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FROM GOOD TO BAD CONCENTRATION? U.S. INDUSTRIES OVER THE PAST
30 YEARS

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ABSTRACT

We study the evolution of profits, investment and market shares in US industries over the past 40 years. 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, decreasing competition and increasing barriers to entry, as leaders become more entrenched and concentration is associated with lower investment, higher prices and lower productivity growth.

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We analyze the evolution of concentration in US industries over the past 40 years. Figure 1 summarizes the four stylized facts that motivate our work. Concentration and Profits have increased, while the labor share and investment have decreased (Panels A to D, respectively).¹ This is true across most US industries as shown by Grullon et al. (2019) (concentration and profits), Autor et al. (2017a) (labor shares) and Gutiérrez and Philippon (2017b) (investment and profits). While these stylized facts are well established, we are still far from consensus on what is causing them and what they tell us about the health of the U.S. economy. The most prominent explanations can be organized in two groups:

- **Good Concentration:** the observed trends may be explained by good sources of concentration, such as increases in the elasticity of substitution (henceforth σ) or technological change leading to increasing returns to scale and intangible capital deepening (henceforth γ). Autor et al. (2017a) argue for σ , noting 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.” Haskel and Westlake (2017) argue for γ , emphasizing how scalability and synergies of intangible capital can lead to increasing returns to scale. Under σ and γ , concentration is good news: more productive firms expand yet competition remains stable or increases.
- **Bad Concentration:** alternatively, the trends may reflect bad sources of concentration, which we summarize as rising barriers to competition (henceforth κ).² Furman (2015), for example, 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 According to κ , concentration is bad news: it increases economic rents and decreases innovation.

The goal of this paper is to differentiate between these explanations at the aggregate- and industry-level. Before discussing our approach and results, however, it is important to clarify three points. 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 the rise of barriers to entry (Crouzet and Eberly, 2018). Indeed, a combination of these explanations is often heard in the discussion of internet giants Google, Amazon, Facebook or Apple.

Second, intangibles can play a role in all theories. They may increase the elasticity of substitution (e.g., through online price comparison), increase returns to scale (e.g., organizational capital), and also create barriers to entry (e.g., through patents and/or the compilation of Big Data).

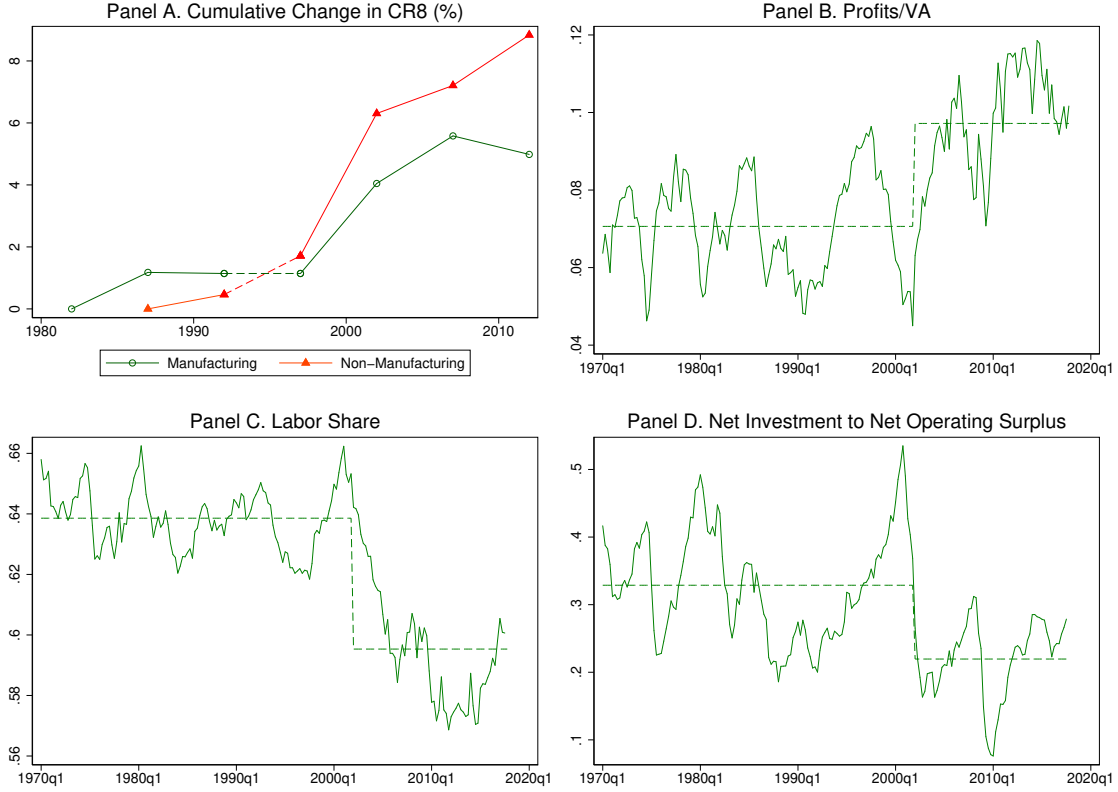
Third, these specific patterns are unique to the US. Panel A of Figure 2 shows that profits margins have increased in the US but they have remained stable or decreased in Europe, Japan and South Korea. Panel B

¹See Autor et al. (2017a) for a longer time-series of US census-based concentration measures under a consistent segmentation. The series in Autor et al. (2017a) exhibit similar trends: concentration begins to increase between 1992 and 1997 for Retail Trade and Services, and between 1997 and 2002 for the remaining sectors.

²One 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.

³Furman (2015) also 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).

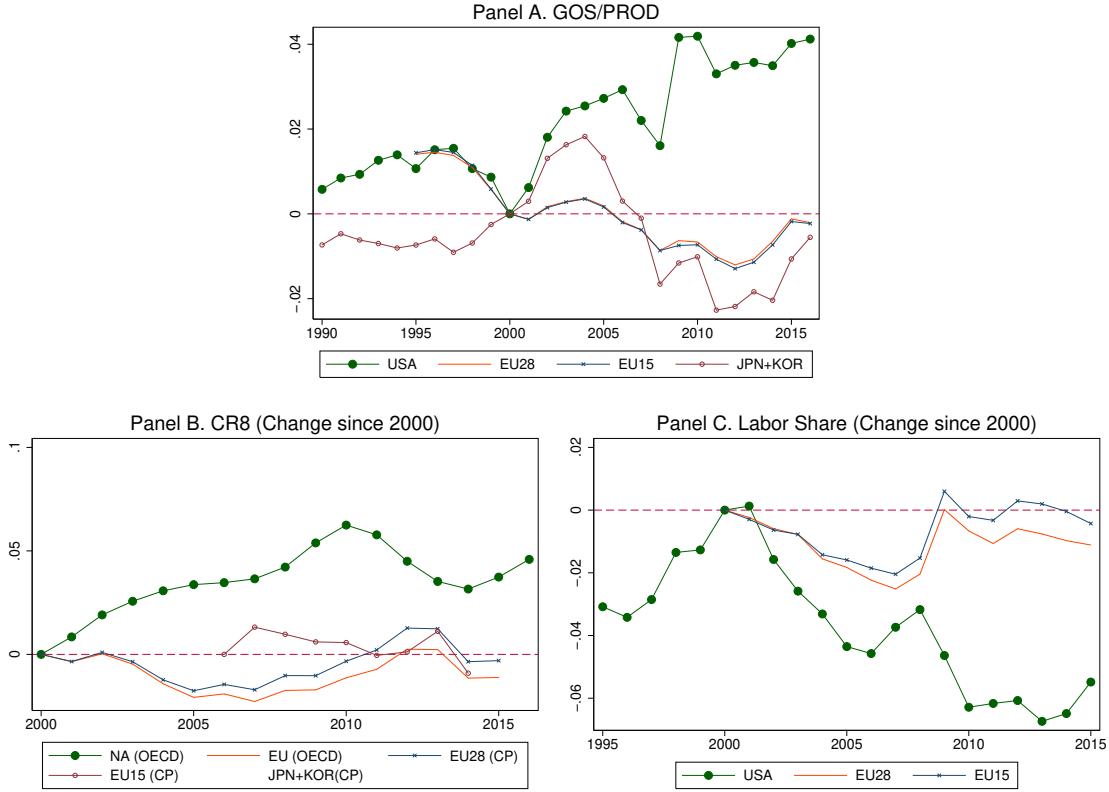
Figure 1: Evolution of US Concentration, Profits, Labor Shares and Investment



Notes: Panel A based on the cumulated sales-weighted average change in 8-firm Concentration Ratio (CR8). Data from the US Economic Census based on SIC-4 codes before 1992 and NAICS-6 codes after 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. We include only those industries that are consistently defined over each 5-year period. Change from 1992 to 1997 imputed from [Autor et al. \(2017b\)](#). 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 NCBGFCA027N minus NCBCFCA027N) to net operating surplus (series NCBOBNQ027S). Dotted lines show the average of the corresponding series before and after 2002.

shows that concentration has increased in the US but it has remained roughly stable in Europe and Asia.⁴ Lastly, panel C shows that the labor share has declined in the US but it has remained stable in Europe since 2000.⁵ Assuming that all advanced economies use similar technologies, the uniqueness of US trends suggests that technology – alone – cannot explain the trends.

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



Notes: GOS/PROD for Non-Agriculture business sector excluding Real Estate, 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.

⁴For 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 \(2018\)](#) provide a detailed comparison across a wide range of concentration measures for the US and Europe. [Bajgar et al. \(2019\)](#) use ORBIS data to include private firms; and take into account that some firms are part of larger business groups. When they measure concentration at the business group-level within 2-digit industries they find a moderate increase in concentration in Europe, with the unweighted average CR8 increasing from 21.5% to 25.1%. In North America, CR8 increases from 30.3% to 38.4%.

⁵These comparisons aggregate across industry categories, and may therefore be affected by changes in industry mix. However, [Gutiérrez and Philippon \(2018\)](#) 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 US, while investment decreased. By contrast, concentration and investment remained (relatively) stable in Europe, 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. For more on the labor share see [Gutiérrez and Piton \(2019\)](#) and [Cetté et al. \(2019\)](#).

Table 1: *Summary of Test Measures and Predictions*

		Theories	
	Data	“Good”	“Bad”
(i)	Exit Rate	–	+
(ii)	Corr($\Delta CR, \Delta TFP$)	+	–
	Corr($\Delta CR, \Delta P$)	–	+
(iii)	Aggregate investment rate	–	+
	Leader investment rate	–	+
(iv)	Leader turnover	–	+

Approach We begin by using a sequence of simple models to clarify the theories of good and bad concentration. We derive a broad set of predictions regarding the joint evolution of competition, concentration, productivity, prices and investment under each theory. We then evaluate these predictions empirically, first at the aggregate-, then at the industry-level. While some of these predictions have been studied by the literature, we contribute new facts/results for each of them. We also clarify several measurement issues and, perhaps more importantly, we show how the combination of all the facts helps us differentiate good and bad concentration.

Aggregate Results Table 1 summarizes our aggregate results. It contrasts the theoretical prediction of theories of good and bad concentration against the observed evolution of each measure.⁶ Predictions colored green are consistent with the data after 2000. Predictions colored red are not.

According to theories of good concentration, the growth of large firms is an efficient response to technological change. Under σ , competition increases as consumers become more price elastic. More productive firms expand to capture a larger share of the market, while less productive firms either shrink or exit. Economic activity reallocates towards more productive firms, increasing industry-level productivity and decreasing prices. Under γ , technological change leads to increasing returns to scale. Large firms again respond by expanding, which increases concentration and productivity while decreasing prices. The productivity gap between small and large firms grows.

If the economy experiences good concentration, we should observe: (i) concentration driven in part by exit; (ii) concentration associated with higher productivity and lower prices; and (iii) stable or increasing investment rates relative to Tobin’s Q – particularly for leaders. (iv) If the increase is driven by σ , we should also find higher volatility of market shares as demand responds more strongly to cost shocks. If the increase is driven by γ , however, the prediction could flip: volatility of market shares could fall as leaders’ comparative advantage become (potentially) more persistent (e.g., [Aghion et al. \(2018\)](#)).

We already know that σ and γ are important for certain industries during certain periods. For instance, they describe well the evolution of the retail industry from 1990 to 2005 ([Basu et al., 2003](#); [Blanchard, 2003](#)). The rise of superstores and e-commerce led to more price competition, higher concentration, higher productivity and the exit of inefficient retailers ([Hortacsu and Syverson, 2015](#)). The question is whether these theories explain the evolution of the economy as a whole, over the past 30 years. We test these pre-

⁶We derive most but not all of these in section 1. For predictions on leader investment, see [Gutiérrez and Philippon \(2017a\)](#).

dictions in the data and find some support for them during the 1990's. During this period, concentration is correlated with rising productivity, falling prices and high investment – particularly in intangibles. Since 2000, however, these predictions are rejected by the data. The correlation between concentration and productivity growth has become negative while the correlation between concentration and price growth has become positive; exit rates have remained stable; investment relative to Q has fallen; and market shares have become more persistent. Estimates of returns to scale based on the methodology of [Basu et al. \(2006\)](#) have remained stable, as have other estimates in the recent literature ([Ho and Ruzic, 2017](#); [Diez et al., 2018](#)). All these predictions are consistent with the κ theory.

