \mu} \left(\frac{a_i}{A^*} \right)^{\sigma-1} \frac{PY}{N} - \phi$$

For simplicity we consider again the log-industry demand case, so PY is exogenous and equal to \bar{Y} . This defines a cutoff a^* such that only firms above the cutoff are active producers

$$\pi(a^*; a^*, \bar{Y}, N) = 0$$

Using $N = (1 - F(a^*)) \hat{N}$ and $dF^*(a) = \frac{dF(a)}{1-F(a^*)}$ we get

$$\begin{aligned} \frac{\mu}{1 + \mu} (a^*)^{\sigma-1} \bar{Y} &= \phi \hat{N} \int_{a > a^*} a^{\sigma-1} dF(a) \\ \frac{\mu}{1 + \mu} \bar{Y} &= \phi \hat{N} \int_{a > a^*} \left(\frac{a}{a^*} \right)^{\sigma-1} dF(a) \end{aligned}$$

The RHS is increasing in σ and decreasing in a^* , and we have the standard selection effect.

Lemma 1. *The cutoff a^* increases with the demand elasticity σ .*

From the free entry condition we have

$$(r + \delta) \kappa = (1 - F(a^*)) \times E[\pi \mid a > a^*].$$

Since $1 - F(a^*)$ decreases with σ it follows that $E[\pi \mid a > a^*]$ increases with σ .

Proposition 2. *For a given free entry condition, an increase in σ leads to higher rate of failed entry (early exits) and higher profits for remaining firms. An increase in κ , on the other hand, leads to lower entry, lower exit, and higher profits.*

This proposition allows us to distinguish the σ hypothesis from the κ hypothesis.

1.3 Increasing Returns

Now suppose that firms can choose between two technologies after entry: low fixed cost & low productivity (A_L, ϕ_L) or high fixed cost high productivity (A_H, ϕ_H). Let us ignore idiosyncratic productivity differences for now. Profits are then

$$\pi(a, \phi) = \frac{\mu}{1 + \mu} \left(\frac{a}{A}\right)^{\sigma-1} \frac{PY}{N} - \phi$$

The choice clearly depends on the size of the market and the elasticity of demand.

Lemma 2. Firms are more likely to switch to the high returns to scale technology when σ is high.

Assume that the parameters are such that the firms decide to switch: $a_i = A_H$ for all i . Equilibrium profits are then $\pi = \frac{\mu}{1 + \mu} \frac{PY}{N} - \phi_H$. Free entry then requires $\pi = (r + \delta) \kappa$

$$N = \frac{\mu}{1 + \mu} \frac{PY}{\phi_H + (r + \delta) \kappa}.$$

Concentration increases. The behavior of equilibrium profits depends on the selection effect. Without idiosyncratic risk, profits are simply pinned down by free entry. If we take into account idiosyncratic risk, then equilibrium profits increase when firms switch to the high return to scale technology because the selection effect intensifies.

Proposition 3. *A switch to increasing return technology is more likely when demand is more elastic. Increasing returns to scale lead to more concentration, higher profits and higher productivity for remaining firms.*

Note that we can measure the degree of returns to scale as the ratio of average cost to marginal cost

$$\gamma - 1 \equiv \frac{A_H \phi_H}{y} = \frac{\phi_H}{\phi_H + (r + \delta) \kappa} \frac{\mu}{N^{\frac{1}{\sigma-1}}}$$

which is increasing with ϕ since N is decreasing in ϕ .

1.4 Dynamics of Market Shares

Finally, consider the case where, after entry, firms are subject to demand and productivity shocks. In the general case, we have $j \in [0, 1]$ industries and $i \in [0, N_j]$ firms in each industry. The output of industry j is aggregated as $Y_{j,t}^{\frac{\sigma_j-1}{\sigma_j}} = \int_0^{N_j} h_{i,j,t}^{\frac{1}{\sigma_j}} (y_{i,j,t})^{\frac{\sigma_j-1}{\sigma_j}} di$, where σ_j is the elasticity between different firms in the same industry and $h_{i,j,t}$ are firm-level demand shocks. The demand for good (i, j) is given by

$$y_{i,j,t} = h_{i,j,t} Y_{j,t} \left(\frac{p_{i,j,t}}{P_{j,t}} \right)^{-\sigma_j}$$

where $P_{j,t}$ is the industry price index. The nominal revenues of firm i are

$$p_{i,j,t} y_{i,j,t} = p_{i,j,t}^{1-\sigma_j} h_{i,j,t} P_{j,t}^{\sigma_j} Y_{j,t}$$

and the market share is

$$s_{i,j,t} = \frac{p_{i,j,t} y_{i,j,t}}{P_{j,t} Y_{j,t}} = \frac{h_{i,j,t}}{N_j} \left(\frac{(1 + \mu_j) a_{i,j,t}}{(1 + \mu_{i,j}) A_{j,t}} \right)^{\sigma_j - 1}$$

where μ_j is the industry average markup and $A_{j,t}$ is the industry average productivity, as defined earlier. If we track the market shares of firms over time, we have the following proposition.

Proposition 4. *The volatility of log-market shares is*

$$\Sigma_{\log s}^2 = \Sigma_{\log h}^2 + (\sigma_j - 1)^2 \Sigma_{\log a}^2$$

where $\Sigma_{\log a}^2$ is the volatility of idiosyncratic productivity shocks.

and therefore

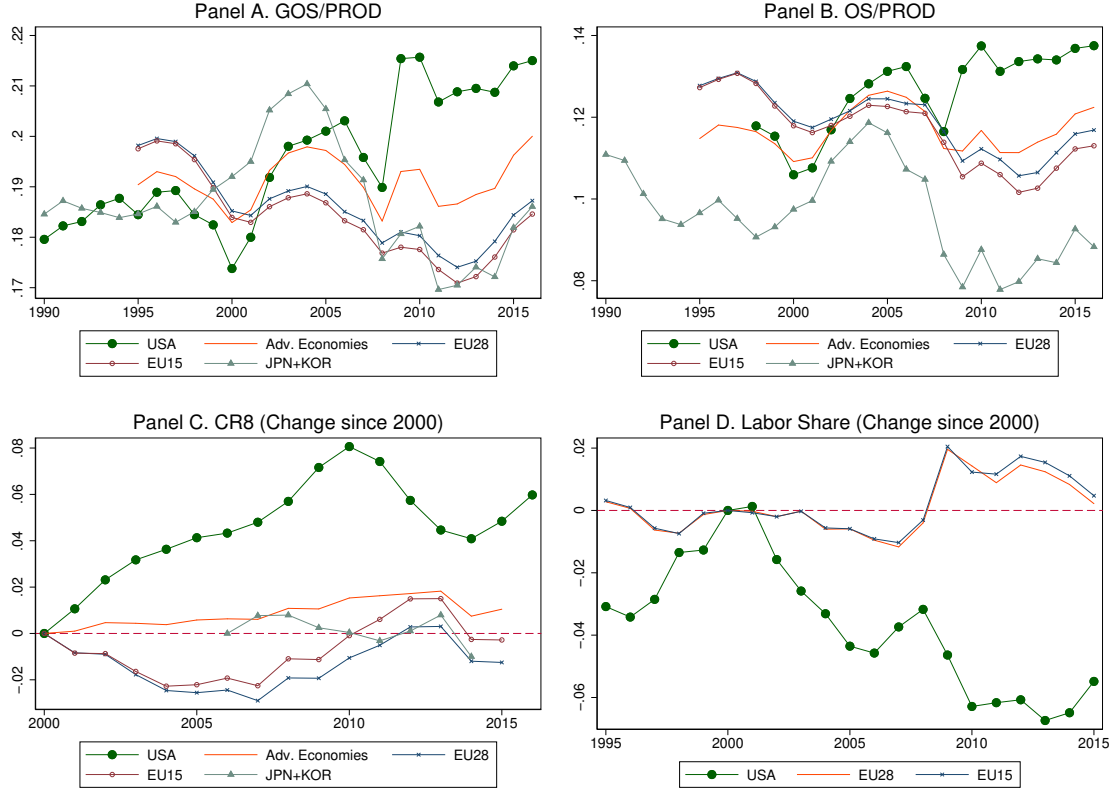
Corollary 2. *All else equal, an increase in σ leads to an increase in the volatility of market shares.*

2 International Evidence

If our four baseline facts (rising concentration and profits, with falling labor share and investment) are the result of technological change in the form of rising α (capital shares), σ (elasticity of substitution) or γ (returns to scale), we would presumably find similar profit, concentration and labor share trends across regions. Figure 2 and 3 test this prediction. Panel A and B of figure 2 show that profits increased only in the US, while they remained stable or decreased in Europe and advanced Asian economies (Japan and South Korea). Panel C shows that concentration increased only in the U.S., while it remained roughly stable in Europe and Asia.⁵ Last, Panel D shows that the labor share declined in the US, and remained stable in Europe.

⁵For this figure, we measure concentration as the ratio of sales by the 8 largest firms in Compustat that belong to a given KLEMS industry x region to total Gross Output reported in OECD STAN. Corporate consolidation is therefore accounted for, as dictated by accounting rules. The appendix provides additional details on the calculation, while [Gutiérrez and Philippon \(2018\)](#)

Figure 2: Profits, Concentration and Labor Shares across Advanced Economies



Notes: Advanced Economies include EU28 countries plus JPN, KOR, NOR, USA. AUS, CAN and CHE omitted due to limited data availability. GOS/PROD and OS/PROD for Non-Agriculture business sector excluding RE, from OECD STAN. Change in CR8 for Non-Agriculture business sector excluding RE, based on Compustat but adjusted for coverage using OECD STAN. CR8 for JPN + KOR reported only since 2006 because Compustat coverage increases rapidly beforehand. Change in labor share for Market Economy, from EU KLEMS. See data appendix for details.

Figure 3 compares the evolution of the sales-weighted average ratio of SALES to COGS (the main input for De-Loecker et al. (2019)’s measure of mark-ups⁶) against gross profit rates by region. The trends towards intangible expenditures is clearly present across all advanced economies, but it is only in the US that we observe a large increase in profits. Profit rates fell for the EU15 and the UK, remained stable in Japan, and increased only in the US.

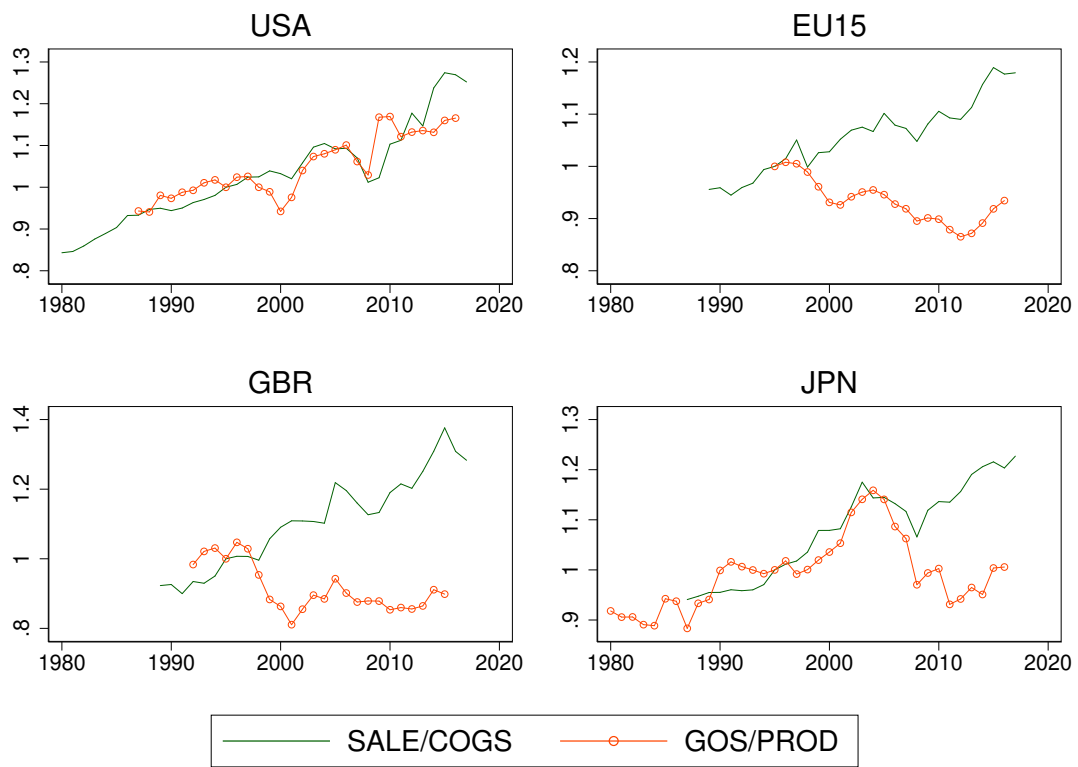
The international evidence shows that the technological change towards intangible expenses is a global phenomenon.⁷ The divergence in US profits, concentration and labor shares, however, suggests the presence

provide a detailed comparison across a wide range of concentration measures for the US and Europe. Bajgar et al. (2019) and Kalemli-Ozcan et al. (2019) report small increases in EU concentration over a similar period, though the level of concentration remains well-below that of the US. Our results are broadly similar after 2005 but, in contrast to them, we find an offsetting decline in concentration from 2000 to 2005 when using Compustat. Figure 18 compares the level of concentration across regions, which is much lower in Europe than the US. Bajgar et al. (2019) find similar levels.

⁶SALE/COGS relates to the benchmark measure of De-Loecker et al. (2019) up to a measurement error correction and a (time-varying) industry-level scaling factor, which measures the elasticity of SALES to COGS.

⁷The above comparisons aggregate across industry categories, and may therefore be affected by changes in industry mix. However, Gutiérrez and Philippon (2018) and Gutiérrez and Piton (2019) reach similar conclusions using industry-level data. Moreover, in Gutiérrez and Philippon (2017a), we compare the evolution of the 5 industries that concentrate the most in the US against Europe. We find that Concentration, profits and Q increased in the U.S., while investment decreased. By contrast, concentration and

Figure 3: Weighted Average SALE/COGS vs. Gross Profit Rates by Region (1995 = 1)



Notes: SALE/COGS equals the sales-weighted average ratio of SALE to COGS across all Compustat firms in a given region. GOS/PROD based on OECD STAN for non-agriculture business sector excluding Real Estate.

of an additional, US-specific mechanism. We use the remaining measures to identify it.