Barriers to competition therefore emerge 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.

Industry Results Aggregate trends are interesting, but the dynamics of individual industries are more informative: σ and γ cannot explain the broad trends but they probably matter for some industries. To obtain a systematic classification of industry-level changes, we perform a Principal Components Analysis (PCA) on a wide range of measures related to competition. We find that the first principal component, PC1, captures the σ and γ theories of good concentration while the second principal component, PC2, captures theories of bad concentration. This distinction is quite stark and allows us to show which industries have experienced good vs. bad concentration, and to compare the importance of each theory over time.

Durable computer manufacturing exhibits the highest loading on PC1. It exhibits high intangible capital intensity but remains relatively competitive, likely as a result of intense foreign competition. By contrast, Telecom, Banking and Airlines are predominantly explained by κ , consistent with the results of [Gutiérrez and Philippon \(2018\)](#). They exhibit high concentration, high profits and low productivity growth. Interestingly, some industries – such as nondurable chemical manufacturing and information - data – load heavily on both PC1 and PC2. These industries hold large amounts of intangible assets but also exhibit high barriers to entry. They are good examples of intangible assets giving rise to barriers to entry, as emphasized by [Crouzet and Eberly \(2018\)](#). In fact, [Crouzet and Eberly \(2018\)](#) argue that the Healthcare sector – which includes nondurable chemical manufacturing – is one where market power derived from intangible assets is largest.

Looking at the evolution of loadings over time further emphasizes the transition from good to bad concentration. The average PC1 score (reflecting good concentration) was substantially higher than PC2 in 1997, and increased faster from 1997 to 2002. But PC2 caught up afterwards and, by 2012, explained a larger portion of industry dynamics. Our results therefore indicate that the US economy has transitioned from good to bad concentration over the past 30 years.

Related Literature Our paper contributes to a growing literature studying trends in competition and concentration in the US economy. The literature began by (separately) documenting the stylized facts. [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 ob-

served in selected sectors (notably retail), the decline was observed across all sectors in the 2000's, including the traditionally high-growth information technology sector. [CEA \(2016\)](#) and [Grullon et al. \(2019\)](#) document the broad increases in profits and concentration; [Elsby et al. \(2013\)](#) and [Karabarbounis and Neiman \(2014\)](#) document the decline in the labor share; and [IMF \(2014\)](#); [Hall \(2015\)](#); [Fernald et al. \(2017\)](#) discuss the decline in investment in the context of weak overall growth. [Akcigit and Ates \(2019\)](#) review some of the literature.

Over time, the literature began to connect these facts and propose theories of “good” and “bad” concentration (we use “good” and “bad” for didactic purposes). The most prominent explanations of good concentration include [Autor et al. \(2017a\)](#) and [Van Reenen \(2018\)](#) who argue that rising concentration and declining labor shares are explained by an increase in σ , which results in “winner take most/all” competition; and [Alexander and Eberly \(2016\)](#) and [Crouzet and Eberly \(2018\)](#) who link the rise in concentration and the decline in investment to intangible capital. [Bessen \(2017\)](#) links IT use to industry concentration, while [Ganapati \(2018\)](#) links concentration to increasing labor productivity and stable prices. [Aghion et al. \(2018\)](#) and [Ridder \(2019\)](#) develop models where Information and Communication Technologies (ICT) increase returns to scale, leading to higher concentration and lower labor shares.

Moving to bad concentration, [Grullon et al. \(2019\)](#) show that firms in concentrating industries exhibit higher profits, positive abnormal stock returns and more profitable M&A deals. [Barkai \(2017\)](#) documents a rise in economic profits and links it to concentration and labor shares. [De-Loecker et al. \(2019\)](#) argue that markups have increased. [Gutiérrez and Philippon \(2017b\)](#) link the weakness of investment to rising concentration and market power, while [Lee et al. \(2016\)](#) find that capital stopped flowing to high Q industries in the late 1990's. [Eggertsson et al. \(2018\)](#) introduce time-varying market power to a standard neoclassical model to explain several of our stylized facts. [Gutiérrez and Philippon \(2018\)](#), [Jones et al. \(2019\)](#) and [Gutiérrez and Philippon \(2019\)](#) argue that domestic competition has declined in many US industries because of increasing entry costs, lax antitrust enforcement, and lobbying.

Our paper is also 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 US 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.

The remainder of this paper is organized as follows. Section 1 derives theoretical predictions. Section 2 discusses measurement issues related to common empirical proxies of competition. Section 3 tests aggregate predictions related to business dynamism, productivity, prices, investment and returns to scale. Section 4 replicates the exercise at the industry-level, using PCA. Section 5 concludes.

1 Theory

We use a few simple models to derive testable predictions for the various hypotheses. 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.

Let us start with the simple case where there is no heterogeneity. Consider, then, 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 mark-up μ over marginal cost. In other words, firms set the price

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

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

$$y_i = \frac{Y}{N} \text{ for all } i \in [0, N]$$

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 $N \geq \frac{\mu}{1 + \mu} \frac{\bar{Y}}{(r + \delta) \kappa + \phi}$. We then have the following proposition

Proposition 1. *In response to shocks to ex-post mark-ups 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 as a proxy for 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 and θ is the elasticity of the mark-up to concentration. In a standard CES-monopolistic competition model, for instance, we have $\theta = 0$ and $\bar{l} = 1/\sigma$. We can then write the free entry condition as $N^{1+\theta} \geq \frac{\bar{l}\bar{Y}}{(r+\delta)\kappa+\phi}$ which shows that our propositions are valid when markups vary with concentration.

1.2 Selection and Ex-Post Profits

Consider now the case of heterogenous marginal costs. Heterogeneity creates a selection effect and we need to distinguish between the number of firms that enter (\hat{N}) and the number of firms that actually produce (N). Formally, consider the following industry entry game:

- 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 mark-up μ_i .

Let $N \leq \hat{N}$ be the number of active producers. We re-order the varieties so that $i \in [0, N]$ are active while $i \in (N, \hat{N}]$ exit early. The demand system is given by the CES aggregator

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

where $\sigma > 1$ is the elasticity of substitution 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 mark-up $\mu^m = \frac{1}{\sigma-1}$ 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 mark-up $\mu < \frac{1}{\sigma-1}$, strategic interactions among firms, and so on. For now we simply keep μ as a parameter.

Firms with productivity $a_i < a^*$ 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' 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 average productivity is

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

Equilibrium profits are then

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

There is a cutoff a^* such that only firms above the cutoff are active producers

$$\pi(a^*; a^*, PY, N) = 0$$

The productivity cutoff a^* solves $\frac{\mu}{1 + \mu} (a^*)^{\sigma-1} \frac{PY}{N} = \phi (A^*)^{\sigma-1}$. For simplicity we consider again the log-industry demand case, so PY is exogenous and equal to \bar{Y} . Using the definition of A^* in equation (1), and $N = (1 - F(a^*)) \hat{N}$ and $dF^*(a) = \frac{dF(a)}{1 - F(a^*)}$, we find that

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

The RHS is increasing in σ and decreasing in a^* , so 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 $E[\pi \mid a > a^*]$ must increase with σ for a given κ .

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 (selection effect). 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 of technology 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 to $a_i = A_H$ 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 when firms switch to the high return to scale technology. 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. A higher degree of increasing returns to scale leads to more concentration, higher profits and higher productivity for the remaining firms.*

This proposition connects σ and γ , as often discussed in the literature. Note that we can measure the degree of returns to scale γ as the ratio of average cost $\frac{\phi}{y} + \frac{1}{A}$ to marginal cost $\frac{1}{A}$:

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

which is increasing with ϕ since N is decreasing in ϕ . Therefore if we were to measure γ under the old and the new technologies, we would indeed find $\gamma_H > \gamma_L$.

1.4 Dynamics of Market Shares

Consider finally 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 of firm i in industry j 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 mark-up 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_j leads to an increase in the volatility of market shares in industry j .*

In summary, we have that an increase in σ leads to an increase in concentration, productivity, exit, the volatility of market shares and investment. Similarly, an increase in γ results in more concentration, higher profits and higher productivity for surviving firms.⁷ Finally, an increase in κ leads to an increase in concentration, and a decrease in productivity, exit rates, market share volatility and investment (relative to Q).

2 Measurement Issues

Before testing our predictions, we discuss two important issues related to the measurement of concentration and mark-ups.

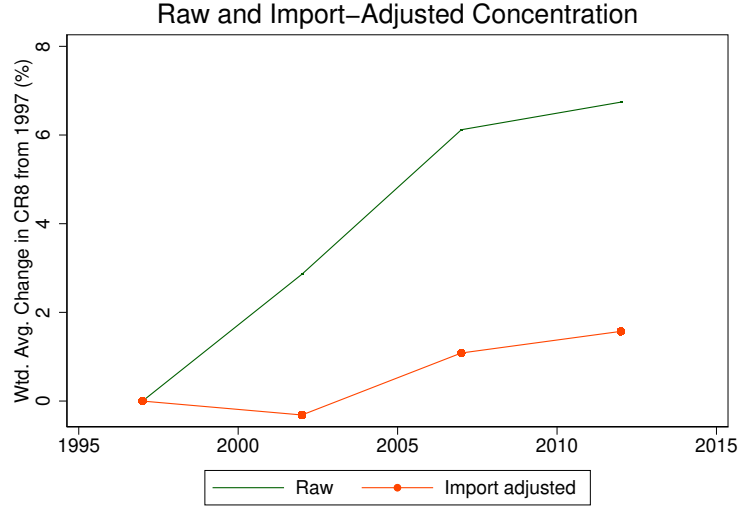
2.1 Foreign Competition and Concentration

First, when computing industry concentration, it is important to control for imports. We compute import-adjusted concentration measures ($CR8^{IA}$) and use them throughout the paper. Figure 3 shows the importance of the correction, focusing on manufacturing industries that are highly exposed to foreign competition. While domestic concentration increased by 6.7 percentage points in these industries, import-adjusted concentration (dotted line) increased by only 1.6 points.⁸ Foreign competition, therefore, plays an important role in manufacturing. But import-exposed industries only account for about 10% of the private economy, so foreign competition cannot explain the aggregate trends that we have presented earlier.

⁷In this model, an increase in returns to scale correspond to a shift towards a high productivity, high fixed cost technology.

⁸Gutiérrez and Philippon (2017a) reports similar results using Herfindahls and the data of Feenstra and Weinstein (2017).

Figure 3: Domestic vs. Import Adjusted Concentration for High Import Manufacturing Industries



Notes: weighted average absolute change in domestic (solid) and import-adjusted (dotted) CR8 across NAICS-6 manufacturing industries in the top three quantiles of import shares as of 2012. Imports accounted for 29% of sales + imports in these industries, on average. Domestic concentration from US 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 appendix for details.

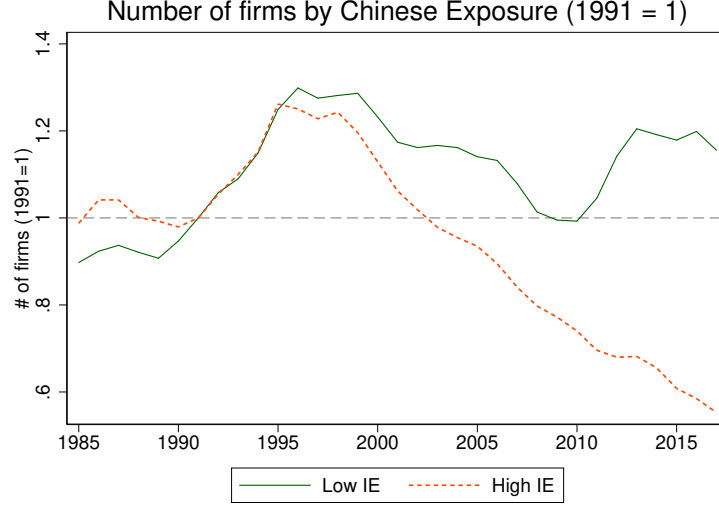
2.2 Mark-up Measurement

The second issue relates to measurement of mark-ups. 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. DLEU implement this methodology using COGS (cost of goods sold) as their main measure of variable input. While this approach is promising in theory, the question 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 mark-up measures.

Identification: The China Shock. We use the China shock to illustrate this issue, following Autor et al. (2016) and Pierce and Schott (2016). Chinese competition led 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.

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.

Figure 4: *Number of firms by Chinese exposure*



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.

Realized imports are endogenous so, in the rest of the section, we use the instrument proposed by [Pierce and Schott \(2016\)](#). The instrument 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 industries facing larger NTR gaps experienced a larger increase in Chinese imports and a larger decrease in US 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:

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

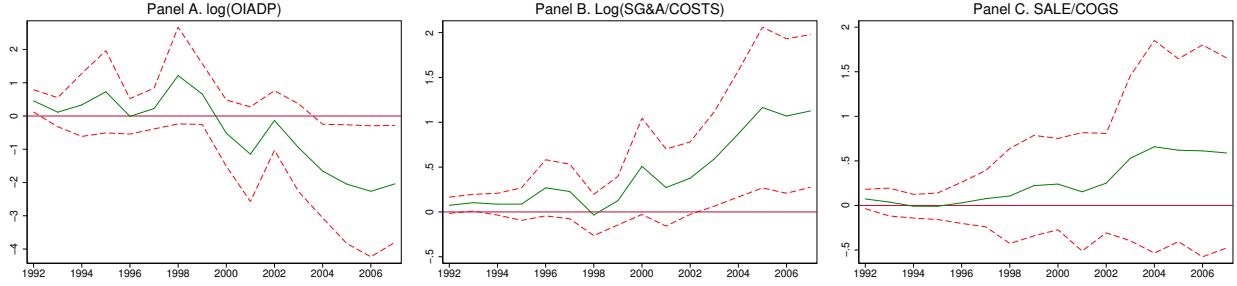
This measure is plausibly exogenous to industry demand and technology after 2001. The vast majority of the variation in NTR gaps is due to variation in non-NTR rates set 70 years prior to passage of PNTR. See [Pierce and Schott \(2016\)](#) for additional discussion.

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

$$\pi_{i,j,t} = \sum_{y=1991}^{2007} \beta_t \times NTRGap_j + \delta_i + \gamma_t + \varepsilon_{i,j,t} \quad (2)$$

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, US Presidents began temporarily granting NTR tariff rates to China, but required annual re-approval by congress. The re-approval process introduced substantial uncertainty around future tariff rates and limited investment by both US and Chinese firms (see [Pierce and Schott \(2016\)](#) for a wide range of anecdotal and news-based evidence). This ended in 2001, when 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 2, 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.

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. Consistent with the increase in exits, the operating income of US companies falls upon Chinese accession to the WTO (Panel A).

What is more remarkable, however, is the increase in the share of Sales General & Administrative expenditures (SG&A) in total costs. SG&A is the second major component of costs and includes all intangible-building activities (e.g., R&D, Advertising and IT staff expense). US firms react to the increased competition by almost doubling their SG&A intensity (Panel B), a result consistent with the shift towards intangible capital documented in Table 4 below, as well as the increased product differentiation documented by [Feenstra and Weinstein \(2017\)](#). The increase in SG&A is precisely the type of technological change that may affect the validity of COGS-based mark-ups. Indeed, panel C shows that SALE/COGS appears to *increase* rather than *decrease* upon the shock.¹¹ COGS-based mark-up measures would fail to classify the China shock as an increase in competition, while exit and profit margins do.¹²

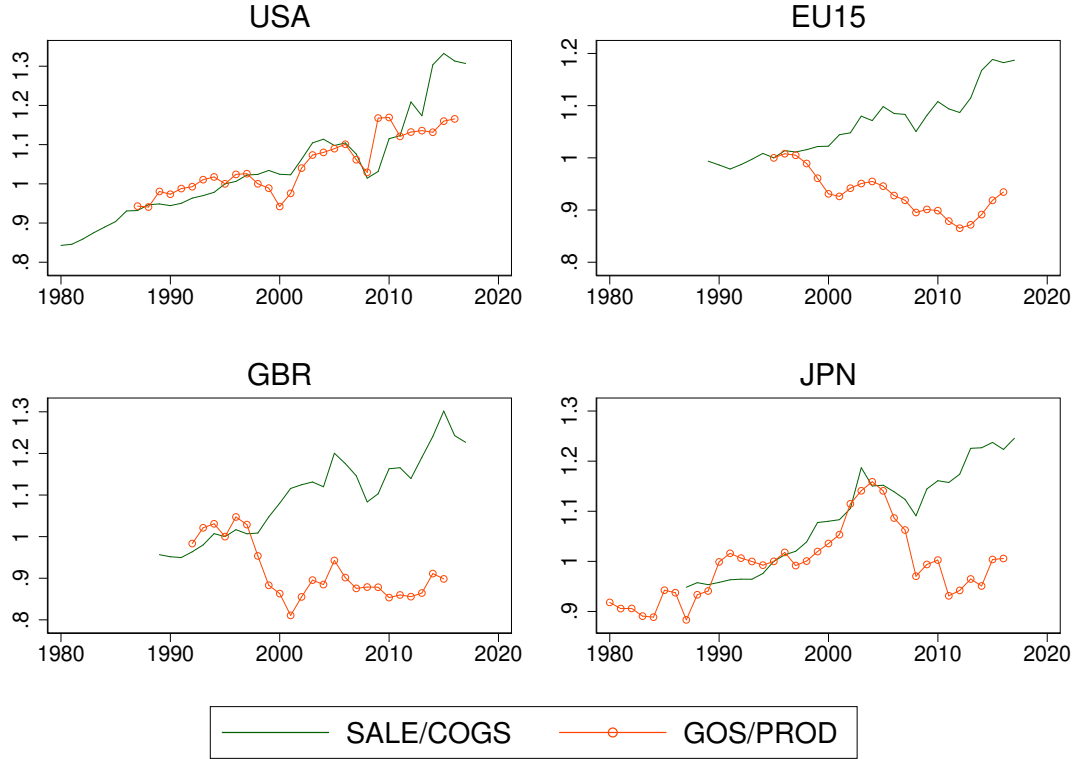
We can also get a broad evaluation of the usefulness of mark-ups by studying the evolution across regions. Figure 6 plots the sales-weighted average ratio of SALES to COGS against gross profit rates by region.¹³ The shift towards intangible expenditures is clearly present across all advanced economies: SALE/COGS rises everywhere as the cost-share of COGS falls. This may suggest a global rise in market power, but profits shows us the opposite – especially for the EU15 and the UK. Only in the US do we observe a large increase in profits. In the remaining regions, the decline in COGS is fully offset by a rise in SG&A so that profits remain flat (operating income before depreciation equals sales minus COGS and SG&A.). Given the inability of mark-up estimates to control for technology, we focus on profits and market share dynamics

¹¹ SALE/COGS is related to the benchmark measure of DLEU up to a measurement error correction and a (time-varying) industry-level scaling factor, which measures the elasticity of SALES to COGS. Both the measurement error correction and the elasticity of output remain largely stable even in the long-run so that SALE/COGS dominates the evolution of mark-ups.

¹² In 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. \(2018\)](#)).

¹³ See [De Loecker and Eeckhout \(2018\)](#) for actual mark-up estimates globally. As expected, their results closely follow the SALE/COGS series.

Figure 6: *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.

in the rest of the paper.¹⁴

3 Aggregate Evidence

3.1 Entry, Exit and Turnover

Having clarified some measurement issues, let us return to the main goal of the paper: differentiating theories of good vs. bad concentration. We begin with market share turnover. IO economists rightly complain about the use of HHIs or Concentration Ratios at the broad industry \times country 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.¹⁵ But there is a more fundamental problem: depending on the nature of competition, technology as well as supply and

¹⁴This is not to say that profits are a perfect measure. Accounting rules often deviate from economic concepts, and estimates of economic profits are prone to errors given the difficulty in measuring the capital stock and the user cost of capital. We can gain some comfort, however, by comparing a wide range of measures from alternate sources. In [Gutiérrez and Philippon, 2018](#), for example, we 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.

¹⁵See [Rossi-Hansberg et al. \(2018\)](#), among others, for related evidence; but note that their conclusions are controversial ([Ganapati, 2018](#)).

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, 2019).

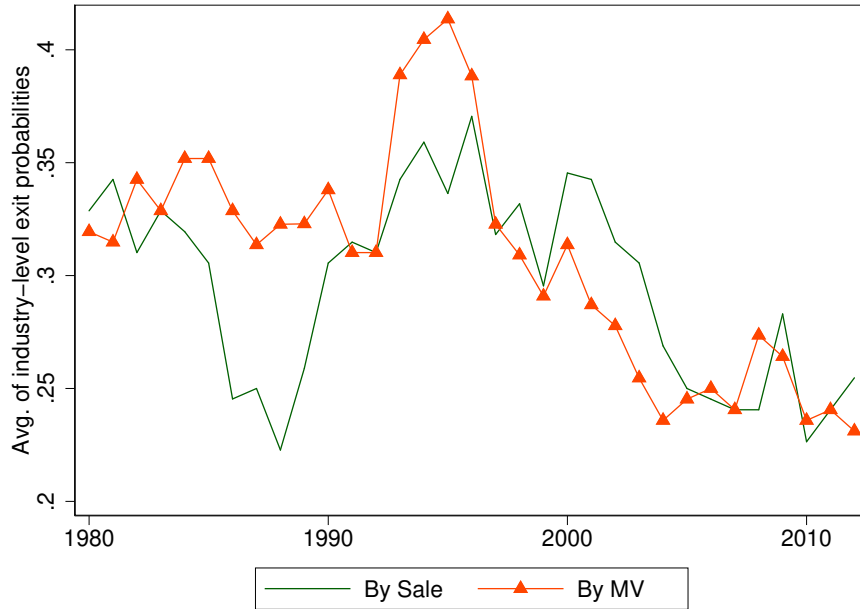
Leader Turnover. To obtain an alternate measure of market power, we consider turnover of market shares and market leadership. In particular, one can ask: given that a firm is at the top of its industry now (top 4, top 10% of market value), how likely is it that it will drop out over the next 5 years.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

Figure 7 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 .¹⁶ We then average turnover across all industries in a given year. 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.

Figure 7: 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. Leader turnover focuses on the right tail of the distribution. Let us now broaden the sample to include all firms, and study the persistence of market shares. We follow proposition

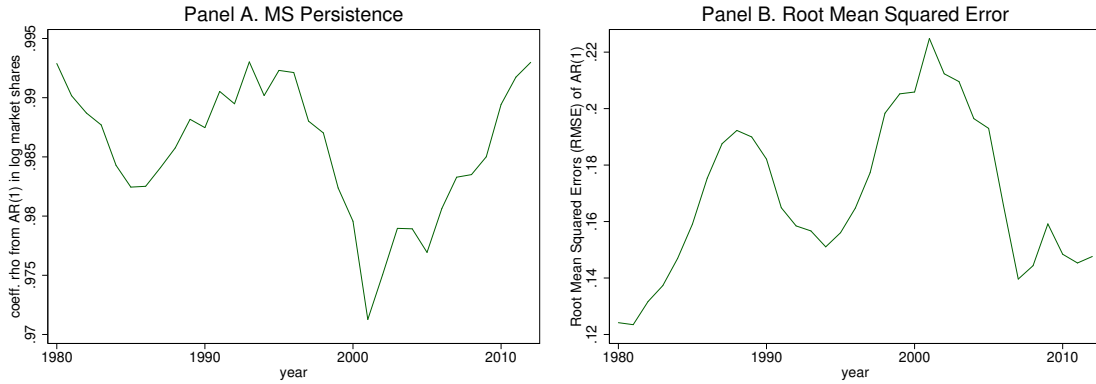
¹⁶We use a constant number of leaders because they account for a roughly stable share of sales. In unreported tests, we consider the top 10% of firms and obtain similar results, though this broader group accounts for a rising share of sales.

4 and 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:

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

Panels A and B of figure 8 plot the sales-weighted average $\rho_{j,t}$ and root mean squared error (RMSE), respectively. In line with the decline in turnover, the persistence of market shares increases after 2000, while the RMSE falls.¹⁷

Figure 8: 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.