3 Measurement Issues

De-Loecker et al. (2019) (DLEU hereafter) estimate mark-ups using the methodology of De Loecker and Warzynski (2012). The idea is to compare the elasticity of output to a variable input with the cost share of that input. To implement the methodology in large firm-level datasets the authors use COGS as their main measure of variable input. While this approach is promising in theory, the question for us is whether it provides a reliable measure of market power. There are measurement issues with COGS that we discuss in Appendix A. Our main concern, however, is that technology can change over time in a way that creates challenges for COGS-based measure of markups.

We use the China shock to illustrate this issue. We find that COGS-based markup measures do not classify the China shock as an increase in competition, while exit and profit margins do. The Appendix illustrates this issue further with the examples of IBM and Walmart.⁸

3.1 China Shock

We focus on the increase in competition from China during the 2000’s, following Autor et al. (2016) and Pierce and Schott (2016). We find that foreign competition forces laggards to shrink or exit and domestic concentration rises. What is more interesting, however, is the response of leaders.

Exit. Chinese competition leads to a strong replacement effect. Figure 4 shows the normalized number of firms in industries with high and low Chinese import penetration.⁹ Both groups have the same pre-existing trends, including during the dot-com boom, but start to diverge after 2000. In unreported tests, we confirm this relationship is strongly statistically significant.

Identification. Realized imports are endogenous so, in the rest of the section, we use the instrument proposed by Pierce and Schott (2016), which exploits changes in barriers to trade following the United States granting Permanent Normal Trade Relations (PNTR) to China.¹⁰ Pierce and Schott (2016) show that

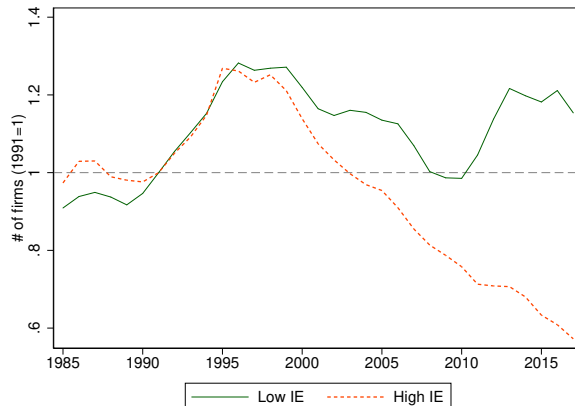
investment remained (relatively) stable, despite lower profits and lower Q . This is true even though these industries use the same technology and are exposed to the same foreign competition.

⁸Walmart invested heavily in intangible assets to improve logistics and gain market share. SG&A costs increased relative to COGS, retail prices went down and profit margins were flat or declining. But Sales over COGS increased and COGS-based markup would signal a decrease in competition.

⁹We follow Autor et al. 2016 and define import penetration for industry j at time t as $\Delta IP_{jt} = \frac{\Delta M_{jt}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}$, where ΔM_{jt}^{UC} denotes the change in US imports from China from 1991 to t ; and $Y_{j,91} + M_{j,91} - E_{j,91}$ denotes the initial absorption (defined as output, $Y_{j,91}$, plus imports, $M_{j,91}$, minus exports, $E_{j,91}$). $Y_{j,91}$ is sourced from the NBER-CES database; while $M_{j,91}$ and $E_{j,91}$ are based on Peter Schott’s data. Only NAICS level 6 industries where data are available across all sources are included in the analyses.

¹⁰Until 2001 China was considered a non-market economy. It was subject to relatively high tariff rates (known as “Non-Normal Trade Relations” tariffs or “non-NTR rates”) as prescribed in the Smoot-Hawley Tariff Act of 1930. From 1980 onward, U.S. Presidents began temporarily granting NTR tariff rates to China, but required annual re-approval by congress. The re-approval

Figure 4: Number of firms by Chinese exposure (1991 = 1)



Notes: Annual data. Number of firms from Compustat; import penetration based on NBER-CES and Peter Schott’s data. Manufacturing industries only, split into ‘high’ (above-median) and ‘low’ (below-median) exposure based on import penetration from 1991 to 2015. See data appendix for details.

industries facing a larger NTR gap experienced a larger increase in Chinese imports and a larger decrease in U.S. employment. We follow [Pierce and Schott \(2016\)](#) and quantify the impact of granting PNTR on industry j as the difference between the non-NTR rate (to which tariffs would have risen if annual renewal had failed) and the NTR rate as of 1999:

$$NTR\ Gap_j = Non\ NTR\ Rate_j - NTR\ Rate_j.$$

This measure is plausibly exogenous to industry demand and technology after 2001. The vast majority of the variation in NTR gaps is due to variation in non-NTR rates set 70 years prior to passage of PNTR. See [Pierce and Schott \(2016\)](#) for additional discussion.

Profits vs. Mark-ups. Figure 5 reports results of the following regressions across firms i in industry j

$$\pi_{ijt} = \sum_{y=1991}^{2007} (\beta_y 1\{y = t\} \times NTR\ Gap_j) + \delta_i + \gamma_t + \varepsilon_{jt} \quad (1)$$

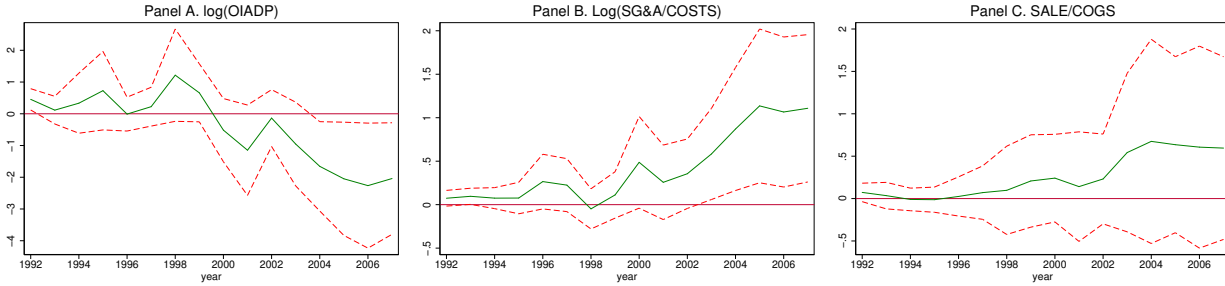
where π_{ijt} denotes a given outcome variable (profits, etc.). All regressions include firm and year fixed effects, and are weighted by firm sales. Standard errors are clustered at the NAICS-6 industry-level. Consistent with the identification assumption, we see no significant pre-trends before 2000, and strong responses afterwards.

As expected, the operating income of US companies falls upon Chinese accession to the WTO (Panel A). This is consistent with the increase in exits.

What is more remarkable, however, is the increase in the share of SG&A in total costs. US firms react to

process introduced substantial uncertainty around future tariff rates and limited investment by both U.S. and Chinese firms (see [Pierce and Schott \(2016\)](#) for a wide range of anecdotal and news-based evidence). This ended in 2001, when the China entered the WTO and the US granted PNTR. The granting of PNTR removed uncertainty around tariffs, leading to an increase in competition.

Figure 5: Profits, SG&A Intensity and Mark-ups around China Shock



Notes: Firm financials from Compustat. NTR gap from [Pierce and Schott \(2016\)](#). Figure reports regression results following equation 1, including 95% confidence intervals. Only firms that existed before 1997 are included. SALE/COGS and XSGA/XOPR are winsorized at the 2% and 98% level, by year. See text for details.

the increased competition by almost doubling their SG&A intensity (Panel B), a result consistent with the shift towards intangibles documented above, as well as the increased product differentiation documented by [Feenstra and Weinstein \(2017\)](#).

The increase in intangible expenditures may bias mark-up estimates based on cost of goods sold. Panel C considers SALE/COGS, which appears to *increase* rather than *decrease* upon the shock. COGS-based markup measures do not classify the China shock as an increase in competition, while exit and profit margins do.¹¹ We therefore focus on profits and market shares dynamics in the rest of our paper.¹²

Investment. Figure 6 plots the average stock of K across Compustat firms in a given year, split by the 1999 NTR gap. K includes PP&E as well as intangibles, as estimated by [Peters and Taylor \(2016\)](#). As shown, average K increased faster in high exposure industries than low exposure industries.

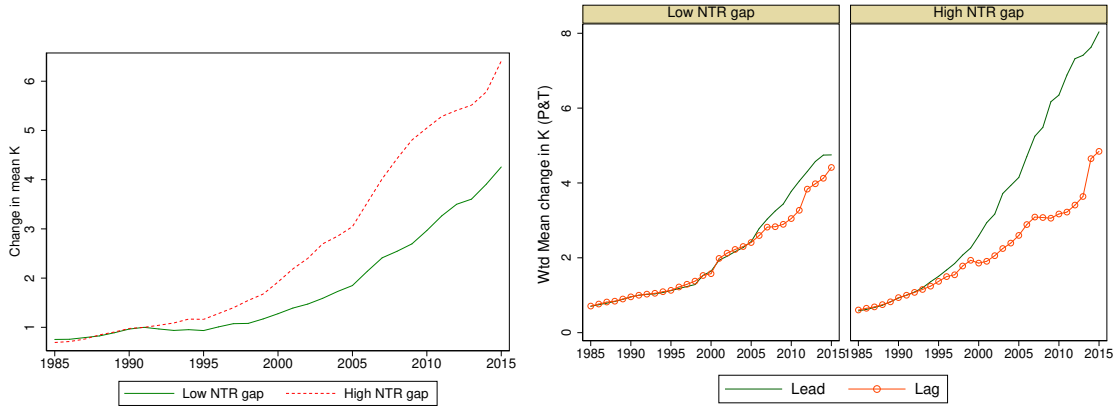
Moreover, the increase is concentrated in Leaders. Figure 6 shows the weighted average change in capital among surviving firms, separating leaders and laggards as well as high and low exposure industries. In low exposure industries, leaders and laggards exhibit similar growth rates of capital. By contrast, leaders increase capital much faster than laggards in high exposure industries.

This suggests that leaders and laggards may have reacted differently to foreign competition, in line with our model’s predictions. We examine this using a generalized difference-in-differences (DiD) specification:

¹¹In unreported tests, we find similar conclusions (i) using the firm-level user-cost mark-ups first reported in the appendix of [Gutiérrez and Philippon \(2017a\)](#); and studying regulatory shocks (the entry of Free Mobile in France and the implementation of large product market regulations, as compiled by [Duval et al. \(2018\)](#)).

¹²This is not to say that profits are a perfect measure. Accounting rules often deviate from economic concepts, while estimates of economic profits depend on a (challenging) estimation of the user cost of capital, and are subject to mis-measurement of the capital stock (particularly with the rise of intangibles). We can gain some comfort by comparing a wide range of measures, from alternate sources. [Gutiérrez and Philippon, 2018](#), for example, show that accounting profits from Compustat and national accounts, economic profits in the style of [Barkai \(2017\)](#) as well as firm-level user-cost implied profits are consistent with each other in both the US and Europe.

Figure 6: Change in average firm K^{PT} by Chinese Exposure (1991 = 1)



Notes: Annual data from Compustat, [Peters and Taylor 2016](#), [Schott \(2008\)](#) and [Pierce and Schott \(2016\)](#). Manufacturing industries only, split into high (above-median) and low (below-median) exposure based on the 1999 NTR gap. Leaders defined as firms with market value in top quartile of the distribution within each NAICS Level 6 industry, as of 2001. Only firms-year pairs with non-missing K^{PT} included.

$$\begin{aligned} \log(K_{i,j,t}) = & \beta_1 Post01 \times NTRGap_j \times \overline{\Delta IP}_t \\ & + \beta_2 Post01 \times NTRGap_j \times \overline{\Delta IP}_t \times Leader_{i,j,0} \\ & + \mathbf{X}_{j,t}'\gamma + \eta_t + \mu_i + \varepsilon_{it}, \end{aligned} \quad (2)$$

where the dependent variable is a given measure of capital for firm i in industry j during year t . $\overline{\Delta IP}_t$ captures time-series variation in Chinese competition averaged across all industries.¹³ The first two terms on the right-hand side are the DiD terms of interest. The first one is an interaction between the NTR gap and $\overline{\Delta IP}_t$ for the post-2001 period. The second term adds an indicator for leader firms to capture differences in investment between leaders and laggards. The third term includes several industry-level characteristics as controls, such as capital and skill intensity.¹⁴ We include year and firm fixed effects η_t and μ_i .

Table 2 reports the results. It shows that leaders increase investment in response to an exogenous increase in competition. We consider three different measures of capital: PP&E, Intangibles (from [Peters and Taylor \(2016\)](#)) and total capital (equal to the sum of PP&E and Intangibles).¹⁵ Columns 1 to 3 include all U.S. incorporated manufacturing firms in Compustat over the 1991 to 2015 period. Columns 4 to 6 focus on continuing firms (i.e., firms that were in the sample before 1995 and after 2009); and show that leaders invested more than laggards, even when compared to firms that survived the China shock.

¹³[Gutiérrez and Philippon \(2017a\)](#) presents results excluding $\overline{\Delta IP}_{j,t}$ to mirror the specification of [Pierce and Schott \(2016\)](#), as well as following the approach of [Autor et al. \(2016\)](#) – which instruments $\Delta IP_{j,t}^{US}$ with the import penetration of 8 other advanced economies ($\Delta IP_{j,t}^{OC}$).

¹⁴These industry characteristics are sourced from the NBER-CES database. We include the (i) percent of production workers, (ii) log-ratio of capital to employment; (iii) log-ratio of capital to value added; (iv) log-average wage; and (v) log-average production wage.

¹⁵In unreported robustness tests, we confirm that our results are robust to including only balance sheet intangibles or excluding goodwill in the PT measure.

Table 2: Investment of Leaders and Laggards following Chinese Accession to WTO

Table shows the results of firm-level panel regressions of measures of capital on $NTRGap_j \times \overline{\Delta I P_{j,t}^{US}}$, following equation (2). We consider three measures of capital: gross PP&E, intangibles defined as in Peters and Taylor (2016) and their sum (total). Regression over 1991 - 2015 period. Leaders defined as firms with market value in top quartile of the distribution within each NAICS Level 6 industry, as of 2001. All regressions include measures of industry-level production structure as controls (see text for details). Only US-headquartered firms in manufacturing industries with non-missing K^{PT} included. Standard errors in brackets, clustered at the industry-level. + p<0.10, * p<0.05, ** p<0.01.