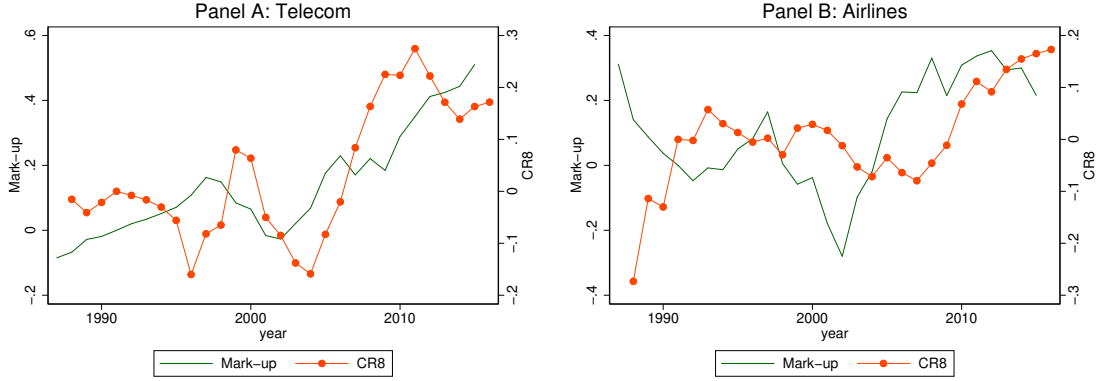
Leaders clearly have less to worry about today than 30 years ago. Their market shares and leadership positions are far more persistent today than even 15 years ago. Why might this be? In [Gutiérrez and Philippon \(2019\)](#), we study competitive pressures directly, focusing on the entry and exit margins. 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 .

3.2 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, while [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.

¹⁷Appendix figure 20 presents an additional test, based on the correlation of firm rankings over time. It yields consistent results.

Figure 9: *Change in Mark-up and Concentration since 1991: Airlines and Telecom*



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

BLS & Compustat. We begin our analysis with relatively aggregated data from the BLS Multifactor Productivity tables. This dataset includes TFP, prices, wages and labor productivity. We complement it with Compustat-based concentration measures to obtain the same industry classification in left- and right-hand side variables. We assess the joint evolution of productivity, prices and mark-ups using regressions of the form

$$\Delta_5 \log(Z_{j,t}) = \beta \Delta_5 \log(CR4_{j,t}) + \gamma_t + \varepsilon_{jt}.$$

where Z is the variable of interest and Δ_5 denotes a 5-year change. We consider TFP, prices and mark-ups of prices over unit labor costs (ULC): $\Delta_5 \log \mu = \Delta_5 \log P - \Delta_5 \log ULC$, where $\Delta_5 \log(ULC) \equiv \Delta_5 \log(W) - \Delta_5 \log(LP_t)$.

Table 2 summarizes the results. 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 9 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 the PCA of section 4. However, using broad industry definitions limits the power of our regressions – hence the large confidence intervals above. Let us now bring in more granular data.

BEA, NBER and Census. We roughly follow [Ganapati \(2018\)](#) and combine concentration data from the US Economic Census with price data from the NBER-CES database for manufacturing and the BEA's

Table 2: *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 import-adjusted 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)	(2)	(3)	(4)	(5)	(6)
	Pre-00	Post-00	Pre-00	Post-00	Pre-00	Post-00
$\Delta_5 \log(CR4^{IA})$	0.186* (0.070)	-0.044 (0.051)	-0.093 (0.069)	0.077 (0.088)	-0.102* (0.047)	0.116+ (0.064)
Cons	0.016 (0.013)	0.025** (0.009)	0.074** (0.013)	0.097** (0.010)	0.048** (0.012)	0.045** (0.011)
Year FE	Y	Y	Y	Y	Y	Y
R^2	.12	.1	.048	.07	.041	.082
Observations	94	141	94	141	94	141

detailed GDP by Industry accounts for non-manufacturing.¹⁸ 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:

$$\Delta_5 \log(Z_{jt}) = \beta \Delta_5 \log(CR4_{j,t}) + \gamma_{s,t} + \varepsilon_{jt}.$$

where j denotes industries and t denotes years. $\gamma_{s,t}$ denotes sector-year fixed effects. Table 3 reports results for prices and mark-ups. Before 2002, the correlation is small and often insignificant, in line with the results of 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 mark-ups. When concentration reaches a high level, however, the correlation is much stronger, especially in the non-manufacturing sector. See appendix 3 for additional results, including a decomposition of the correlation between concentration and mark-ups into the underlying components: prices, wages and labor productivity.

¹⁸For 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 ‘detailed’ GDP by industry accounts include prices. The ‘detailed’ GDP by industry accounts include ~ 400 industries, so that our non-manufacturing dataset is more aggregated than that of Ganapati (2018). We use the more aggregated dataset given the concerns with skewness described below and because, even at that level of aggregation, the BEA cautions of potential measurement error. That said, our results are largely consistent.

Table 3: 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
$\Delta_5 \log(CR4_{jt})$	-0.01 (0.03)	0.05* (0.02)	-0.03 (0.04)	0.02 (0.04)	0.10** (0.03)	-0.00 (0.05)	0.12* (0.05)	0.12** (0.04)	0.12* (0.06)
$\Delta_5 \log(CR4_{jt}) \times 1_{>2002}$	0.17** (0.04)	0.20** (0.06)	0.17** (0.05)	0.23** (0.06)	0.13+ (0.07)	0.26** (0.07)			
$\Delta_5 \log(CR4_{jt}) \times \text{High CR}$							0.18* (0.09)	0.08 (0.07)	0.41** (0.14)
High CR							0.03* (0.02)	0.07** (0.02)	-0.01 (0.02)
$\Delta_5 \log(LP_{jt})$	-0.39** (0.05)	-0.37** (0.07)	-0.39** (0.08)						
$\Delta_5 \log(w_{jt})$	0.58** (0.14)	0.74** (0.28)	0.48** (0.12)						
Cons	0.05** (0.02)	0.06+ (0.03)	0.06** (0.02)	0.05** (0.01)	0.11** (0.02)	0.03** (0.01)	0.04** (0.01)	0.06** (0.01)	0.02+ (0.01)
Sec x Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	.47	.45	.5	.39	.34	.36	.38	.38	.35
Observations	2,083	1,682	401	2,083	1,682	401	2,083	1,682	401

The joint evolution of concentration, TFP and prices appears consistent with the 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 mechanical 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.¹⁹ The reasoning above suggests that this claim is incorrect.

3.3 Investment and Profits

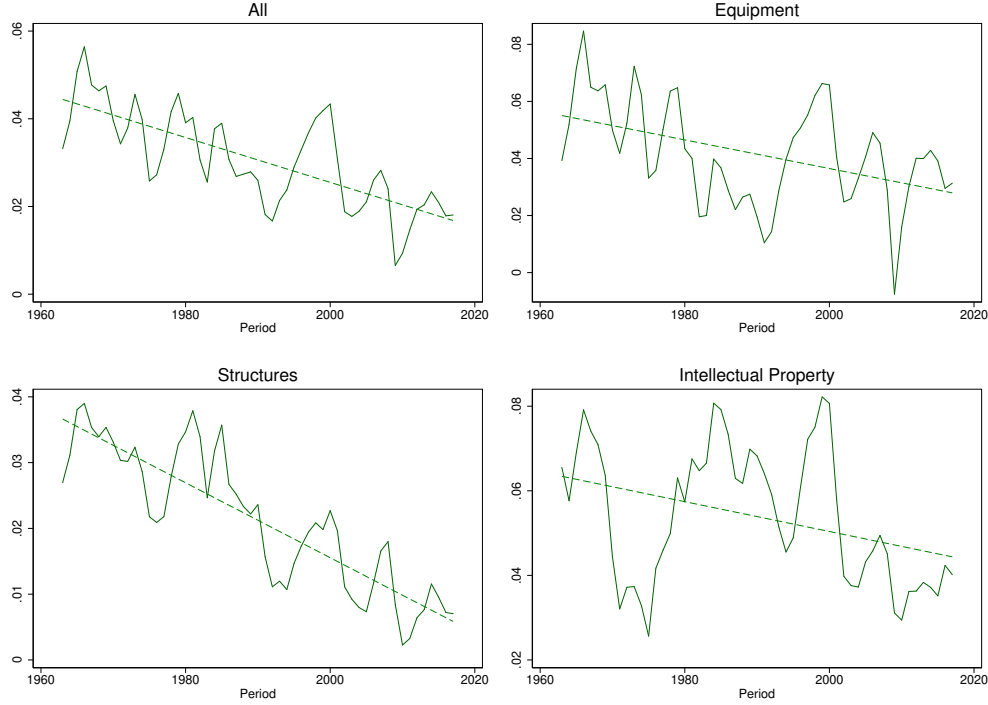
Under σ and γ , the increase in concentration is driven by technological change linked to the rise of intangibles. In that case, aggregate investment would remain in line with Q , while intangible investment would increase. However, as shown in [Figure 10](#), the growth of the capital stock has fallen across all asset types since 2000 – notably including intellectual property assets. Moreover, the decline in investment is not explained by Tobin's Q , as shown by [appendix figure 24](#). In fact, investment is near it's historical trough while Q is near it's historical peak.

¹⁹[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 10: 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 4, we define leaders by constant shares of market value to ensure comparability over time.²⁰ 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. As shown in appendix figure 25, the increase in leader profits is not fully explained by a reallocation effect with higher profit firms becoming leaders: profits increased within-firms for leaders and decreased slightly for laggards.

Is the decline in investment by leaders linked to concentration? According to σ and γ , leaders should increase investment in concentrating industries, reflecting an escape-competition strategy (σ) or their increasing relative productivity (γ). We test this at the firm-level, by estimating the following regression for firm i that belongs to BEA industry j :

$$\begin{aligned} \Delta \log(K_{ijt}) = & \beta_1 Q_{it-1} + \beta_2 CR8_{jt-1}^{IA} \times Lead_{i,j,t} + \beta_3 CR8_{jt-1}^{IA} \\ & + \beta_4 Lead_{ijt-1} + \beta_5 \log(Age_{it-1}) + \eta_t + \delta_i + \varepsilon_{it}, \end{aligned} \quad (3)$$

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 δ_i). β_2 is the coefficient of

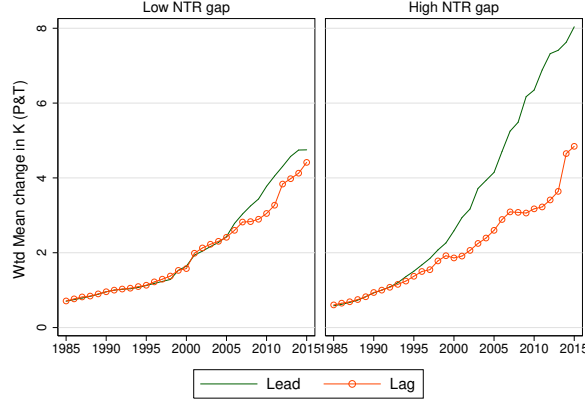
²⁰OIBDP shares are stable which is consistent with stable shares of market value and stable relative discount factors. Because firms are discrete, the actual share of market value in each grouping varies from year to year. To improve comparability, we scale measured shares as if they each contained 33% of market value.

Table 4: *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 11: 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.

interest. Table 5 shows that with the exception of manufacturing, leaders in more concentrated industries under-invest. This is inconsistent with σ and γ but consistent with κ .

Case study: the china shock again. Another way of investigating the role of κ for investment is to examine the behavior of leaders and laggards following the China shock. Figure 11 plots the average stock of K across Compustat firms in a given year, split by the 1999 NTR gap (see section 2 for details). K includes PP&E as well as intangibles, as estimated by [Peters and Taylor \(2016\)](#). 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 figure suggest that leaders react to increased competition from China by increasing investment. We confirm this by estimating a generalized difference-in-differences (DiD) regression:

$$\begin{aligned} \log(K_{i,j,t}) = & \beta_1 Post01 \times NTRGap_j \times \overline{\Delta IP}_t \\ & + \beta_2 Post01 \times NTRGap_j \times \overline{\Delta IP}_t \times Leader_{i,j,0} \\ & + \mathbf{X}_{j,t}'\gamma + \eta_t + \mu_i + \varepsilon_{it}, \end{aligned} \quad (4)$$

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.²¹ 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

²¹[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 ($\Delta IP_{j,t}^{OC}$).