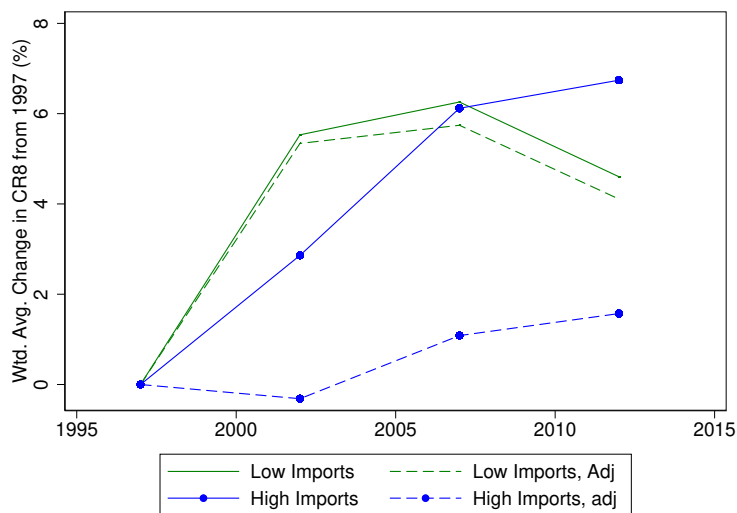
	All firms			Continuing Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(PPE_t)^a$	$\log(Imt_t^{PT})^b$	$\log(k_t^{PT})^{a+b}$	$\log(PPE_t)^a$	$\log(Imt_t^{PT})^b$	$\log(k_t^{PT})^{a+b}$
$Post01 \times NTRGap$	-8.594** (2.100)	-0.611 (2.081)	-2.041 (1.689)	-11.968** (2.283)	-3.641+ (2.038)	-5.059** (1.653)
$Post01 \times NTRGap \times Lead$	9.407** (2.018)	7.108** (1.191)	6.761** (1.174)	9.842** (2.480)	8.611** (1.507)	8.290** (1.510)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry Controls	Y	Y	Y	Y	Y	Y
R^2	.14	.52	.48	.18	.57	.54
Observations	34,747	35,101	35,133	15,912	16,023	16,040

Our results are consistent with [Frésard and Valta \(2015\)](#) and [Hombert and Matray \(2015\)](#). [Frésard and Valta \(2015\)](#) find a negative average impact of foreign competition in industries with low entry costs and strategic substitutes. They briefly study within-industry variation, and find that investment declines primarily at financially constrained firms. [Hombert and Matray \(2015\)](#) studies within-industry variation with a focus on firm-level R&D intensity. They show that R&D-intensive firms exhibit higher sales growth, profitability, and capital expenditures than low-R&D firms when faced with Chinese competition, consistent with our finding of increased intangible investment. They find evidence of product differentiation using the index of [Hoberg and Phillips \(2017\)](#). In the Appendix of [Gutiérrez and Philippon 2017a](#), we study the dynamics of employment and find that leaders increase both capital and employment, while laggards decrease both. Employment decreases faster than capital so that K/Emp increases in both groups of firms. Since initial publication of these results in [Gutiérrez and Philippon 2017a](#), [Pierce and Schott \(2018\)](#) obtained similar results using Census data to cover the entire sample of US firms.

3.2 Globalization

Let us now move beyond China and consider global trade more broadly. Globalization creates a challenge for measures of domestic concentration. We compute import-adjusted measures of concentration (CR8). We consider low import and high import manufacturing industries. [Figure 7](#) shows the naive concentration measures and the import-adjusted ones (dashed lines). In high import industries, the naive domestic concentration *increases* about 6.7% while the import adjusted concentration increases by only 1.6%.¹⁶

Figure 7: Domestic vs. Import Adjusted Concentration for Manufacturing Industries



Notes: weighted average absolute change in domestic (solid) and import-adjusted (dashed) CR8 across NAICS-6 manufacturing industries. Low import industries (green) are those in the bottom quantile of import shares as of 2012. High import industries (blue) include the rest. Imports accounted for 3% of sales + imports in low import industries and 29% in high import industries, on average. Domestic concentration from U.S. Economic Census. Import adjusted concentration defined as $CR8_{jt}^{IA} = CR8_{jt} \times \frac{sale_{jt}}{sale_{jt} + imp_{jt}} = CR8_{jt} \times US\ Share_{jt}$. NAICS-6 industries are included if they are consistently defined from 1997 to the given year. See data appendix for details.

¹⁶[Gutiérrez and Philippon \(2017a\)](#) reports similar results using Herfindahls and the data of [Feenstra and Weinstein \(2017\)](#).

Figure 7 shows why it is critical to control for foreign competition when analyzing concentration. Highly exposed industries account for about 75% of manufacturing output, or about 10% of the private economy – so foreign competition cannot explain the aggregate trends. But it does play an important role in manufacturing.

4 Entry, Exit and Turnover

IO economists rightly complain about the use of HHIs or Concentration Ratios at the broad industry x country/region level as measures of market power. The limitations of national CRs and HHIs are well understood. NAICS industries and countries are much broader than product markets – and concentration may evolve differently at more granular levels.¹⁷ But there is a more fundamental problem: depending on the nature of competition, technology as well as supply and demand primitives, concentration may be positively or negatively correlated with competition and mark-ups. In other words, concentration “is a market outcome, not a market primitive” (Syverson, 2018).

Leader Turnover. To obtain an alternate measure of market power, we consider turnover of market shares and market leadership. In particular, one can ask: given that a firm is at the top of its industry now (top 4, top 10% of market value), how likely is it that it will drop out over the next 5 years. Per proposition 4, increases in σ would result in higher leader turnover, while increases in κ would result in lower turnover.

Figure 8 tests this prediction. We define turnover in industry j at time t as the probability of leaving the top 4 firms of the industry over a five-year period,

$$TopTurn_{jt} = \Pr \left(z_{i,j,t+5} < z_{j,t+5}^{\#4} \mid z_{i,j,t} \geq z_{j,t}^{\#4} \right),$$

where $z_{i,j,t}$ denotes either the sales of firm i at time t or its market value of equity, and $z_{j,t}^{\#4}$ is the value of $z_{i,j,t}$ for the fourth largest firm at time t in industry j .¹⁸ We then average turnover across all industries in a given sector. We focus on the post-1980 period, after the addition of NASDAQ into Compustat. As shown, the likelihood of a leader being replaced was 35% in the 1980s – rose to 40% at the height of Dot-Com bubble – and is only 25% today. Appendix A presents results by sector.

Correlation of Ranks. Turnover focuses on the top of the firm distribution. Figure 9 broadens the sample to all firms, showing the correlation of firm ranking over time. For a particular measure Z (sales, market value, etc.), we define

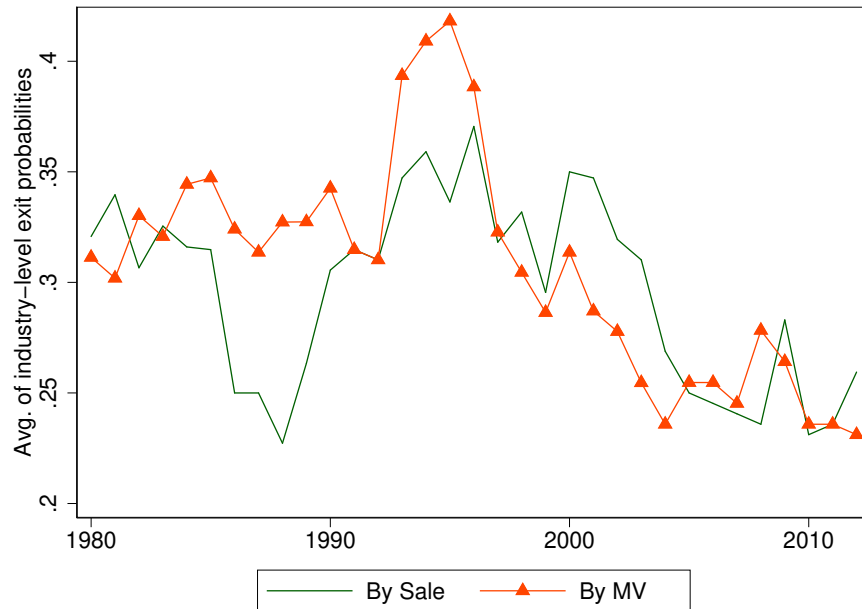
$$RkCorr = Corr_{i \in j} (rank(z_{i,j,t}); rank(z_{i,j,t+5})),$$

where $rank(z_{i,t})$ is the rank of firm i in industry j at time t according to the measure z . We again find a sharp increase in persistency after 2000.

¹⁷See Rossi-Hansberg et al. (2018), among others, for related evidence; but note that their conclusions are controversial (Ganapati, 2018).

¹⁸We use a constant number of leaders because they account for a roughly stable share of sales. In unreported tests, we consider the top 10% of firms and obtain similar results, though this broader group accounts for a rising share of sales.

Figure 8: Turnover of Leaders by Sale and MV



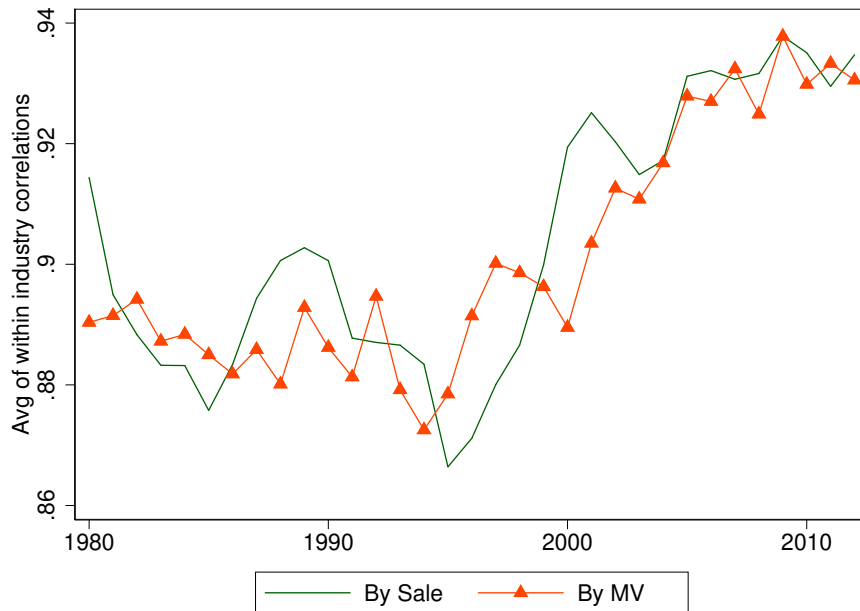
Source: Compustat NA, following BEA industries. Only industry-years with 5 or more firms are included. See text for details.

Persistence of market shares. Last, we can evaluate the persistence of market shares directly. We estimate an AR(1) model of the log-market share for firm i that belongs to SIC-3 industry j , using a 5-year rolling window:

$$\log s_{i,j,t} = \rho_{j,t} \log s_{i,j,t-1} + \epsilon_{i,j,t}$$

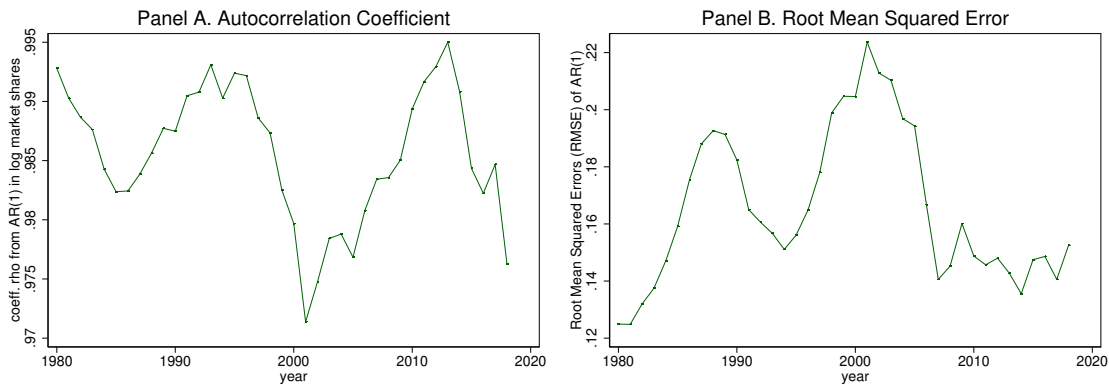
Figure 10 plots the evolution of the sale-weighted annual average of $\rho_{j,t}$ as well as the root mean squared error (RMSE) in Panels A and B, respectively. Again, we find a decline in the volatility of market shares starting in the 2000s. We obtain the same results if we use within-industry shares but we pool all the firms and estimate a ρ_t .

Figure 9: Correlation of 5Y-ahead Firm Ranks



Source: Compustat NA, following BEA industries. Only industry-years with 5 or more firms are included. See text for details.

Figure 10: Persistence and Volatility of Market Shares



Notes: Autocorrelation and RMSE for AR(1) model of firm-level log-market shares, following SIC-3 industries. Estimates based on a 5-year rolling window. Only industry-years with 5 or more firms and firms with a market share higher than 0.02 are included.

Leaders clearly have less to worry about today than 30 years ago. Their market shares and leadership positions are far more persistent today than even 15 years ago. Why might this be? In [Gutiérrez and Philippon \(2019\)](#), we study competitive pressures directly, focusing on the entry and exit margins. We show that exit rates have remained stable, while the elasticity of entry with respect to Tobin's Q was positive and significant until the late 1990s but fell close to zero afterwards. The behavior of entry, exit and turnover is inconsistent with σ , but consistent with κ .

5 Concentration, Productivity and Prices

According to σ and γ , concentration rises as high productivity leaders expand, increasing industry-level productivity and decreasing prices. If more productive firms have lower labor shares, the aggregate labor share also falls. [Autor et al. \(2017b\)](#) document a reallocation from high- to low-labor-share establishments. [Ganapati \(2018\)](#) finds that changes in concentration are uncorrelated with changes in prices, but positively correlated with changes in productivity. [Kehrig and Vincent \(2017\)](#) and [Hsieh and Rossi-Hansberg \(2019\)](#) make similar arguments for manufacturing and service industries, respectively.

We investigate the link between concentration prices and productivity using two datasets, with different levels of aggregation.

5.1 BLS & Compustat

We begin our analysis with relatively aggregated data from the BLS Multifactor Productivity. The dataset includes TFP, prices, wages and labor productivity. We assess the joint evolution of productivity, prices and mark-ups using regressions of the form

$$\Delta_5 \log(Z_{j,t}) = \beta \Delta_5 \log(CRA_{j,t}) + \gamma_t + \varepsilon_{jt}.$$

where Z is the variable of interest and Δ_5 denotes a 5-year change. We consider TFP, prices and the markup of prices over unit labor costs (ULC): $\Delta \log \mu = \Delta \log P - \Delta \log ULC$. For concentration measures we use Compustat to obtain the same industry classification as for our LHS variables.

Table 3 summarizes the results.¹⁹ Columns 1, 3 and 5 are based on pre-2000 changes, and exhibit correlations in line with σ and γ : positive and significant with TFP, and negative (although insignificant) with prices and mark-ups. However, the relationship seems to have collapsed after 2000. The correlation between concentration and TFP turns negative (though insignificant), while the correlation with prices and mark-ups turns positive.

To illustrate the transition, Figure 11 plots the evolution of mark-ups and concentration for the Telecom and Transportation - Air industries. While they exhibit little (or negative) correlation before 2000, both rise sharply afterwards. This is consistent with the cross-country analyses of [Gutiérrez and Philippon \(2018\)](#).

The BLS multifactor productivity tables provide several advantages. They cover the full economy, include TFP estimates and follow a consistent segmentation that can be mapped to other BEA datasets. This allows us to include the evolution of prices, unit-labor costs and mark-ups in our PCA in section 8. However, using broad industry definitions limits the power of our regressions – hence the large confidence intervals above. In the next section, we bring in more granular data.

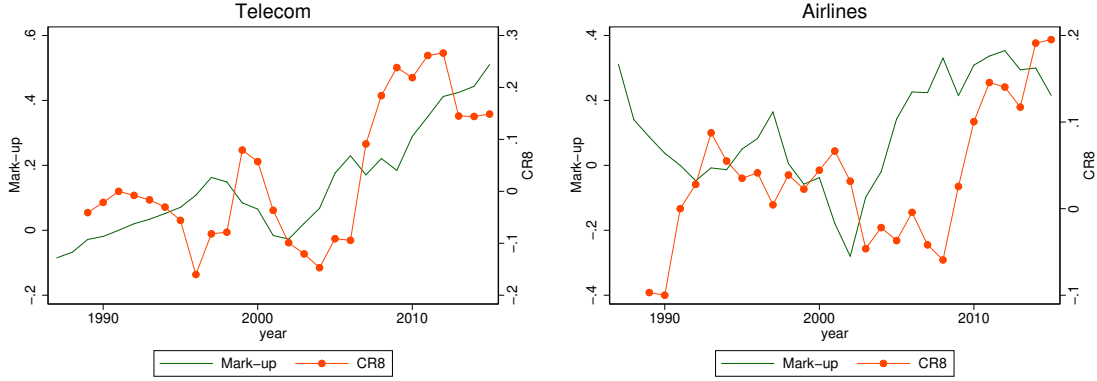
¹⁹In unreported tests, we confirm that results are consistent using census-based concentration after 1997.

Table 3: Concentration, TFP, Prices and Mark-ups: BLS industries

Table shows the results of industry-level OLS regressions of contemporaneous 5-year changes in TFP, Prices, Mark-ups and Concentration over the periods specified. Data includes all industries covered in the BLS multifactor tables. CR4 from Compustat. Standard errors in brackets, clustered at industry-level. + p<0.10, * p<0.05, ** p<0.01.

	$\Delta_5 \log(TFP)$		$\Delta_5 \log(P)$		$\Delta_5 \log(\mu)$	
	(1) Pre-00	(2) Post-00	(3) Pre-00	(4) Post-00	(5) Pre-00	(6) Post-00
$\Delta_5 \log(CR4)$	0.174* (0.066)	-0.049 (0.050)	-0.090 (0.061)	0.092 (0.091)	-0.102* (0.042)	0.121+ (0.067)
Cons	0.017 (0.014)	0.027** (0.009)	0.073** (0.013)	0.095** (0.010)	0.052** (0.012)	0.046** (0.011)
Year FE	Y	Y	Y	Y	Y	Y
R^2	.12	.11	.049	.074	.049	.083
Observations	92	138	92	138	92	138

Figure 11: *Change in Mark-up and Concentration since 1991: Airlines and Telecom*



Source: BLS multifactor tables for mark-ups. Compustat for import-adjusted concentration.

5.2 BEA, NBER and Census

To better understand the rise in mark-ups, we combine concentration data from the US Economic Census with price data from the NBER-CES database for manufacturing and the BEA’s detailed GDP by Industry accounts for non-manufacturing.²⁰ Combined, these datasets allow us to estimate real labor productivity and analyze the evolution of mark-ups using the definitions above.

We estimate regressions of the following form:

$$\Delta_5 \log(z_{jt}) = \beta \Delta_5 \log(CR_{4j,t}) + \gamma_{s,t} + \varepsilon_{jt}.$$

where j denotes industries and t denotes years. $\gamma_{s,t}$ denotes sector-year fixed effects. Table 4 investigates the correlation between increases in concentration and changes in prices and markups. Before 2002, the correlation is small and often insignificant, which is consistent with the results in Ganapati (2018). After 2002, however, increases in concentration are systematically correlated with increases in prices.

Columns (7) to (9) show a similar effect but instead of sorting on time (pre/post 2002), we sort by ending levels of concentration. When ending concentration is low, there is not much correlation between changes in concentration and changes in markups. When concentration reaches a high level, however, the correlation is much stronger, especially in the non-manufacturing sector.

²⁰Our data is then roughly comparable to that in Ganapati (2018). For manufacturing, the NBER-CES database includes nominal output, prices, wages and employment. For non-manufacturing, the concentration accounts include nominal output, payroll and employment, while the BEA’s GDP by industry accounts include prices.

Table 4: Concentration vs. Prices: pre and post-2002

Table shows the results of industry-level OLS regressions of contemporaneous 5-year changes in prices, mark-ups and concentration over the periods specified. Observations are weighted by sales. Standard errors in brackets, clustered at industry-level. + p<0.10, * p<0.05, ** p<0.01.

	$\Delta_5 \log(P)$			$\Delta_5 \log(\mu)$			$\Delta_5 \log(\mu)$		
	(1) All	(2) Mfg	(3) NonMfg	(4) All	(5) Mfg	(6) NonMfg	(7) All	(8) Mfg	(9) NonMfg
$\Delta_5 \log(CR4_{jt})$	-0.03 (-0.77)	0.04* (2.43)	-0.03 (-0.75)	0.00 (0.01)	0.09** (3.73)	0.00 (0.01)	0.12* (2.06)	0.10** (3.35)	0.12* (2.01)
$\Delta_5 \log(CR4_{jt}) \times 1_{>2002}$	0.17** (3.23)	0.20** (3.29)	0.17** (3.16)	0.26** (3.70)	0.14* (2.16)	0.26** (3.62)			
$\Delta_5 \log(CR4_{jt}) \times \text{High CR}$							0.40** (2.87)	0.10 (1.61)	0.40** (2.81)
High CR							-0.01 (-0.40)	0.07** (2.95)	-0.01 (-0.39)
$\Delta_5 \log(LP_{jt})$	-0.39** (-5.20)	-0.40** (-7.41)	-0.39** (-5.08)						
$\Delta_5 \log(w_{jt})$	0.48** (3.95)	0.73** (3.05)	0.48** (3.85)						
Cons	0.06** (3.04)	0.07+ (1.94)	0.06** (2.97)	0.03** (3.42)	0.10** (7.18)	0.03** (3.35)	0.02+ (1.92)	0.07** (11.97)	0.02+ (1.88)
Sec x Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	.49	.59	.49	.36	.33	.36	.35	.36	.35
Observations	3,141	2,743	398	3,141	2,743	398	3,141	2,743	398

The joint evolution of concentration, TFP and prices appears somewhat consistent with σ and γ theories before 2000. Over the past 15 years, however, concentration is correlated with lower TFP and higher prices. The evidence is now more closely aligned with the κ theory.

Our data and correlations are consistent with the ones in [Ganapati \(2018\)](#) but our interpretation is quite different. Regarding prices we agree that the full sample correlation is small, but as we have shown the correlations after 2000 and at high level of concentration are large and positive.

The most important disagreement, however, relates to the correlation with productivity. The existing literature has failed to recognize that, given what we know about firm-level data, we should expect a quasi-mechanical correlation between concentration and productivity at the level of detailed industries (NAICS level 4 or 5 for instance).

We know that the firm-size distribution is skewed. At NAICS level 5 the top 4 firms account for about 1/3 of output. We also know that firm-level shocks are large. Therefore changes in industry output at level 5 are strongly affected by idiosyncratic firm-level shocks. If a large firm experiences a positive shock, industry output increases and concentration increases at the same time. Therefore, in the regressions run by [Ganapati \(2018\)](#) or [Autor et al. \(2017b\)](#), one would expect a positive correlation between changes in CR4 and changes in output or productivity or both (depending on the details of the shocks). At level 4 the kurtosis of log changes in CR4 is 8.8. Once we move to level 2 or level 3, the law of large number kicks in and these effects are muted. At level 2, for instance, log changes in CR4 have a skewness of 0 and a kurtosis of 2.5. In other words, the changes are basically normal. This has nothing to do with synergies or with the value of concentration per-se. It's just fat-tail econometrics. [Ganapati \(2018\)](#) claims that, since changes in concentration and changes in industry productivity are positively correlated on average, we need not worry about the (smaller) impact of concentration on prices.²¹ The reasoning above suggests that this claim is incorrect.

6 Investment and Profits

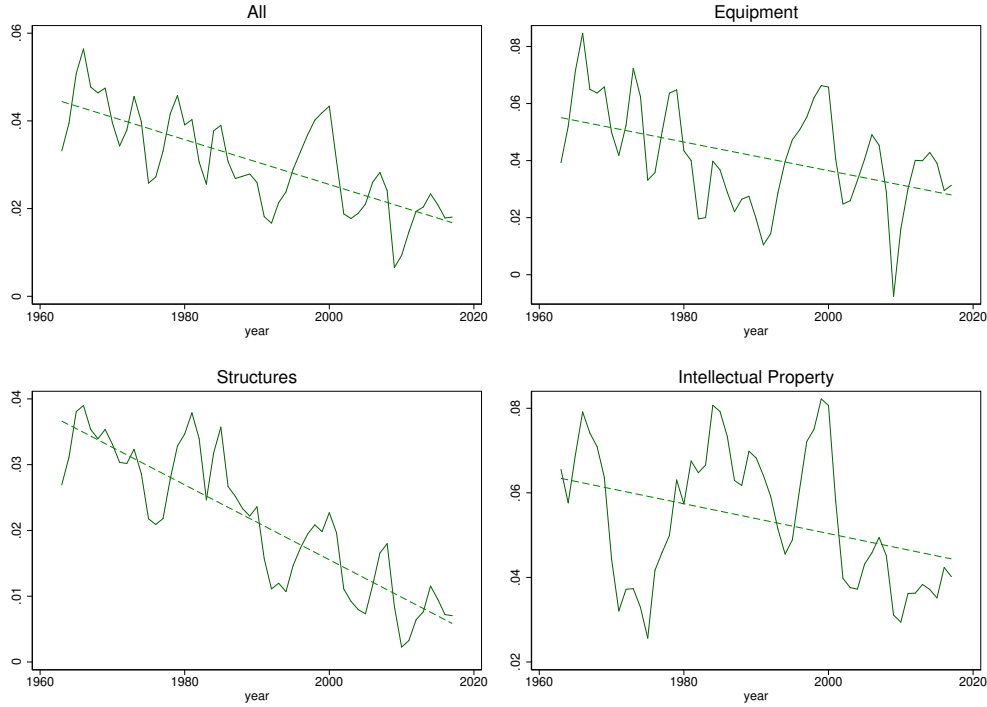
Under the capital deepening hypothesis, α , the evolution of profits and investment is explained by capital deepening, either due to a fall in the price of equipment ([Karabarbounis and Neiman, 2018](#)), the rise of intangibles ([Alexander and Eberly, 2016](#)) or automation ([Acemoglu and Restrepo, 2017](#); [Charles et al., 2018](#); [Martinez, 2018](#)). The main prediction, therefore, is that the capital stock would grow faster – at least for the relevant asset type. However, as shown in [Figure 12](#), the growth of the capital stock has fallen across all asset types – notably including intellectual property assets. The fall is particularly severe after 2000, precisely when concentration increases.

²¹[Ganapati \(2018\)](#) estimates the following relationship

$$\Delta_5 \log(P_{jt}) = 0.00992 \times \Delta_5 \log(CR4) - 0.0520 \times \Delta_5 \log(LP) + \gamma_{s,t} + \varepsilon_{jt},$$

which implies that “a one standard deviation increase in monopoly power offsets 1/5 of the price decrease from a one standard deviation increase in productivity.” He argues that “the most pessimistic reading is that after controlling for productivity, monopolies do increase prices. But this argument assumes that all other conditions including productivity remain constant. In the light of the close linkage of productivity and concentration, this seems untenable.”

Figure 12: Growth Rates of Capital Stock



Notes: Growth rate of private nonresidential fixed assets; based on section 4.2 of the BEA's fixed assets tables.

Is the fall in investment pervasive across firms? In Table 5, we define leaders by constant shares of market value to ensure comparability over time.²² Capital K includes intangible capital as estimated by Peters and Taylor (2016). As shown, the leaders' share of investment and capital has decreased, while their profit margins have increased. By contrast, laggards exhibit much more stable investment and profit rates.