Table 5: 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 (3). 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) $\Delta \log(PPE)^a$	(2) $\Delta \log(Int_{PT})^b$	(3) $\Delta \log(K_{PT})^{a+b}$	(4) $\Delta \log(PPE)^a$	(5) $\Delta \log(Int_{PT})^b$	(6) $\Delta \log(K_{PT})^{a+b}$	(7) $\Delta \log(PPE)^a$	(8) $\Delta \log(Int_{PT})^b$	(9) $\Delta \log(K_{PT})^{a+b}$
$CR8_{jt-1}^{IA}$	-10.98 ⁺ (5.96)	0.58 (6.00)	-4.82 (5.38)	-17.10 ⁺ (9.21)	-3.49 (8.29)	-3.81 (7.52)	-7.06 (9.19)	12.13 (10.75)	-2.35 (9.18)
$CR8_{jt-1}^{IA} \times lead_{it-1}$	-11.95* (4.66)	-18.92** (5.80)	-15.14** (4.51)	1.44 (7.20)	-1.35 (9.58)	-1.15 (7.25)	-13.64* (6.10)	-23.92** (7.53)	-17.44** (5.90)
$\log Q_{it-1}$	13.45** (0.43)	11.66** (0.37)	12.90** (0.35)	11.99** (0.53)	9.85** (0.42)	10.66** (0.40)	15.60** (0.73)	14.16** (0.67)	15.96** (0.61)
$Lead_{it-1}$	4.19** (0.99)	3.83** (1.13)	3.03** (0.91)	3.69** (1.42)	2.39 (1.67)	2.37 ⁺ (1.32)	2.47 ⁺ (1.38)	2.99 ⁺ (1.72)	1.51 (1.38)
$\log age_{it-1}$	-15.11** (0.78)	-18.85** (0.72)	-17.17** (0.64)	-15.50** (1.03)	-18.31** (0.86)	-17.34** (0.83)	-14.36** (1.18)	-19.29** (1.25)	-16.75** (1.00)
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	.098	.14	.16	.11	.12	.15
Observations	63,680	63,342	65,285	33,700	34,293	34,308	29,980	29,049	30,977

$\overline{\Delta IP}_t$ 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.²² We include year and firm fixed effects η_t and μ_i .

Table 6 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).²³ Columns 1 to 3 include all US 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.

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.

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

3.4 Returns to Scale

So far, we have evaluated the different theories indirectly by looking at their predictions about observable measures. In the case of γ , however, we can test the theory directly.

In Gutiérrez and Philippon (2019), we use industry- and firm-level data to estimate returns to scale. Industry-level estimates are based on BLS KLEMS data, following the methodology of Basu et al. (2006) while incorporating the instruments of Hall (2018). These estimates have the advantage of relying on well-measured inputs, outputs and prices, while following an established literature and set of instruments. However, the limited data availability implies that we can only estimate long-run average changes – such as an increase from before to after 2000. We perform this estimation and find a small increase in returns to scale – from 0.78 before 2000 to 0.8 afterwards.

²²These 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.

²³In unreported robustness tests, we confirm that our results are robust to including only balance sheet intangibles or excluding goodwill in the PT measure.

Table 6: *Investment of Leaders and Laggards following the Accession of China to the WTO*

Table shows the results of firm-level panel regressions of measures of capital on $NTRGap_j \times \overline{\Delta IP_{j,t}^{US}}$, following equation (4). 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) $\log(PPE_t)^a$	(2) $\log(Int_t^{PT})^b$	(3) $\log(k_t^{PT})^{a+b}$	(4) $\log(PPE_t)^a$	(5) $\log(Int_t^{PT})^b$	(6) $\log(k_t^{PT})^{a+b}$
$Post01 \times NTRGap \times \overline{\Delta IP_{j,t}^{US}}$	-8.035** (2.008)	-0.426 (1.962)	-1.884 (1.578)	-11.214** (2.138)	-3.284+ (1.921)	-4.670** (1.534)
$Post01 \times NTRGap \times \overline{\Delta IP_{j,t}^{US}} \times Lead$	9.267** (2.005)	6.978** (1.159)	6.643** (1.149)	9.601** (2.457)	8.319** (1.457)	7.998** (1.459)
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	.49	.18	.57	.54
Observations	34,711	35,043	35,075	15,906	16,017	16,034

We complement industry-level estimates with firm-level estimates based on Compustat, roughly following Syverson (2004) and De-Loecker et al. (2019). In particular, we estimate

$$\Delta \log q_{it} = \gamma [\alpha_V \Delta \log v + \alpha_K \Delta \log k + \alpha_X \Delta \log x] + \omega,$$

where γ measures the average return to scale across all firms. v, k and x denote COGS, capital costs and overhead costs (SG&A), respectively. $\alpha_V = \frac{P^V V}{P^V V + rK + P^X X}$, denotes the cost share of the COGS (likewise for α_K and α_X).²⁴ We again find stable estimates since 1970.

The relative stability of returns to scale is consistent with a variety of estimates in the literature, including Ho and Ruzic (2017) for manufacturing in the US; and Salas-Fumás et al. (2018); Diez et al. (2018) across EU industries. Thus, γ cannot explain the aggregate trends – though it likely matters for some industries.

4 Industry Evidence

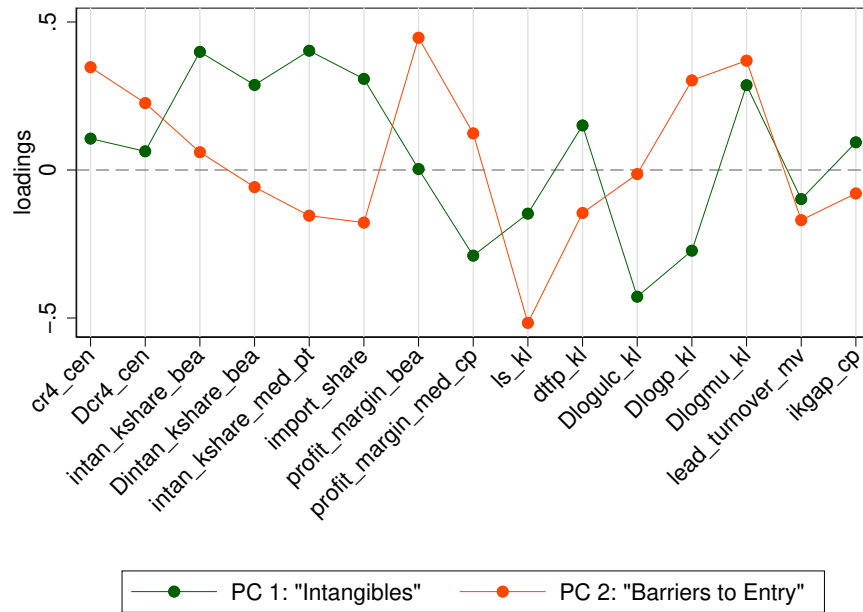
Aggregate trends are interesting, but they obscure the dynamics of individual industries: one size does not fit all. In this section, we perform a Principal Components Analysis on a wide range of variables related to competition (and covering all types of measures in Table 1) to obtain a systematic classification of the drivers of industry-level changes. We follow the industry segments in the BLS KLEMS, and perform the PCA on the correlation matrix so all measures contribute equally. Because we include census-concentration ratios, Agriculture and Mining are excluded from the analysis.

Figure 12 shows the variables included in the analysis and the resulting loadings of the first two principal components. Together, these components explain 34% of the variance. They have an intuitive interpretation. PC1 seems to capture the σ and γ theories of good concentration. It exhibits a positive loading on the level and changes in concentration (cr4_cen), and a high loading on intangible capital intensity (intan_kshare). The corresponding industries face significant import competition (import_share), and exhibit stable or declining profits (profit_margin). TFP increases (dtfp_kl), and unit-labor costs fall (Dlogulc). Prices also fall (Dlogp), but less than unit-labor costs so that mark-ups rise (Dlogmu). Leader turnover falls while the investment gap is close to zero.

PC2, by contrast, seems closely related to the κ theories of bad concentration. It captures a sharp increase in concentration despite limited growth in intangibles and negative import competition. Profits rise and the labor share falls. Mark-ups also rise, but for inefficient reasons: prices rise while productivity and unit labor costs remain largely flat.

²⁴De-Loecker et al. (2019) perform the same estimation in levels and find an increase in returns to scale from 0.97 to 1.08. However, levels regressions are likely affected by the inability to control for differences in firm-level prices or accurately measure intangible capital. For example, an increase in the mark-ups of large relative to small firms would appear as an increase in quantities, and result in an over-estimation of the increase in returns to scale. The estimation based on changes better controls for this, hence is likely more robust.

Figure 12: Principal Component Loadings



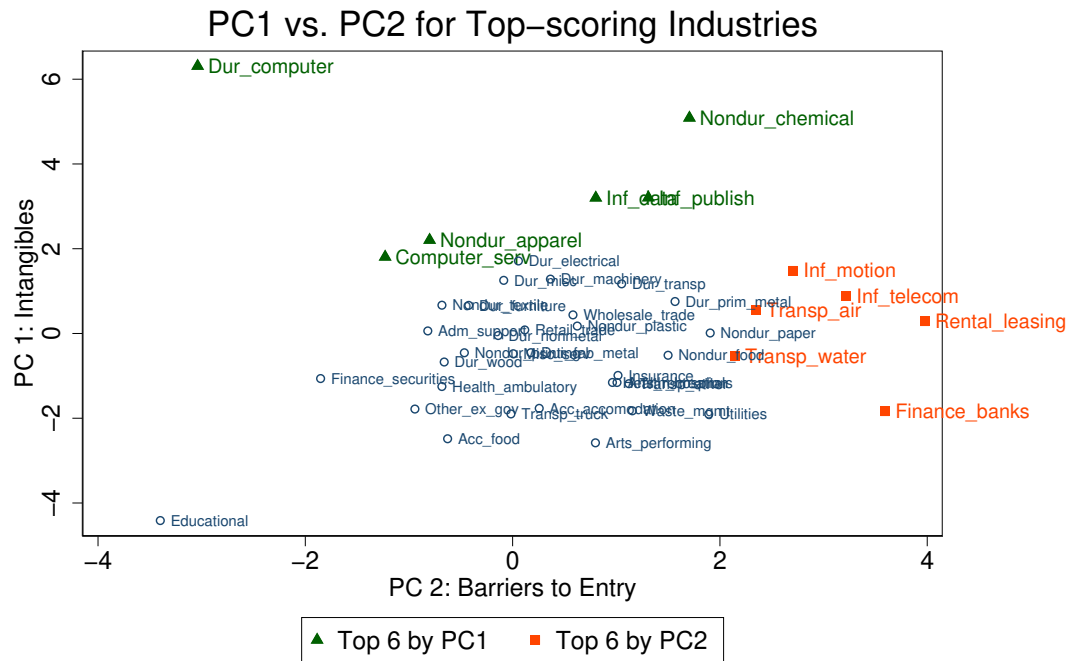
Notes: see text for details and data appendix for variable definitions. Cen: Census. BEA: BEA industry accounts. PT: Peters and Taylor (2016). CP: Compustat. KL: Klems.

Figure 13 contrasts the 2012 loadings on PC1 and PC2 for each industry. We highlight the 6 industries with the highest score according to PC1 and PC2. Durable computer manufacturing, Computer services and Nondurable apparel exhibit high loadings on PC1 and low loadings on PC2. They appear to remain strongly competitive despite increases in intangibles and concentration – likely as a result of foreign competition as shown in Figure 14. In fact, Figure 14 confirms the importance of foreign competition for domestic concentration, and serves as a comforting validation of our PCA.

Nondurable chemical manufacturing, Information - data and Information - publish present a mix of intangible-driven concentration and barriers to entry. These industries include Pfizer and Dow DuPont; Google and Facebook; and Microsoft, respectively. They are good examples of industries with large amounts of intangible assets – including patents – where leaders have become more efficient but also more entrenched over time.

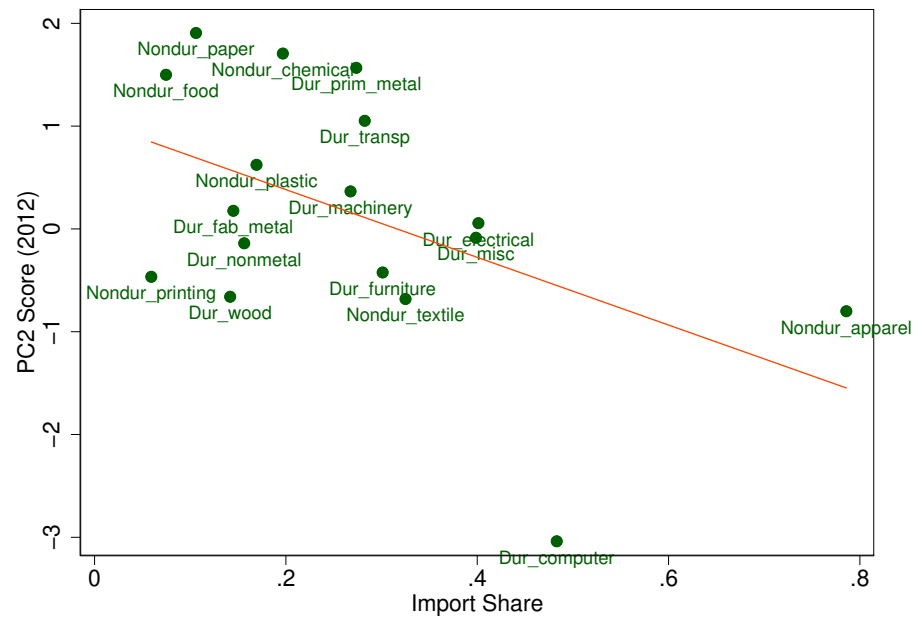
Information/Telecom, Banking, and Transportation/Airlines score near the top according to PC2. As discussed in Gutiérrez and Philippon (2018), these industries exhibit higher concentration, prices and profitability in the US than in Europe – despite using similar technologies. Accommodation/Food (i.e., Restaurants) scores near the bottom according to both measures. This is an industry with limited use of intangible assets that remains largely competitive. The fact that Education is the only real outlier is also comforting.