Is the increase in profits entirely a between effect – driven by high profit firms growing to become leaders, as predicted by σ – or did profits increase within firms too? How does this differ for leaders and laggards? Figure 13 shows that within-firm profits increased for leaders and decreased for laggards. In particular, we estimate

$$\left(\frac{OIADP}{SALE}\right)_{i,j,t} = \beta_t \times Lead_{i,j,t} + \delta_i + \gamma_t + \varepsilon_{jt}, \quad (3)$$

where $Lead_{i,j,t}$ is an indicator equal to one for firms in the top quantile of the market value distribution, by industry; while δ_i and γ_t denote firm and year fixed effects, respectively. Observations are weighted by sales. Coefficient γ_t captures the average within-firm change in profits, while β_t captures an incremental effect for leaders firms. We plot $\beta_t + \gamma_t$ as the total effect on leaders.

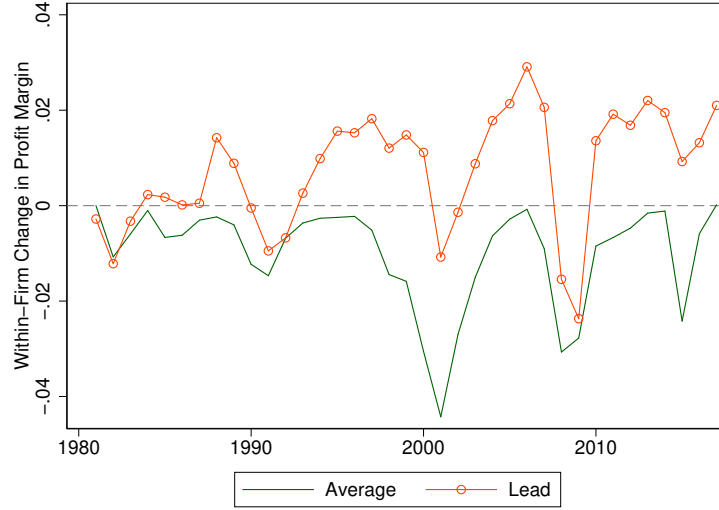
²²OIBDP shares are stable which is consistent with stable shares of market value and stable relative discount factors. Because firms are discrete, the actual share of market value in each grouping varies from year to year. To improve comparability, we scale measured shares as if they each contained 33% of market value.

Table 5: Investment, Capital and Profits by Leaders and Laggards

Table shows the weighted average value of a broad set of investment, capital and profitability measures by time period and market value. Leaders (laggards) include the firms with the highest (lowest) MV that combined account for 33% of MV within each industry and year. Annual data from Compustat. See data appendix for details.

	1980-1995			1996-2017			Difference		
	Leaders 0-33 pct	Mid 33-66 pct	Laggards 66-100 pct	Leaders 0-33 pct	Mid 33-66 pct	Laggards 66-100 pct	Leaders 0-33 pct	Mid 33-66 pct	Laggards 66-100 pct
Share of OIBDP	0.36	0.33	0.32	0.35	0.32	0.33	0.00	-0.01	0.01
Share of CAPX + R&D	0.36	0.32	0.32	0.33	0.30	0.36	-0.02	-0.02	0.04
Share of PP&E	0.34	0.33	0.33	0.33	0.29	0.37	0.00	-0.04	0.04
Share of K	0.33	0.33	0.33	0.32	0.31	0.36	-0.01	-0.02	0.03
(CAPX+R&D)/OIBDP	0.59	0.58	0.60	0.43	0.44	0.52	-0.16	-0.14	-0.08
OIADP/SALE	0.13	0.11	0.09	0.16	0.14	0.10	0.03	0.03	0.01

Figure 13: Within-firm Change in Profit Margin for Leaders vs. Laggards



Notes: Compustat NA. Figure plots the estimated within-firm change in profits for leaders and laggards, following equation 3. See text for details.

According to σ and γ , leaders should increase investment in concentrating industries, reflecting their increasing relative productivity. We test this at the firm-level, by performing the following regression for firm i that belongs to BEA industry j :

$$\begin{aligned} \Delta \log(K_{ijt}) = & \beta_1 Q_{it-1} + \beta_2 CR8_{jt-1}^{IA} \times Lead_{i,j,t} + \beta_3 CR8_{jt-1}^{IA} \\ & + \beta_4 Lead_{ijt-1} + \beta_5 \log(Age_{it-1}) + \eta_t + \mu_i + \varepsilon_{it}, \end{aligned} \quad (4)$$

where K_{it} is firm capital (PP&E, Intangibles, or Total), $CR8_{jt}^{IA}$ the import-adjusted census-based CR8, and $Lead_{i,j,t}$ is an indicator for a firm having a market value in the top quartile of segment k . We include Q_{it-1} and $\log(Age_{it-1})$ as controls, along with firm and year fixed effects (η_t and μ_i). β_2 is the coefficient of interest. Table 6 shows that leaders in concentrated industries under-invest. This is inconsistent with σ, γ theories and consistent with κ .

Leader profit margins increased while investment relative to Q decreased, in line with κ . The falling growth rate of the capital stock – including intangibles – is inconsistent with α . Similarly, the decline in leader investment – particularly in concentrated industries – is inconsistent with σ and γ .

7 Returns to Scale

We evaluate the extent to which the returns to scale have increased since the 2000's using the Basu et al. (2006) methodology. Under the assumptions of cost-minimizing firms, homogenous industry-level production functions and quasi-fixed capital stock and number of employees, Basu et al. (2006) show that we can recover the returns to scale for each industry i using the following regression:

$$d \log y_{it} = c_i + \gamma_i d \log x_{it} + \beta_j dh + \epsilon_{it} \quad (5)$$

Table 6: Investment by Leaders in Concentrating Industries

Table shows the results of firm-level panel regressions of the log change in the stock of capital (deflated to 2009 prices) on import-adjusted Concentration Ratios, following equation (4). Regression from 1997 to 2012 given the use of Census concentration measures. We consider three measures of capital: PP&E, intangibles defined as in Peters and Taylor (2016) and their sum (total). Leaders include firms with market value in the top quartile of the corresponding BEA segment j for the given year. Q and log-age included as controls. As shown, leaders decrease investment with concentration, rather than increase it. Annual data, primarily sourced from Compustat. Standard errors in brackets, clustered at the firm-level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	All			Mfg			Non-Mfg		
	(1) $\Delta \log(PP\&E)^a$	(2) $\Delta \log(Int_{PT})^b$	(3) $\Delta \log(K_{PT})^{a+b}$	(4) $\Delta \log(PP\&E)^a$	(5) $\Delta \log(Int_{PT})^b$	(6) $\Delta \log(K_{PT})^{a+b}$	(7) $\Delta \log(PP\&E)^a$	(8) $\Delta \log(Int_{PT})^b$	(9) $\Delta \log(K_{PT})^{a+b}$
$CR8IA_{jt-1}$	-11.59+ (6.05)	-0.46 (6.09)	-5.25 (5.49)	-17.63+ (9.29)	-3.94 (8.25)	-3.83 (7.58)	-9.52 (9.42)	9.49 (10.95)	-4.42 (9.42)
$CR8IA_{jt-1} \times lead_{it-1}$	-11.43* (4.76)	-17.77** (5.99)	-14.49** (4.61)	1.61 (7.28)	-0.12 (9.54)	-0.97 (7.30)	-12.98* (6.22)	-23.03** (7.87)	-16.60** (6.07)
$\log Q_{it-1}$	13.63** (0.44)	11.80** (0.37)	13.09** (0.36)	12.05** (0.54)	9.90** (0.43)	10.72** (0.41)	15.88** (0.74)	14.38** (0.67)	16.26** (0.63)
$Lead_{it-1}$	4.10** (1.00)	3.77** (1.16)	3.00** (0.93)	3.71** (1.43)	2.29 (1.68)	2.43+ (1.33)	2.31+ (1.38)	3.04+ (1.76)	1.45 (1.40)
$\log age_{it-1}$	-15.00** (0.78)	-18.68** (0.72)	-17.19** (0.65)	-15.18** (1.02)	-18.05** (0.85)	-17.22** (0.83)	-14.52** (1.21)	-19.24** (1.26)	-16.91** (1.04)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	.1	.12	.15	.097	.14	.16	.11	.12	.15
Observations	63,758	63,469	65,420	33,737	34,360	34,377	30,021	29,109	31,043

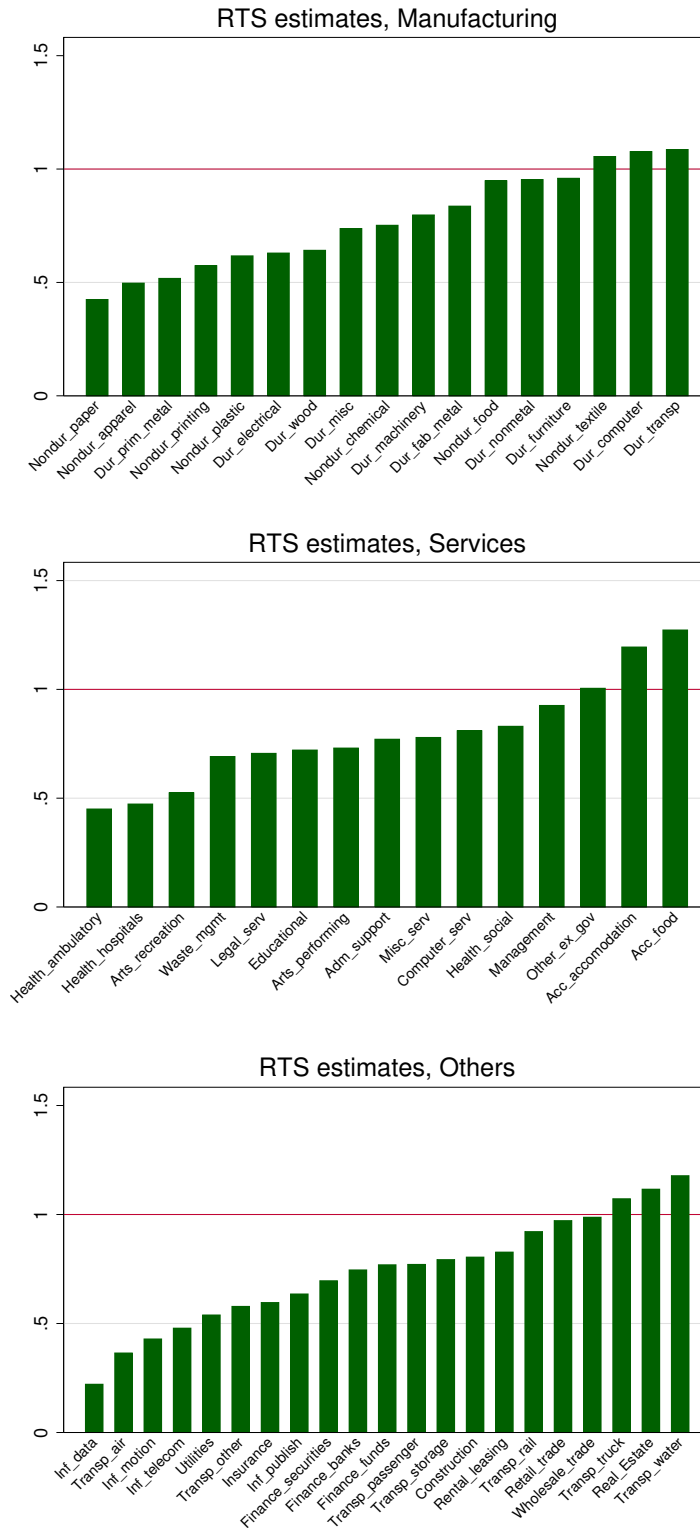
where y is output, x total inputs (capital, labor, and materials), h detrended hours worked and the residual captures log differences in total factor productivity²³. The parameter γ_i represent the returns to scale and β is restricted to be the same for three aggregate industry groups indexed by j : Manufacturing, Services and other Industries. Given the endogeneity of inputs to technology shocks, we instrument the change in inputs using as exogenous variation the lagged values of the price of oil, four government defense spending items, real GDP, real non-durable consumption and real non-residential investment in fixed assets.²⁴

Figure 14 shows the results of the sector level estimation of returns to scale (equation 5) using the BLS multifactor tables described in section 5, which covers from 1987 to 2016.

²³As in Basu et al. (2006) we use Christiano and Fitzgerald band pass filter and we do not include farm and mining. In addition, we exclude petroleum and coal products and pipeline transportation due to the anomalies in price measurement in oil related markets. Basu et al. (2006) use the categories durable manufacturing, non-durable manufacturing and the rest. The results are barely affected, but our categorization facilitates the exposition of changes after 2000.

²⁴The choice of the price of oil and government defense spending as instruments (Equipment, Ships, Software and Research and Development) is common in the literature and our particular implementation follows Hall (2018). We add aggregate business cycle indicators under the assumption that they are uncorrelated with industry-specific technological improvements (such as during the Great Recession for instance). The results are robust to estimate industry-specific β 's instead of using industry groups, as shown in appendix A.

Figure 14: Return to Scale Estimates by Industry



Notes: Primarily based on the 2018 BLS multi-factor tables, which include output, input and hours worked. Instruments based on BEA accounts (government expenditures and aggregate business cycle variables) and FRED (WTI crude oil price).

In order to evaluate whether returns to scale increase after 2000, we run the regression:

$$d \log y_{it} = c_i + \gamma_{i0} d \log x_{it} + \gamma_{1j} d \log x_{it} 1_{year \geq 2000} + \beta_j dh_{it} + \epsilon_{it}$$

where the coefficient γ_{1j} captures the increase on the overall level of returns to scale after 2000 for Manufacturing, Services and the rest of the industries. We obtain low and non-significant estimates $\hat{\gamma}_1$ of approximately 0.02 for manufacturing, 0.005 for services and 0.037 for the rest of the industries. This is broadly consistent with (Ho and Ruzic, 2017), who find a flat return to scale over time for manufacturing. If we aggregate to the national level, weighting the pre 2000 return to scale by the output value in 1994 and the post 2000 by the output value in 2007, we obtain that returns to scale moderately increase from 0.785 to 0.8. Alternatively, if we estimate a different γ_{1i} for each industry, we observe a large heterogeneity in results, with no clear pattern among industries that have gotten more concentrated.²⁵

An alternative methodology, used by De-Loecker et al. (2019) and Salas-Fumás et al. (2018), estimates the production function at the firm level using slight modifications of Olley and Pakes (1996). The estimated increase in return to scale of De-Loecker et al. (2019) is from 1.03 to 1.08, which is similar in percentage terms to our estimated increase from 0.785 to 0.8, even though the levels differ.²⁶

8 Conclusion: One Size Does Not Fit All

To conclude, we would like to move beyond the average effect and analyze differences between industries. We perform a Principal Components Analysis on a wide range of variables covering all types of measures in Table 1, following the industry segments in the BLS KLEMS. All measures are standardized to have mean zero and variance one to ensure they contribute equally. Because we include census-concentration ratios, Agriculture and Mining are excluded from the analysis.

Figure 15 shows the loadings on the first two principal components, which together explain 32% of the total variance. They have an intuitive interpretation. PC1 seems to capture the σ and γ theories. It has a moderately positive impact on concentration and a strong impact on intangible investment. It is more likely to happen in industries facing import competition. TFP growth is positive (dtfp_kl), consistent with a sharp decline in unit-labor costs (Dlogulc_kl). Prices fall slightly less than unit labor costs (Dlogp_kl), resulting in an increase in the average mark-up (Dlogmu_kl).

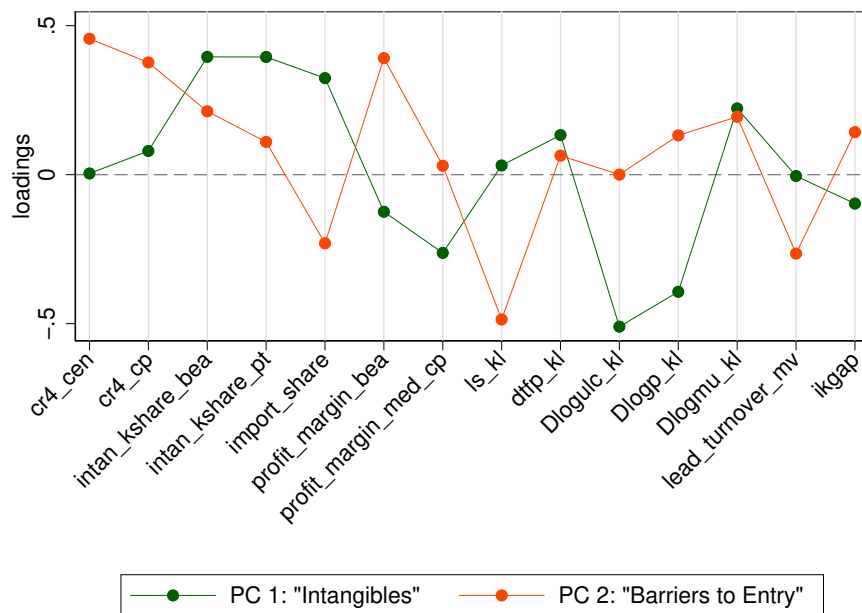
PC2, by contrast, closely tracks an increase in barriers to entry (κ). It captures a sharp increase in concentration despite limited growth in intangibles and negative import competition. Profits rise and the

²⁵Since we are aggregating by groups, in order to control for the size of each industry we weight the observations of each industry by the value of output in 2000 from the B.L.S. multifactor tables. Also, we exclude 4 industries for which the estimated return to scales, when evaluated at the industry level, decrease more than 1 after 2000. This excludes unreasonable estimates and serves as a conservative assumption given the main hypothesis of our paper. The results for γ_{1i} are available upon request.

²⁶There are reasons to expect higher estimates at the firm level. One issue is that we only have data on prices at the industry level. Then, if larger firms charge higher mark-ups, returns to scale are overestimated. Furthermore, if such difference in mark-ups between leaders and laggards widen over time, as suggested by Diez et al. (2018), you would identify that as an increase in return to scale over time. Another issue is that the firm-level data employed by De-Loecker et al. (2019) correspond to Compustat, which contains firms that invest more in intangibles than the average.

labor share falls. An important point is that measured markups increase in both cases.

Figure 15: Principal Component Loadings

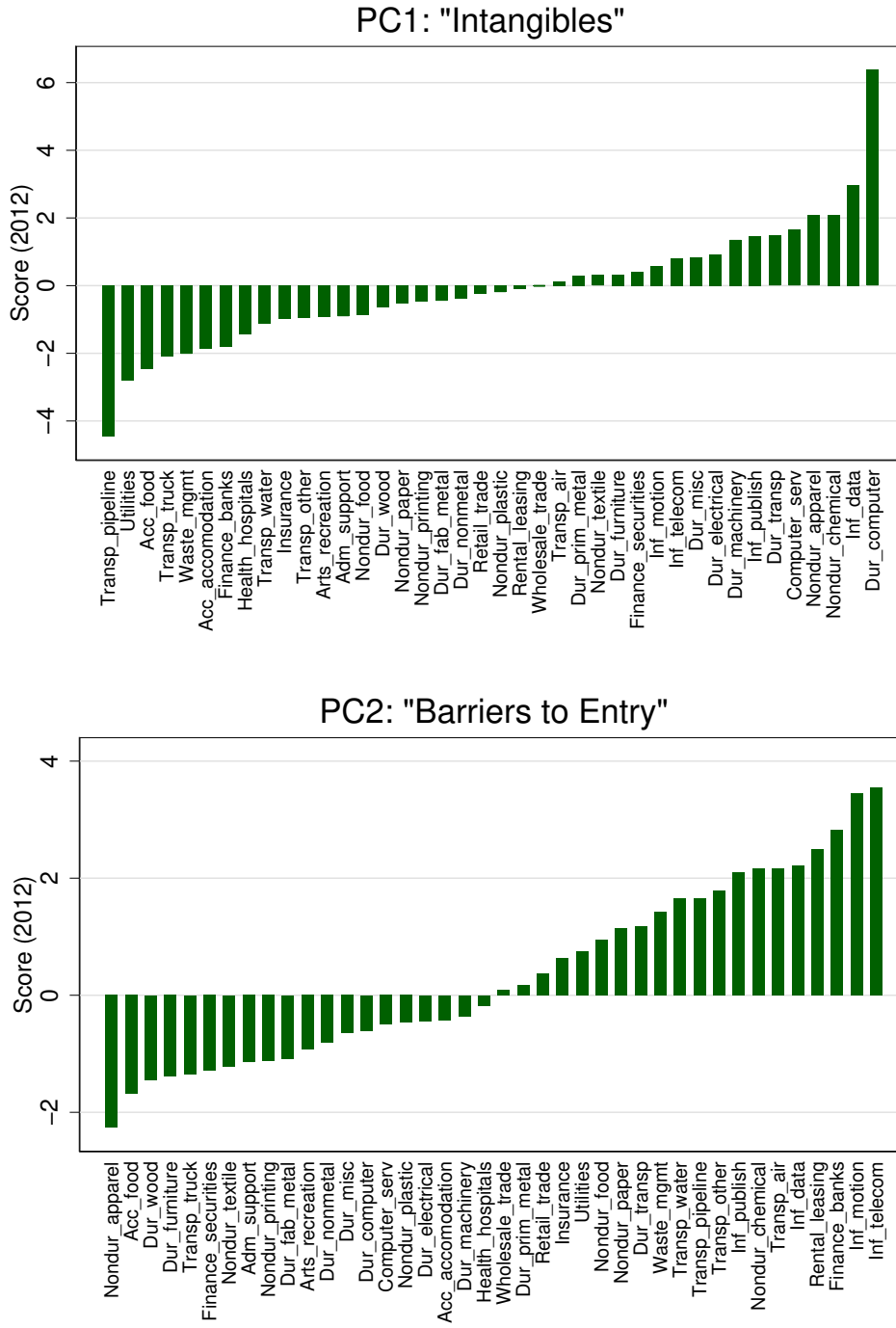


Notes: see text for details and data appendix for variable definitions.

Figure 16 shows the loadings on PC1 and PC2, as of 2012, for each industry. Information - Data and Durable - Computer lead the pack in terms of 'Intangible'-driven concentration. The former includes Google and Facebook, while the later includes Apple and Intel. These industries appear to remain relatively innovative (at least until 2012) despite increases in concentration. Their behavior is consistent with γ . By contrast, Utilities, Transportation - Pipelines and Accommodation - Food (i.e., Restaurants) score near the bottom. These are industries with limited use of intangible assets.

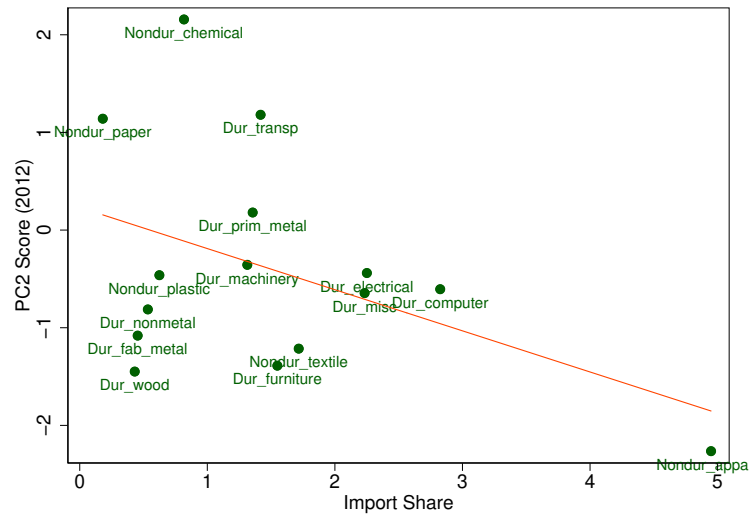
Information - Telecom, Banking and Transportation - Airlines score near the top according to PC2. As discussed in Gutiérrez and Philippon (2018), these industries exhibit higher concentration, prices and profitability in the U.S. than in Europe – despite using similar technologies. Interestingly, several manufacturing industries score near the bottom – including Durable-Computer and Nondurable - Apparel, which face substantial competition from China. Figure 17 confirms this observation across manufacturing industries by contrasting industry-level PC2 scores against the corresponding import shares. The strong relationship between foreign competition and PC2 scores serves a comforting validation of our analysis.

Figure 16: Principal Component Scores, by Industry



Notes: see text for details and data appendix for variable definitions.

Figure 17: PC2 Scores (“Barriers to Entry”) vs. Import Shares



Notes: PC2 scores as of 2012 vs. industry-level import shares, defined as the ratio of industry-level imports to gross output plus imports. Imports from Peter Schott’s website; gross output from the BEA’s GDP By Industry accounts.

Explaining the rise in κ . The last question, of course, is what might explain the rise in κ in the US? [Gutiérrez and Philippon \(2017c\)](#) argues that this is partly explained by weakening competition policy (i.e., antitrust and regulation) compared to Europe. [Gutiérrez and Philippon \(2019\)](#) shows that the decline in the elasticity of entry to Q is partly explained by lobbying and increasing federal and state-level regulations. Last, [Jones et al. \(2018\)](#) combines a rich structural DSGE model with cross-sectional identification from firm and industry data. We use the model to structurally estimate entry cost shocks, and show that model-implied entry shocks correlate with independently constructed measures of entry regulation and M&A activities.

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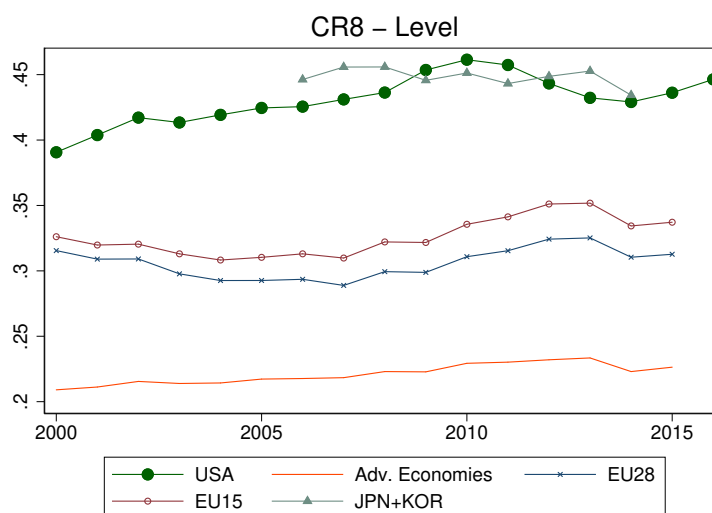
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Appendix

A Additional Discussion and Results

International Evidence. Figure 18 shows weighted average concentration rates by region.

Figure 18: Concentration across Advanced Economies (Level)



Notes: Advanced Economies include EU28 countries for which data are available in STAN, as well as JPN, KOR, NOR, CHE, USA. AUS and CAN omitted due to limited data availability. We report the weighted average concentration across all EU KLEMS industries in the non-Agriculture business sector excluding RE. Industry x region concentration based on Compustat but adjusted for coverage using OECD STAN. See data appendix for details.

Intangibles, Mark-ups and Competition. Under the methodology of [De Loecker and Warzynski \(2012\)](#), mark-up estimates are unbiased as long as the variable input used in the estimation is indeed variable, and is consistently defined over time. Finding such a measure is not trivial, particularly in accounting statements. [De-Loecker et al. \(2019\)](#) argue that COGS – defined as “the cost of inventory items sold during a given period” according to GAAP – satisfies these conditions. This is broadly true for businesses that make, buy or sell goods to produce income, such as manufacturing, retail and wholesale trade. It is much less clear for service and information businesses. Pure service companies such as accounting firms, law offices, business consultants and many information technology firms have no goods to sell and therefore no inventory. As a result, they do not even report COGS on their income statement.²⁷ Some of them report only more granular line items, while others report “Cost of Revenues” instead. Importantly, cost of revenues includes the cost of delivering a product or service in addition to producing it, hence is broader than COGS. Such ambiguity in accounting definitions, coupled with changes in the nature of production, gives firms discretion on what is included as COGS vs. other line items. Ultimately, this leads to the inclusion of some (quasi-)fixed expenditures in COGS, as well as changes in the definition of COGS over time – both of which would violate the assumptions underlying DLEU. Two examples.