Figure 13: Principal Component Scores, by Industry



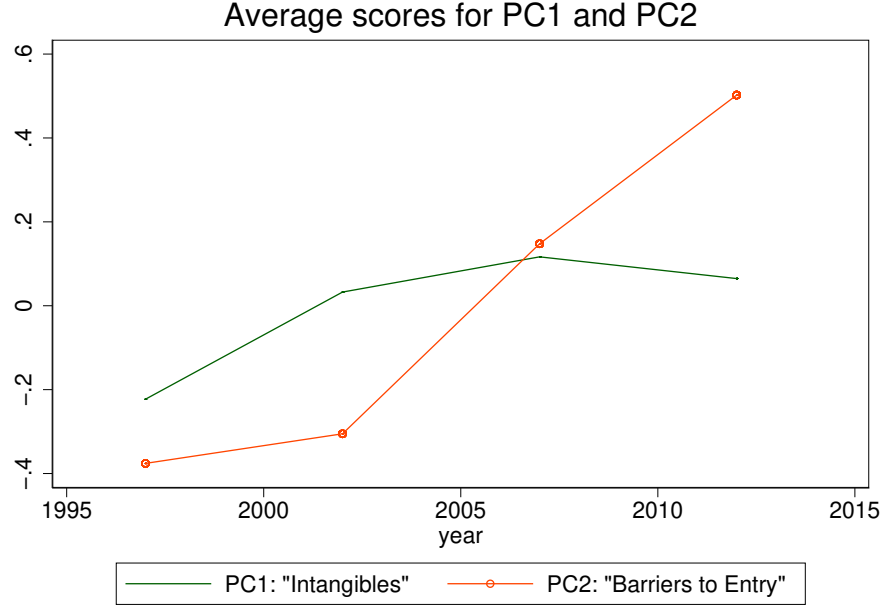
Notes: see text for details and data appendix for variable definitions.

Figure 14: 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.

Figure 15: Evolution of the average scores for PC1 and PC2



The PCA shows that both the κ theory and a combination of σ and γ are important for explaining the evolution of US industries over the past 20 years. But are they equally important at each point in time? Figure 15 plots the average PC1 and PC2 scores over time. The conclusions are striking. The average PC1 score – reflecting “good” concentration – was substantially higher and increased faster from 1997 to 2002. But PC2 (i.e., barriers to entry) caught up afterwards. By 2012, most industries weighted heavily on PC2 while the average PC1 score remained close to zero (with wide dispersion, of course, as shown in figure 13).

5 Conclusion

Internal Consistency of macro-market power literature We have used a wide range of measures of competition throughout this paper – sometimes independently and sometimes jointly, albeit non-parametrically. But all of these measures are connected by economic theory. Let us conclude by bringing together estimates from the macro-market power literature to validate the internal consistency of our conclusions. A decomposition first made by Susanto Basu in his discussion of DLEU is useful. We describe the decomposition briefly, and refer the reader to Syverson (2019) for a discussion of the underlying assumptions.

Consider a standard profit maximizing economy, and rewrite the mark-up by multiplying and dividing by average costs:

$$\mu = \frac{P}{MC} = \frac{P}{AC} \frac{AC}{MC} = \frac{AC}{MC} \frac{\text{Revenue}}{\text{Cost}}$$

The ratio of average to marginal costs, AC/MC , equals the returns to scale for a cost-minimizing firm taking factor prices as given while $\frac{\text{Revenue}}{\text{Cost}}$ can be written as $\frac{1}{1-s_\pi}$ using the profit share in revenues s_π .

Therefore

$$\mu = \frac{\gamma}{1 - s_\pi}. \quad (5)$$

Using equation (5) for two time periods, we obtain

$$\frac{\mu_{2016}}{\mu_{1980}} = \left(\frac{1 - s_{\pi,1980}}{1 - s_{\pi,2016}} \right) \frac{\gamma_{2016}}{\gamma_{1980}},$$

which can be used to assess the internal consistency of the macro-market power literature.

Let us begin by reiterating the discrepancy raised by [Syverson \(2019\)](#) and [Basu \(2019\)](#). DLEU report an increase in mark-ups from 1.21 to 1.61 between 1980 and 2016; and an increase in returns to scale from 1.03 to 1.08. [Barkai \(2017\)](#) estimates rising profit shares from 3% to 16% of value added over the same period, which (roughly) equate to 1.5% and 8% of sales. Plugging in these values, we obtain

$$\frac{1.61}{1.21} = \left(\frac{1 - 0.015}{1 - 0.08} \right) \frac{1.08}{1.03},$$

$$1.33 = 1.12.$$

The relationship appears widely inconsistent but there is an issue with this comparison. The mark-up estimates of DLEU are based on public firms, which likely have higher intangible (and SG&A) intensity than private firms – certainly more than small and medium enterprises. For the reasons discussed in section 2, this leads to an over-estimation of the rise in mark-ups for the full economy. As a rough approximation, let us assume that mark-ups of private firms remained stable – in line with the median Compustat firm as reported in Figure 8a of DLEU. This is valid if the distribution of high intangible firms, and therefore mark-up increases, is concentrated at the top. We can then obtain a rough estimate of the change in economy-wide mark-ups as the product of the Compustat mark-up increase (33%) times the Compustat share of sales in the total economy (40% as reported by [Grullon et al. \(2019\)](#)). The resulting mark-up increase is then 13.2% – which seems consistent with the estimates above. Using our return to scale estimates, the last term would be 0.8/0.78 – again broadly in agreement.²⁵

Explaining the rise in κ Estimates from the macro-market power literature appear reasonably consistent with each other. They include a sharp increase in profits unique to the US, concentrated in the post-2000

²⁵We can perform a similar exercise since 2000, using the results of [Diez et al. \(2018\)](#) which are based on ORBIS and therefore include private firms. According to their estimates, US mark-ups increased by 12% since 2000 while returns to scale increased from 0.91 to 0.93. Over the same period, [Barkai \(2017\)](#) reports profit shares of value added rising from 4.5% to 16%. We then have

$$1.12 = \left(\frac{1 - 0.023}{1 - 0.08} \right) \frac{0.93}{0.91},$$

$$1.12 = 1.09.$$

We may also want to consider total economy profit shares, instead of NFC profit shares. [Gutiérrez \(2017\)](#) uses BEA data for the non-financial private economy. He finds an increase in the profit share from 11% to 21% from 1988-2015, which closely aligns with [Barkai \(2017\)](#) over the same period. Last, performing the same exercise for Europe with mark-up and returns to scale estimates from [Diez et al. \(2018\)](#) and profit share estimates from the appendix of [Gutiérrez and Philippon \(2018\)](#) (accounting only for the cost of debt to mirror [Barkai \(2017\)](#)), we obtain

period and explained mostly by rising barriers to entry. The next question, of course, is what might explain the rise in κ in the US? [Gutiérrez and Philippon \(2018\)](#) 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.²⁶ Last, [Jones et al. \(2019\)](#) combines a rich structural DSGE model with cross-sectional identification from firm and industry data. They 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.

$$1.06 = \left(\frac{1 - 0.036}{1 - 0.038} \right) \frac{0.93}{0.91},$$

$$1.06 = 1.03.$$

Again broadly in agreement.

²⁶In unreported tests, we confirm there is a positive relationship between PC2 and industry-level lobbying intensity.

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Appendix

A Appendix for Section 2: Measurement

This section provides additional results related to the mark-up estimates of [De-Loecker et al. \(2019\)](#) (DLEU hereafter). We begin with a brief discussion of the accounting definition of COGS, and its implications for mark-up estimation; followed by a discussion of technological change and its relation to Sales, General and Administrative (SG&A) expenditures.

A.1 Accounting Definitions

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. DLEU use COGS as their variable input which, according to GAAP, is defined as “the cost of inventory items sold during a given period.” This is clearly defined 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 in COGS vs. SG&A. 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 may violate the assumptions underlying DLEU. Two examples:

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 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 indirectly related to the delivery of services (e.g., software, organizational capabilities, equipment). Again, this may violate the variable cost assumption underlying DLEU. Moreover, Google can exercise discretion on what is classified as SG&A

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

Table 7: 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.

instead of Cost of Revenues. In fact, Google reported stock-based-compensation separate from Cost of Revenues up to 2005 but combined it after 2006.

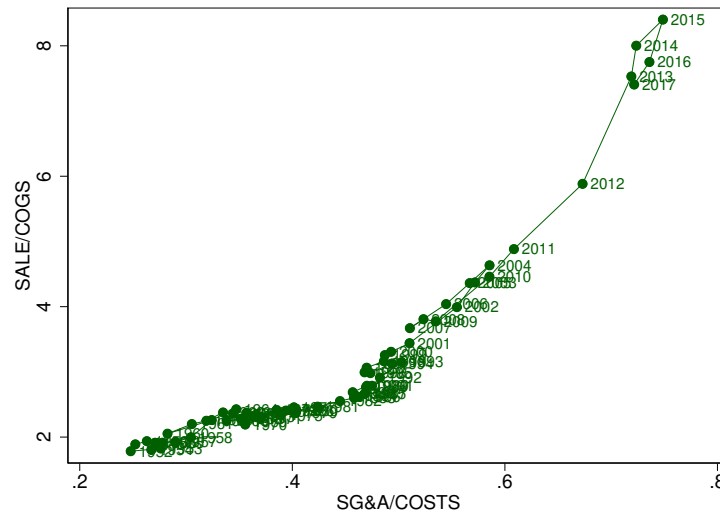
A.2 Role of SG&A and Intangibles

The above issues related to the measurement of variable costs – as well as the treatment of SG&A – pose significant challenges for the estimation. However, even assuming that COGS is a perfect proxy of variable costs and that SG&A is properly accounted for in the production function estimation, there is a more fundamental issue with the interpretation of mark-ups as a proxy of market power: technological change and the rise of fixed costs.

The share of SG&A in total costs has increased over the past 30 years, precisely when the share of COGS has fallen. Table 7 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 of sales. 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 16 shows the sales-weighted average of SALE/COGS and SG&A cost-shares (SG&A/COSTS) 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.

Figure 16: 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.

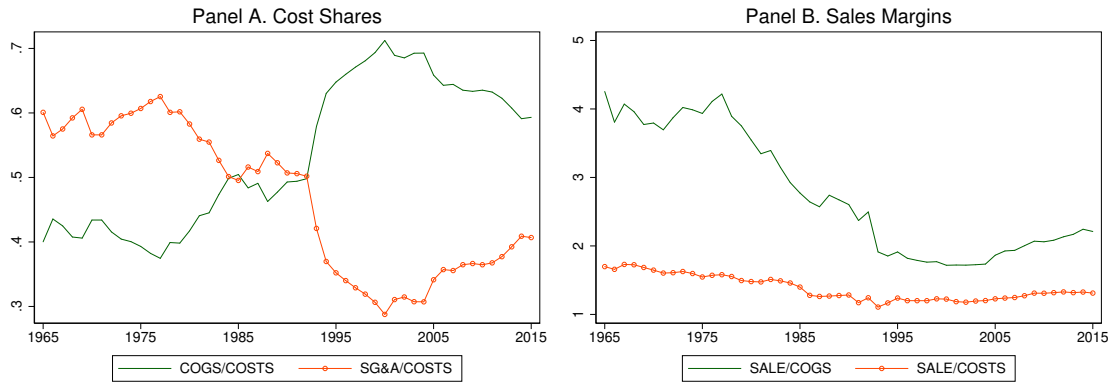
IBM. Consider IBM, a firm that transitioned from providing mostly products to mostly services, beginning in 1994. As shown in Panel A of Figure 17, the cost-share of COGS increased from 40 to 60% while the cost-share of SG&A decreased by a similar amount, precisely as IBM transitioned from a high-overhead, 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). Does this mean that the extent of competition faced by IBM increased sharply from 1965 to 2015? Probably not. In the long-run, IBM's ratio of SALE to COGS is dominated by its SG&A intensity, which is in turn dictated by its product mix. It tells us much about IBM's production function and its share of fixed vs. variable costs, but less about the extent of (dynamic) competition faced by IBM in product markets. In fact, while IBM's SALE/COGS ratio fell by 48% from 1965 to 2015, margins (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 18). This is consistent with IT investments driving concentration, as described in Bessen (2017). SALE/COGS increased rapidly with SG&A, yet profit margins (and the relative price of retail trade) actually fell.

These are specific examples, but as shown in Figure 6 above, the divergence between SALE/COGS and

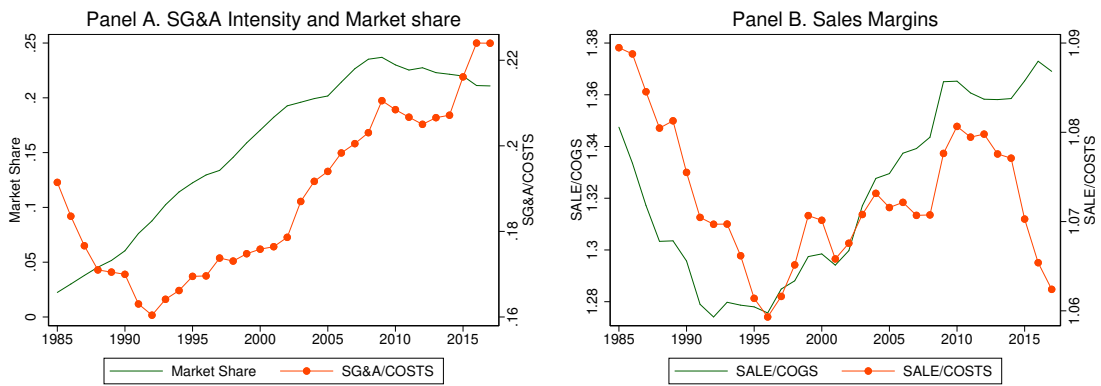
²⁸The composition of COGS also changed, likely affecting the elasticity of sales to COGS. In 1992, costs associated with hardware and software sales accounted for 36.9% of sales. By 2016, the same figure dropped to only 8.2% of sales. Costs associated with services increased from 9.4% to 42.6%. IBM was 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 DLEU, 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 17: IBM: Cost Shares and Sales Margins



Source: Compustat NA. COSTS = COGS + SG&A.

Figure 18: Walmart: Cost Shares, Market Shares and Sales Margins



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

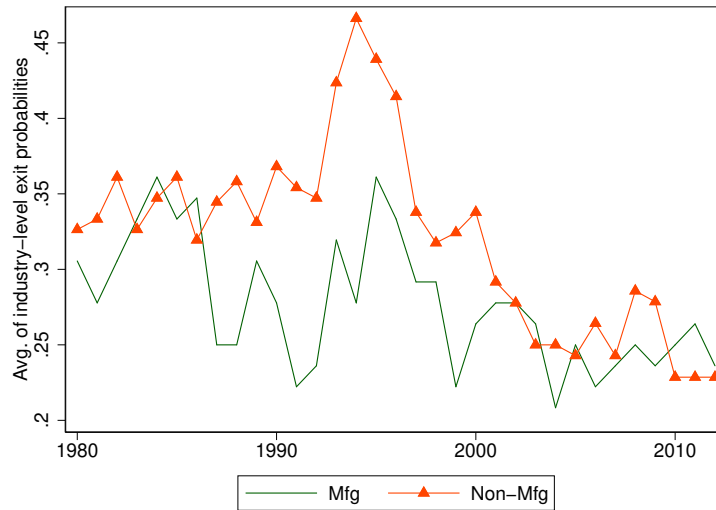
profits remains at the country-level. As a result, rising COGS-based mark-ups – by themselves – tell us little about the long-run evolution of competition and market power. DLEU acknowledge as much, noting that “*technological change will lead to higher mark-ups (due to lower marginal costs), but prices will not drop because firms need to generate revenue to cover fixed costs. As a result, profits will continue to be low and **higher mark-ups do not imply higher market power.***” Profits – therefore – remain the only reliable measure of marker power; and the one we focus on here and in related work.

B Appendix for Section 3: Aggregate Evidence

B.1 Entry, Exit and Turnover

Figures 19 replicates figure 7 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*



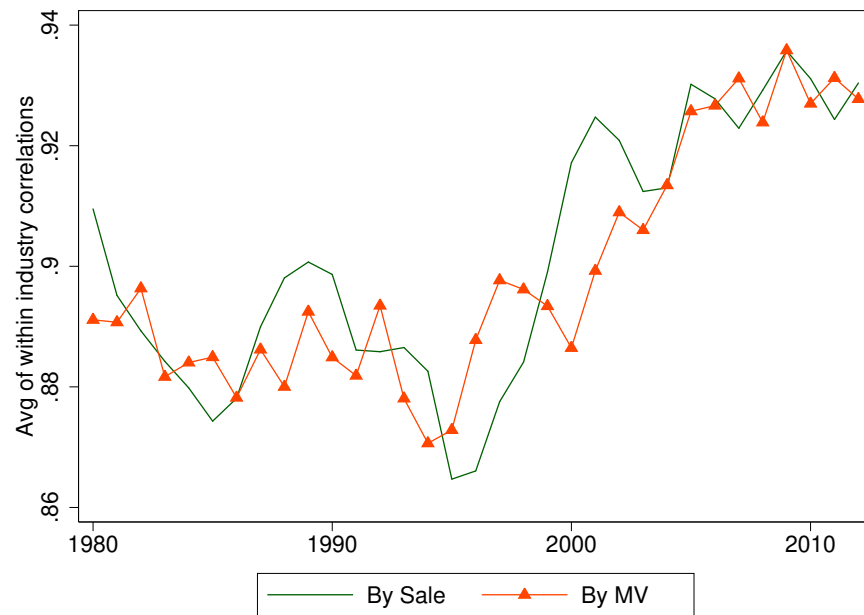
Source: Compustat NA, following BEA industries. Includes only industry-years with 5 or more firms. See text for details.

Figure 20 presents an additional measure of turnover, based on the correlation of firm rankings over time. For a particular measure Z (sales, market value, etc.), we define

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

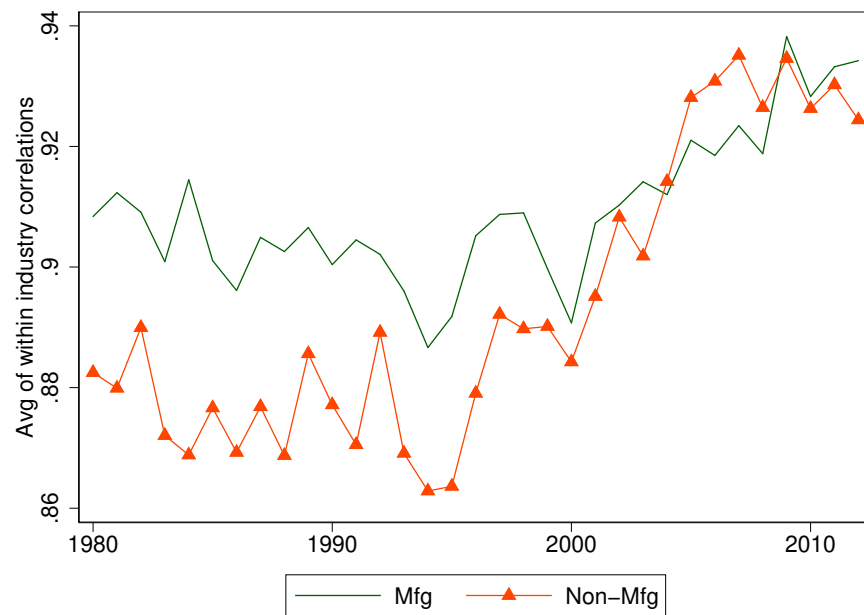
where $rank(z_{i,j,t})$ is the rank of firm i in industry j at time t according to the measure z . We again find a sharp increase in persistence after 2000. Figure 21 presents the same results but separating manufacturing and non-manufacturing sectors.

Figure 20: *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 21: *MV-based correlation of 5Y-ahead rankings by sector*

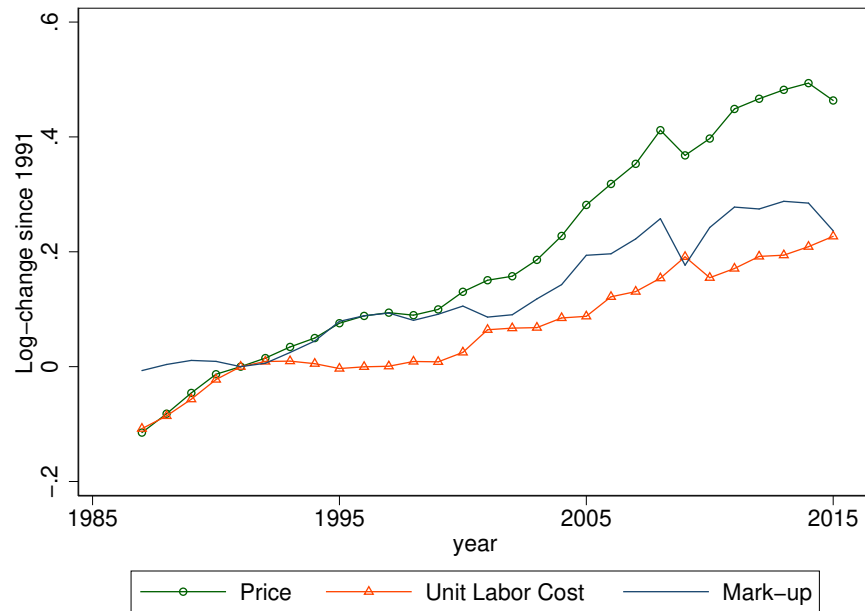


Source: Compustat NA, following BEA industries. Includes only industry-years with 5 or more firms. See text for details.

B.2 Concentration, Productivity and Prices

We are interested in decomposing the correlation between concentration and mark-ups into the underlying components: prices, wages and labor productivity. In Figure 22 we plot the aggregate evolution of prices and unit labor costs since 1989. As shown, prices increased faster than unit labor costs, leading to an increase in mark-ups.

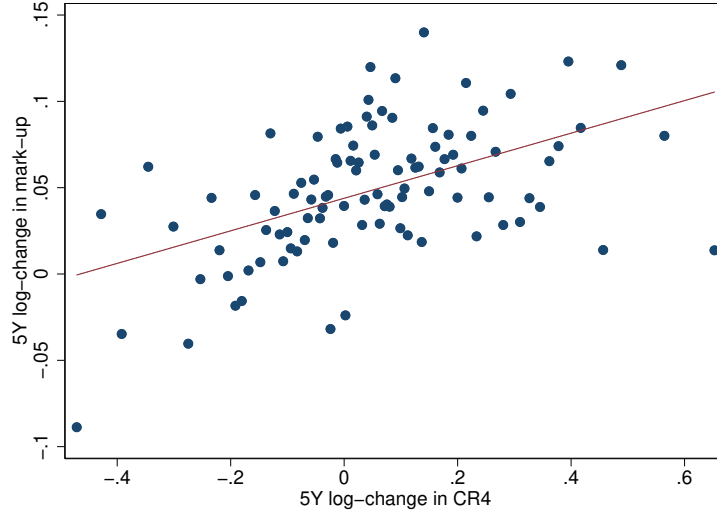
Figure 22: *Prices, ULC and Mark-ups in US*



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

Figure 23: 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 3.2 for details.

Last, Table 8 reports regressions of the following form using our detailed industry dataset of prices and productivity:

$$\Delta_5 \log(Y_{jt}) = \beta \Delta_5 \log(CR4) + \gamma_{s,t} + \varepsilon_{jt}.$$

where j denotes industries and t denotes years. $\gamma_{s,t}$ denotes sector x year fixed effects. To facilitate comparison to Ganapati 2018, we standardize $\Delta_5 \log(CR4)$ to have mean zero and variance one. Outcome variables Y_{jt} are based on the following interlinked outcomes:

$$\begin{aligned} \Delta_5 \log \mu &= \Delta_5 \log P - \Delta_5 \log ULC, \\ &= \Delta_5 \log P - [\Delta_5 \log w - \Delta_5 \log LP]. \end{aligned} \tag{6}$$

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. A doubling of the CR4 is correlated with a 13% increase in labor productivity. Wages rise by only 3% implying that productivity gains are not passed on to workers. Unit labor costs, therefore, fall by 10%. In a competitive economy, this would lead to lower prices and increased welfare for consumers. However, prices remain flat – implying a 11% increase in mark-ups²⁹.

²⁹Our results are fairly consistent with Ganapati (2018). Using Table 4 of Ganapati (2018), we obtain a regression beta between mark-up increases and concentration of 0.05 for non-manufacturing, compared to 0.08 in our data:

Table 8: 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<0.01.