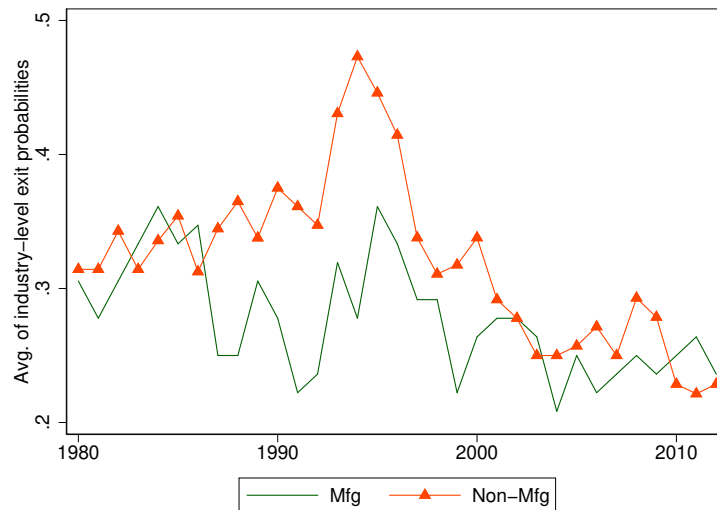
²⁷See [link](#) for example, which lists personal service businesses that do not report COGS.

Consider Delta Airlines, which does not report COGS in its annual statements. Instead, Compustat creates a measure of COGS by combining a series of granular line items. Such items include clearly variable expenses such as aircraft fuel and landing fees – but also quasi-fixed expenses such as aircraft rent expense (typically associated with long term leases) and head-office salaries and profit sharing expenses (typically included in SG&A).

Google (Alphabet Inc), on the other hand, reports using Cost of Revenues. The largest component of Cost of Revenues are traffic acquisition costs (TAC), which are identifiable, direct costs attributable to production. They roughly match the definition of COGS. However, Cost of Revenues also includes “expenses associated with our data centers and other operations (including bandwidth, compensation expense (including stock-based-compensation), depreciation, energy, and other equipment costs).” Clearly, data center and operation expenditures include long term investment in tangible and intangible assets (e.g., software, organizational capabilities, equipment) indirectly related to the delivery of services. Again, this violates the variable cost assumption underlying the DLEU. Moreover, Google can exercise discretion on what is classified as SG&A instead of Cost of Revenues. In fact, Google reported stock-based-compensation separate from Cost of Revenues up to 2005 and combined it only after 2006.

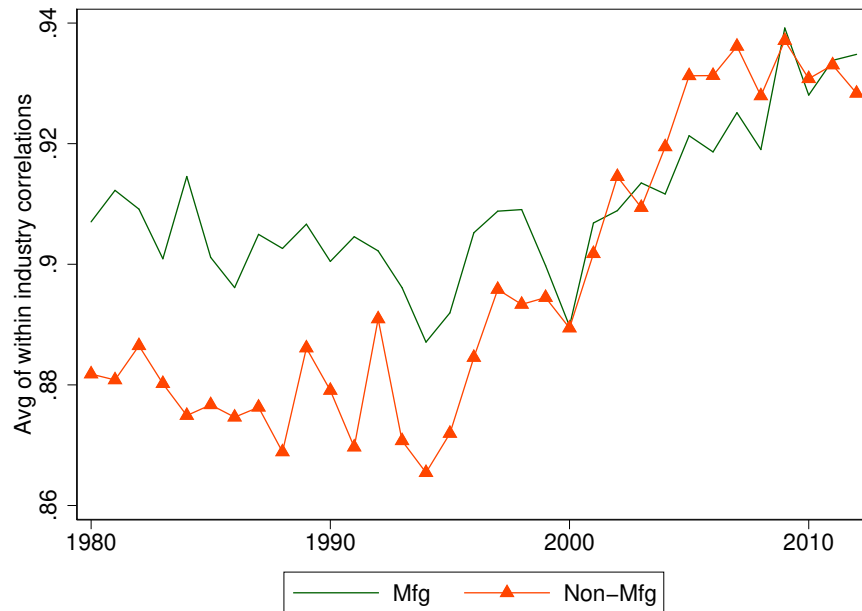
Turnover. Figures 19 and 20 replicate Figures 8 and 9, respectively using market value and separating manufacturing and non-manufacturing industries. As shown, the drop in turnover is more pronounced for non-manufacturing industries.

Figure 19: *MV-based Leader Turnover, by Sector*



Source: Compustat NA, following US KLEMS industries. Includes only industry-years with 5 or more firms. See text for details.

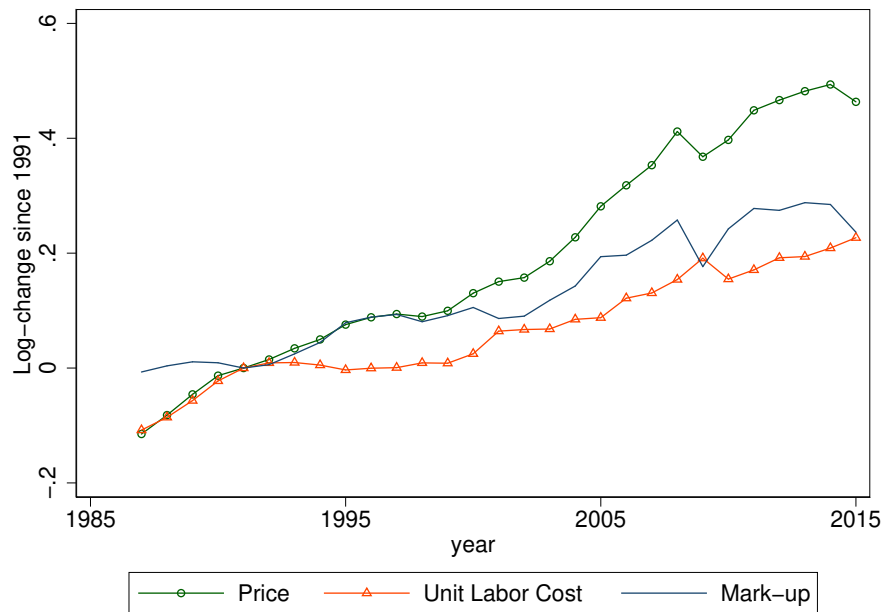
Figure 20: *MV-based correlation of 5Y-ahead rankings by sector*



Source: Compustat NA, following US KLEMS industries. Includes only industry-years with 5 or more firms. See text for details.

Joint evolution of Concentration, TFP and prices. Figure 21 shows the aggregate evolution of prices and ULC since 1989.

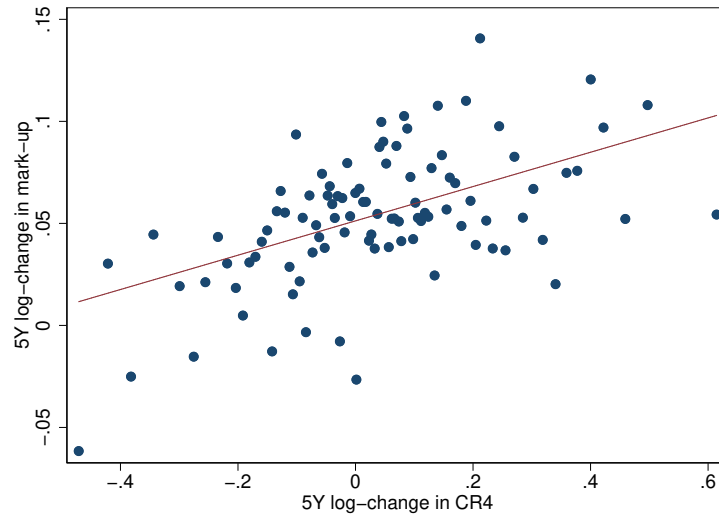
Figure 21: *Prices, ULC and Mark-ups in US*



Notes: weighted average change in prices, per-unit labor costs and mark-ups (computed as the residual) across all industries in our sample. Based on BLS multifactor tables.

Figure 22 provides a bin-scatter plot of changes in mark-ups against changes in CR4. As shown, the relationship is quite robust.

Figure 22: *Mark-ups vs. Concentration*



Notes: Concentration from US Economic Census. Mark-ups from the NBER-CES database for manufacturing and the Economic Census (output, employment and wages) and the BEA detailed GDP By Industry Accounts (prices). See Section 5 for details.

Table 7 presents the results. Panel A includes all industries, while Panels B and C separate manufacturing and non-manufacturing industries. In line with Autor et al. 2017b and Ganapati 2018, concentration is positively correlated with labor productivity growth. This is what one would expect in a world dominated by fat-tail firm level demand (or quality) shocks. An industry grows because some of its firm draw a large positive shock. This mechanically leads to higher concentration.

Table 7: Concentration and Mark-up Decomposition: Granular Industries

Table shows the results of industry-level OLS regressions of contemporaneous 5-year changes in concentration, mark-ups, prices and ULC for as long as data are available. Observations are unweighted to mirror [Ganapati \(2018\)](#). Standard errors in brackets, clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

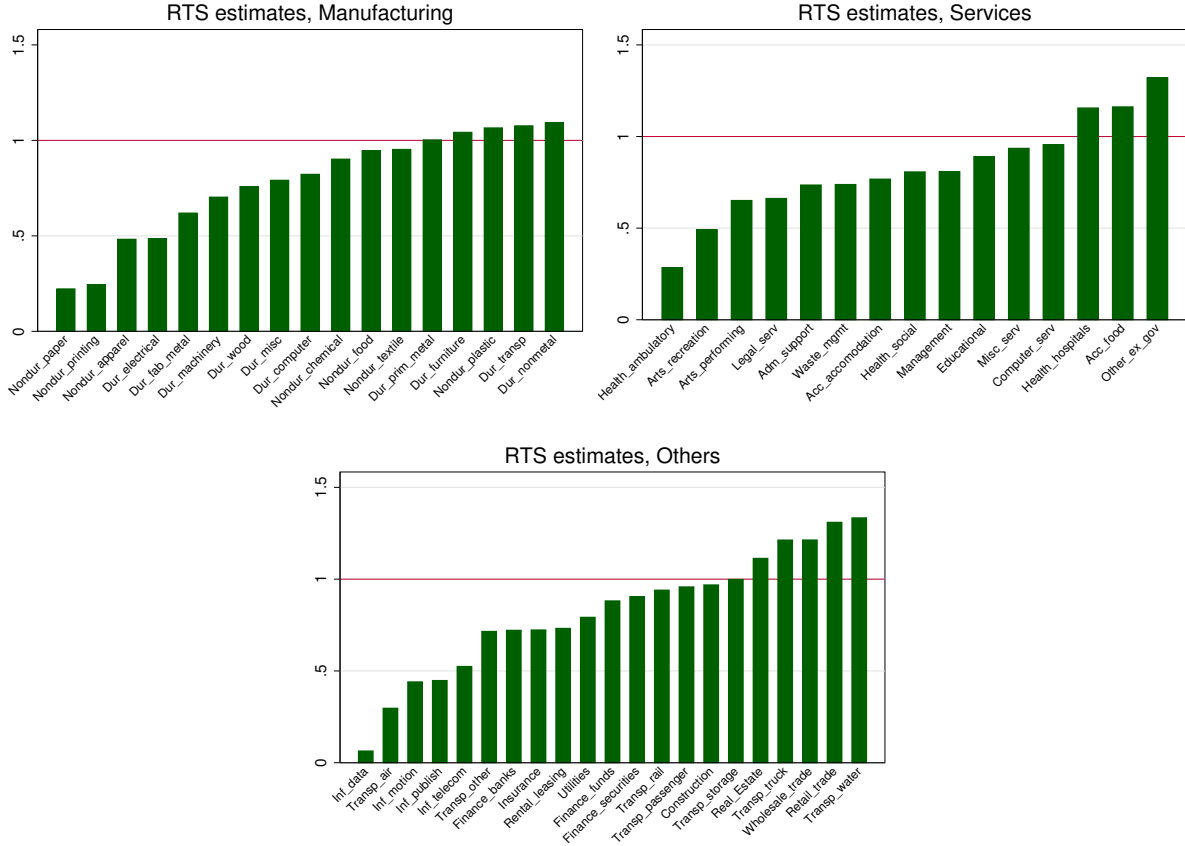
Panel A. All Industries					
	(1)	(2)	(3)	(4)	(5)
	Mark-ups	Prices	ULC	Wages	LP
s5logcr4	0.11** (0.01)	0.01 (0.01)	-0.10** (0.01)	0.03** (0.01)	0.13** (0.01)
Cons	0.05** (0.00)	0.16** (0.00)	0.11** (0.00)	0.21** (0.00)	0.10** (0.00)
Sec x Yr FE	Y	Y	Y	Y	Y
R2	.25	.59	.46	.7	.16
Observations	3,141	3,142	3,141	3,141	3,141
Panel B. Manufacturing					
	(1)	(2)	(3)	(4)	(5)
	Mark-ups	Prices	ULC	Wages	LP
s5logcr4	0.11** (0.01)	0.02 (0.01)	-0.10** (0.02)	0.04** (0.01)	0.14** (0.02)
Cons	0.06** (0.00)	0.17** (0.00)	0.11** (0.00)	0.22** (0.00)	0.10** (0.00)
Sec x Yr FE	Y	Y	Y	Y	Y
R2	.24	.6	.48	.71	.15
Observations	2,743	2,743	2,743	2,743	2,743
Panel C. Non-Manufacturing					
	(1)	(2)	(3)	(4)	(5)
	Mark-ups	Prices	ULC	Wages	LP
s5logcr4	0.08** (0.02)	-0.02 (0.02)	-0.09** (0.03)	0.01 (0.02)	0.11** (0.03)
Cons	0.00 (0.00)	0.11** (0.01)	0.11** (0.01)	0.17** (0.00)	0.06** (0.01)
Sec x Yr FE	Y	Y	Y	Y	Y
R2	.15	.25	.17	.36	.17
Observations	398	399	398	398	398

Returns to scale The results of using industry level β 's, that is, estimating the following regression:

$$dy_{it} = c_i + \gamma_i dx_{it} + \beta_j dh_{it} + \epsilon_{it} \quad (6)$$

are presented in figure 23.

Figure 23: Return to scale estimates



Notes: Sources: B.L.S. multifactor tables, 2018 edition, for output, input and hours worked. We use B.E.A. accounts For government expenditures and aggregate business cycle variables , and for oil price we use the WTI crude oil price available from FRED data.

B Model Appendix

B.1 Demand System

There is a continuum of industries indexed by $j \in [0, 1]$ and a continuum of firms $i \in [0, N_{j,t}]$ in each industry. A particular firm is therefore indexed by (i, j) , i.e., i 'th firm in industry j .

Firms' outputs are aggregated at the industry level as

$$Y_{j,t}^{\frac{\sigma_j-1}{\sigma_j}} = \int_0^{N_{j,t}} h_{i,j,t}^{\frac{1}{\sigma_j}} (y_{i,j,t})^{\frac{\sigma_j-1}{\sigma_j}} di$$

where σ is the elasticity between different firms in the same industry and h are firm-level demand shocks,

with a mean of 1. Industry outputs are aggregated into a final consumption bundle

$$\bar{Y}_t = \int_0^1 H_{j,t}^{\frac{1}{\epsilon}} Y_{j,t}^{\frac{\epsilon-1}{\epsilon}} dj$$

where ϵ is the elasticity of substitution between industries. This demand structure implies that there exists an industry price index

$$P_{j,t}^{1-\sigma_j} \equiv \int_0^{N_{j,t}} h_{i,j,t} p_{i,j,t}^{1-\sigma_j} di$$

such that the demand for good i is given by

$$y_{i,j,t} = h_{i,j,t} Y_{j,t} \left(\frac{p_{i,j,t}}{P_{j,t}} \right)^{-\sigma_j}$$

Similarly, there exists an aggregate price index

$$\bar{P}_t^{1-\epsilon} \equiv \int_0^1 H_{j,t} P_{j,t}^{1-\epsilon} dj$$

such that industry demand is

$$Y_{j,t} = H_{j,t} \bar{Y}_t \left(\frac{P_{j,t}}{\bar{P}_t} \right)^{-\epsilon}$$

B.2 Production

The production function of firm i, j is Cobb-Douglas

$$y_{i,j,t} = a_{i,j,t} k_{i,j,t}^{\alpha_j} n_{i,j,t}^{1-\alpha_j}$$

and there is a fixed cost of production ϕ_j . Firms take the wage W and the rental rate R as given when they hire capital and labor. The Cobb-Douglas function, like any CRS function, leads to a constant marginal cost

$$\chi_{i,j,t} = \frac{1}{a_{i,j,t}} \left(\frac{R_t}{\alpha_j} \right)^{\alpha_j} \left(\frac{W_t}{1-\alpha_j} \right)^{1-\alpha_j}$$

Cost minimization implies that all firms choose the same (optimal) capital labor ratio

$$\frac{\alpha_j}{1-\alpha_j} \frac{n_{i,j,t}}{k_{i,j,t}} = \frac{R_t}{W_t}$$

The average cost is $\chi_{i,j,t} y_{i,j,t} + \phi_j$

Profits are

$$\pi_{i,j,t} = p_{i,j,t} y_{i,j,t} - \chi_{i,j,t} y_{i,j,t} - \phi_j$$

If we define the markup of price over marginal cost

$$p_{i,j,t} \equiv (1 + \mu_{i,j}) \chi_{i,j,t}$$

Then profits are

$$\begin{aligned}
\pi_{i,j,t} &= \frac{\mu_{i,j}}{1 + \mu_{i,j}} p_{i,j,t} y_{i,j,t} - \phi_j \\
&= h_{i,j,t} \frac{\mu_{i,j}}{(1 + \mu_{i,j})^\sigma} (\chi_{i,j,t})^{1-\sigma_j} P_{j,t}^{\sigma_j} Y_{j,t} - \phi_j \\
&= h_{i,j,t} \frac{\mu_{i,j}}{1 + \mu_{i,j}} \left(\frac{1 + \mu_j}{1 + \mu_{i,j}} \frac{a_{i,j,t}}{A_{j,t}} \right)^{\sigma_j-1} P_{j,t} Y_{j,t} - \phi_j
\end{aligned}$$

where $A_{j,t}$ is industry-average productivity and μ_j is industry-average markup.

Nominal revenues are

$$p_{i,j,t} y_{i,j,t} = p_{i,j,t}^{1-\sigma_j} h_{i,j,t} P_{j,t}^{\sigma_j} Y_{j,t}$$

and the market share is

$$s_{i,j,t} = \frac{p_{i,j,t} y_{i,j,t}}{P_{j,t} Y_{j,t}} = \frac{h_{i,j,t}}{N_j} \left(\frac{(1 + \mu_j) a_{i,j,t}}{(1 + \mu_{i,j}) A_{j,t}} \right)^{\sigma_j-1}$$

C Data Appendix

[TO BE COMPLETED]

D SG&A vs COGS

The share of SG&A in total costs has increased over the past 30 years, precisely when the share of COGS has fallen. Table 8 summarizes this fact, by showing the weighted average share of key income statement line items as a percent of sales. The COGS-share of sales declined by nearly 7 percentage points, while the SG&A and depreciation shares increased by 3.5 and 1.3 percentage points, respectively. Thus, most of the decrease in COGS was offset by a rise in SG&A and DP. But operating profits after depreciation also increased, by 2.2 percentage points. The increase in SG&A and depreciation are consistent with a shift towards intangible capital: SG&A includes most intangible-building activities such as R&D, Advertising and Software-development expenses; and intangibles have higher depreciation rates (Corrado and Hulten, 2010). Most SG&A expenses are fixed in the short-run, which requires a careful treatment while estimating production functions. This is the subject of an ongoing debate (Traina, 2018; Karabarbounis and Neiman, 2018).

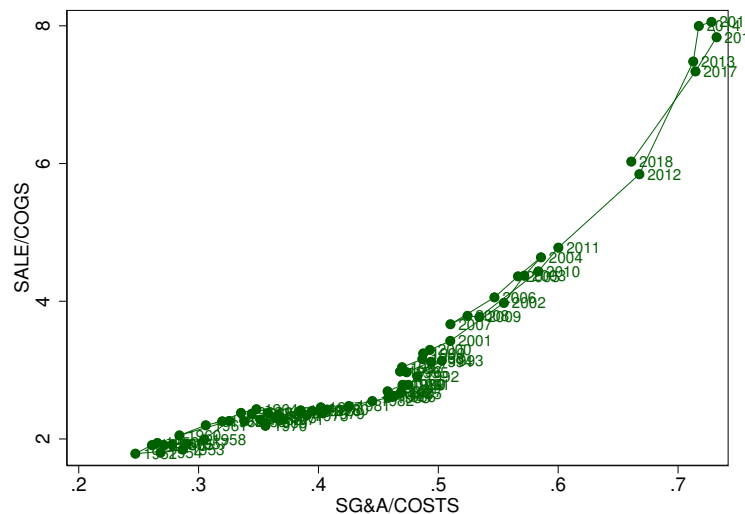
To understand the significance of rising SG&A for mark-up estimation, figure 24 shows the sales-weighted average of SALE/COGS and SG&A cost-shares (SG&A/(SALE-OIADP)) for firms in the the top quantile of the SALE/COGS distribution each year. As shown, SALE/COGS increased precisely at the firms where the SG&A cost-share increased – which points towards a major technological change, likely involving a rise in fixed costs. This has significant implications for the interpretation of mark-ups as a measure of market power. Two examples.

Table 8: Summary of Income Statement (as % of sales)

	1970-1979	1980-1989	1990-1999	2000-2009	2010-2017	$\Delta 00s - 70s$
Sale ^{a+b+c}	100	100	100	100	100	NA
COGS ^a	72.5	70.9	66.1	66.3	65.6	-7.0
SG&A ^b	14.4	16.4	19.3	18.4	17.9	3.5
OIBDP ^c	13.1	12.8	14.7	15.4	16.6	3.5
DP ^d	3.6	4.4	4.8	4.8	4.9	1.3
OIADP ^{c-d}	9.5	8.4	9.9	10.6	11.8	2.2
Intan <i>K</i> share (BEA)	6.2	7.5	11.1	12.5	13.4	7.2
Intan <i>K</i> share (PT)	28.2	33.3	38.5	47.3	49.0	20.8
Firm x year pairs	41045	49809	65295	55549	33304	

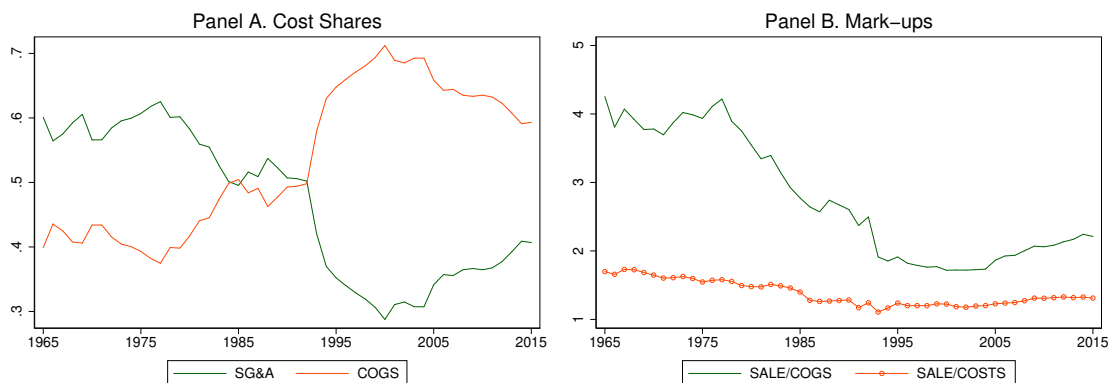
Notes: Annual data. Table shows the weighted average share of each income statement line item as a percent of sales. Source: Compustat for a, b, c and d. BEA and [Peters and Taylor 2016](#) for the share of Intangible Capital.

Figure 24: Average SALE/COGS vs. SG&A intensity for high SALE/COGS firms



Notes: scatter plot of the weighted average SALE/COGS and SG&A cost-share across all Compustat firms in the top quantile of the SALE/COGS distribution, by year.

Figure 25: IBM: Cost Shares and Sales Margins



Source: Compustat NA.

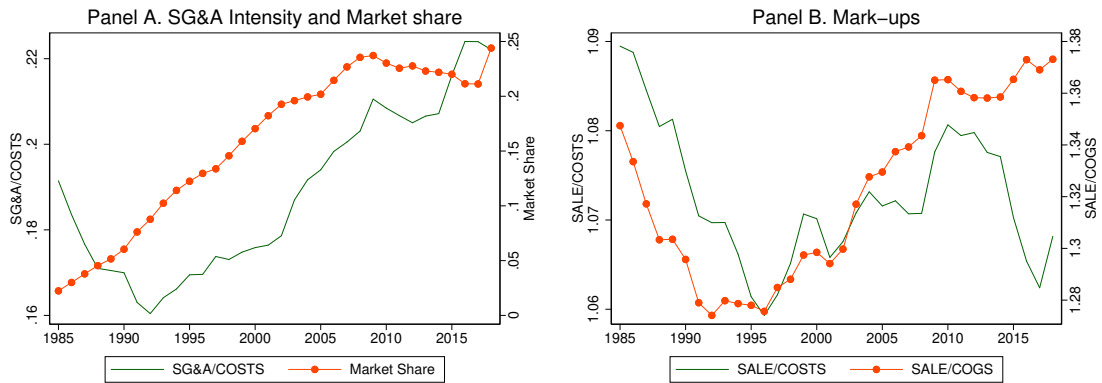
IBM. Consider IBM, a firm that transitioned from providing mostly products to mostly services, beginning in 1994. As shown in Panel A of Figure 25, the cost-share of COGS increased from 40 to 60% while the cost-share of SG&A decreased by a similar amount, precisely as IBM transitioned from a high-overhead, low-COGS business model (Hardware) to a high-COGS, low overhead business model (Consulting, where staff expenditures are included in COGS).²⁸ The implied mark-up fell sharply from 4 to 2 (Panel B). What does this tell us about the extent of competition faced by IBM? What about its market power? Not much, we would argue. In the long-run, IBM's imputed mark-ups are dominated by its SG&A intensity, which is in turn dictated by its product mix. The ratio of SALE to COGS tells us something about IBM's production function and its share of fixed vs. variable costs. It may well be a good proxy of price-to-marginal cost in the short-run. But it tells us very little about the extent of (dynamic) competition faced by IBM in product markets in the long-run. In fact, while IBM's SALE/COGS ratio fell by 48% from 1965 to 2015, average mark-ups (SALE/COSTS) fell by only 10%.

Walmart. IBM is interesting because the firm transitioned across widely different business models (curiously in the opposite direction of the economy, from a high SG&A to a high COGS model). A very different example is Walmart: a firm that maintained its business model but invested heavily in intangible assets to improve logistics and gain market share (Panel A of Figure 26). This is consistent with IT investments driving concentration, as described in Bessen (2017). SALE/COGS increased rapidly with SG&A, yet sales margins (and the relative price of retail trade) actually fell.

These are specific examples, but as shown in Figure 3 above, the divergence between SALE/COGS and profits remains at the country-level. As a result, rising mark-ups – by themselves – tell us nothing about the long-run evolution of competition and market power. DLEU note that “*technological change will lead*

²⁸The composition of COGS also changed, likely affecting the elasticity of sales to COGS. In 1992, costs associated with hardware and software sales accounted for 36.9% of sales. By 2016, the same figure dropped to only 8.2% of sales. Costs associated with services increased from 9.4% to 42.6%. IBM was eventually re-categorized from NAICS 3341 (Computer and peripheral equipment manufacturing) to 5415 (Computer Systems Design and Related Services) in 1998 and to 5191 (Other information services) in 2016. It is not clear to us how the change in industry categorization is dealt with by DLE, but neither using a constant elasticity nor changing IBM from one industry to another in a particular year is entirely satisfactory – though this is a standard problem whenever industry segments are used.

Figure 26: Walmart: Cost Shares and Sales Margins



Source: Compustat NA. Market share for BEA Retail Trade industry.

to higher markups (due to lower marginal costs), but prices will not drop because firms need to generate revenue to cover fixed costs. As a result, profits will continue to be low and **higher markups do not imply higher market power.**” But, if we need to look at profits to figure out what is happening to rents and market power, then it is not clear why we would want to compute mark-ups in the first place.