Panel A. All Industries					
	(1) Mark-ups	(2) Prices	(3) ULC	(4) Wages	(5) LP
s5logcr4	0.12** (0.01)	0.03* (0.01)	-0.09** (0.02)	0.03** (0.01)	0.13** (0.02)
Cons	0.04** (0.00)	0.10** (0.00)	0.06** (0.00)	0.16** (0.00)	0.10** (0.00)
Sec x Yr FE	Y	Y	Y	Y	Y
R2	.25	.21	.15	.18	.12
Observations	2,083	2,084	2,083	2,083	2,083
Panel B. Manufacturing					
	(1) Mark-ups	(2) Prices	(3) ULC	(4) Wages	(5) LP
s5logcr4	0.13** (0.02)	0.04** (0.01)	-0.10** (0.02)	0.04** (0.01)	0.14** (0.02)
Cons	0.05** (0.00)	0.10** (0.00)	0.04** (0.00)	0.15** (0.00)	0.11** (0.00)
Sec x Yr FE	Y	Y	Y	Y	Y
R2	.24	.2	.11	.11	.091
Observations	1,682	1,682	1,682	1,682	1,682
Panel C. Non-Manufacturing					
	(1) Mark-ups	(2) Prices	(3) ULC	(4) Wages	(5) LP
s5logcr4	0.08** (0.02)	-0.01 (0.02)	-0.09** (0.03)	0.00 (0.02)	0.10** (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	.26	.18	.35	.17
Observations	401	402	401	401	401

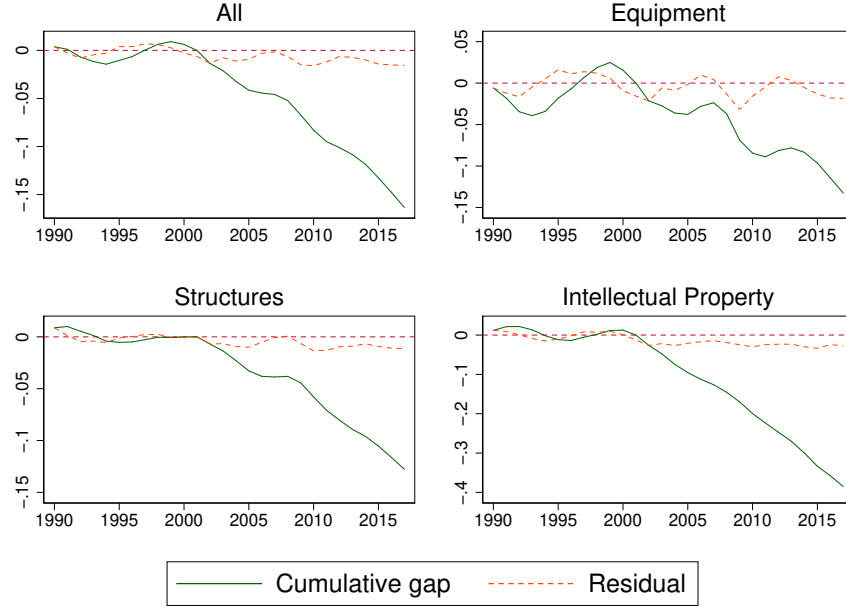
$$\beta_{\mu,CR4} = \beta_{p,CR4} - \beta_{w,CR4} + (\beta_{q,CR4} - \beta_{N,CR4})$$

$$0.05013 = -0.00421 - \underbrace{[0.00596 - (0.0477 - (-0.0126))]}_{-0.05434}$$

B.3 Investment.

In figure 24 we show the residual and cumulative gap from the regression $K_t = \beta_0 + \beta_1 Q_{t-1} + \epsilon_t$, where Q represents Tobin's Q . We run this regression for the entire capital stock and also for the three types of capital reported in BEA's fixed asset tables: Equipment, Structures and Intellectual Property.

Figure 24: *Growth Rates of Capital Stock vs Predicted by Q-theory*



Notes: Annual Data. Growth rate of private nonresidential fixed assets; based on section 4.2 of the BEA's fixed assets tables. Q for Non Financial Business sector from US Flow of Funds accounts.

In order to confirm that changes in the profit rate of leaders is not only a between-firms effect but also within-firms, we estimate

$$\left(\frac{OIADP}{SALE} \right)_{i,j,t} = \beta_t \times Lead_{i,j,t} + \delta_i + \gamma_t + \varepsilon_{jt}, \quad (7)$$

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.

Figure 25: *Within-firm Change in Profit Margin for Leaders vs. Laggards*

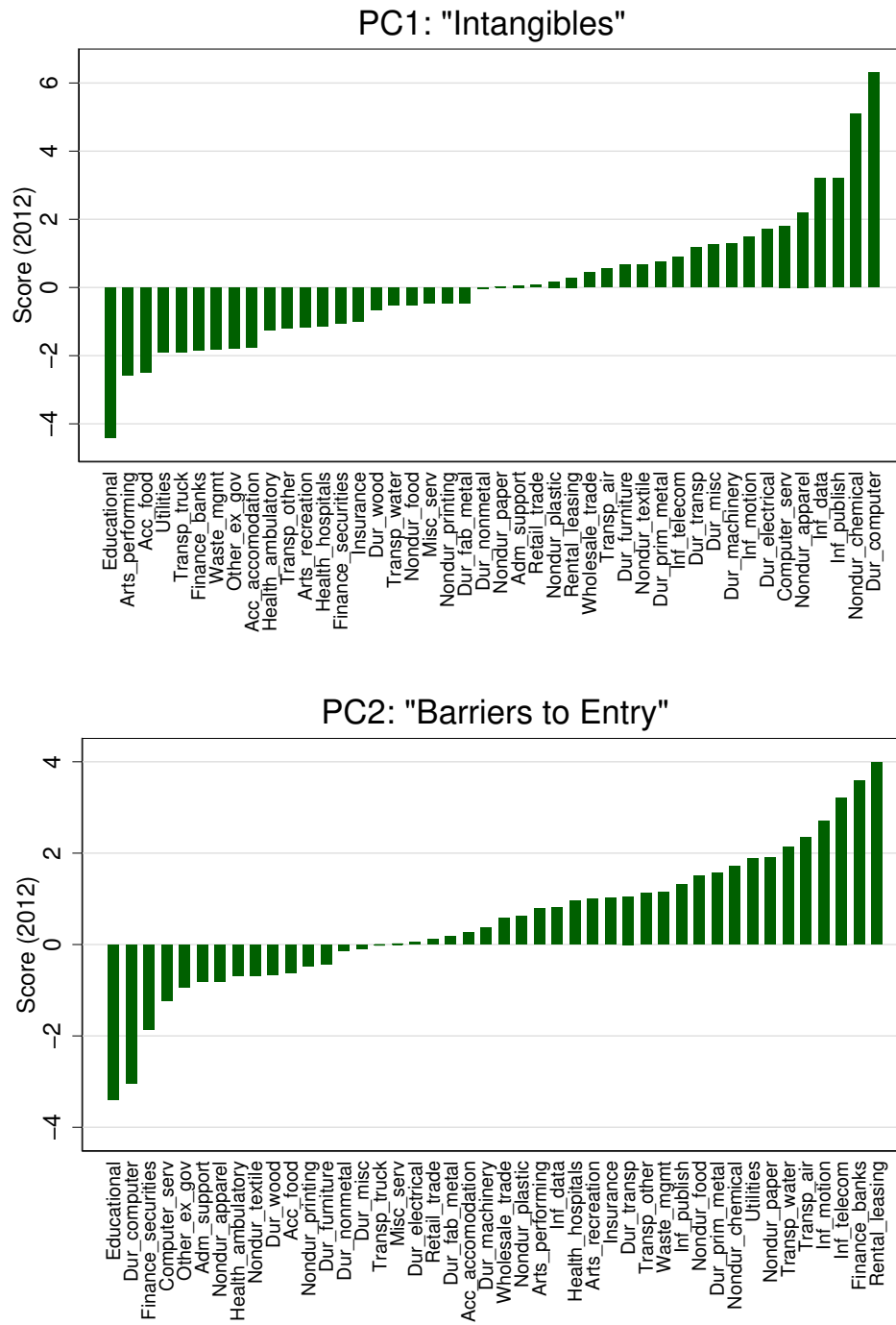


Notes: Compustat NA. Figure plots the estimated within-firm change in profits for leaders and laggards, following equation 7. See text for details.

C Appendix for Section 4: PCA

Figure 26 shows the loadings on PC1 and PC2, as of 2012, for each industry.

Figure 26: Principal Component Scores, by Industry



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

D Model Appendix

D.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

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

D.2 Production

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

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

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-Douglass 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 mark-up 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 mark-up.

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

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

E Data Appendix

We use a wide range of aggregate-, industry- and firm-level data, summarized in Table 9 and described in the rest of this section. We begin by describing the three datasets used repeatedly throughout the paper: Compustat North America, Compustat Global and US Economic Census Concentration Ratios (section E.1). We then discuss how these, and the remaining datasets are used to generate specific results.

E.1 Main dataset

E.1.1 Compustat North America

Sample Selection. Our primary firm-level data is based on tables Funda, Company and Exrt_mth from Compustat North America, obtained via WRDS. Compustat North America includes all public and some private firms in North America. Data are available from 1950, but coverage is fairly thin until the 1970s. We apply standard screens (consol = “C”, indfmt = “INDL”, datafmt = “STD”, popsrc = “D”), and ex-

Table 9: Summary of Key Data Sources

	Source	Key Data fields	Granularity
Sectoral	Financial Accounts of the United States via FRED	I, K, OS, \dots	Sector (NFCB, NFNCB)
	OECD STAN	$OS, PROD$	ISIC L2
	EU KLEMS 2018	LS	~ISIC L2
	BEA GDP by Industry	Output & prices	~NAICS L3 (summary) and ~NAICS L4 (detailed)
Industry	BEA Fixed Assets Tables	I, K	~NAICS L3
	BLS Multifactor Productivity Tables	TFP, P, Q, \dots	~NAICS L3
	Economic Census	Concentration	NAICS L3-L6
	NBER-CES database	P, Q	NAICS L6
	Peter Schott’s website	Imports, NTR Gap	NAICS L6
	Compustat (NA and Global)	Q, I, K and OS	Firm
Firm	Peters & Taylor	Intangible K	Firm

clude firm-year observations with missing year, sales, assets, or *gvkey*.³⁰ We use the exchange rates in `exrt_mth` to convert all financials to USD. We keep all firms for our global analyses, but restrict the sample to US-headquartered firms with USD currency codes for US-specific analyses (LOC = “USA”, CURCD = “USD”). We complement Compustat with the firm-level intangible capital estimates of [Peters and Taylor \(2016\)](#) (WRDS table `total_q`); and use CRSP table `msf` as well as the CRSP-Compustat linking table (`ccmxpf_linktable`) to fill in missing stock prices in Compustat, when needed (see replication file for details).

Industry Segments. We use the industry codes in the Compustat Company table. NAICS codes are populated for all firms that existed after 1985, but are sometimes missing for firms that exited beforehand. We map those firms to the most common NAICS-4 industry among those firms with the same SIC code and non-missing NAICS. We also map all retired/new NAICS codes from the 1997, 2002 and 2012 versions to NAICS 2007 using the concordances in [link](#).

We then map NAICS codes to BEA and EU KLEMS industries. For BEA industries, we use the mapping in tab ‘NAICS codes’ of file `GDPbyInd_GO_1947-2017.xls`. This includes 63 granular industries. We group ‘Motor vehicles, bodies and trailers, and parts’ and ‘Other transportation equipment’, and keep only ‘Hospitals and Nursing’ (which groups ‘Hospitals’ and ‘Nursing and Residential Care facilities’) because only the grouped industries are covered in the BLS’ multifactor tables. We exclude Real Estate given the 2000’s boom, as well as ‘Management of companies and enterprises’ because there are no companies in Compustat that map to this category. This leaves 59 industry groupings, summarized in Table 10. Firms with NAICS codes 999 cannot be mapped to BEA industries. These firms are mapped to an ‘other’ industry, which is included in those analyses that do not rely on aggregate data.

EU KLEMS (and STAN) industries follow the ISIC Rev. 4 hierarchy. We map firms from NAICS 2007

³⁰We also address selected data issues manually (e.g., outliers in sales growth, especially when reported currency changes). See replication code for details.

to ISIC Rev. 4 using the concordance available at [link](#) as follows: first, we map each NAICS-6 segment to the most common ISIC Level 2 segment (by number of mappings) based on the the concordance. This mapping is one-to-one for most NAICS-6 segments; and for the remaining segments there is usually a single most common ISIC Level 2 segment. For the few cases where NAICS-6 segments map with equal likelihood to more than one ISIC Level 2 segment, we follow the same methodology but with NAICS-5 codes (and so on).³¹ We then map each ISIC Rev. 4 Level 2 segments to the 27 EU KLEMS industries.

Concentration Ratios. We use the resulting dataset to compute Compustat-based concentration ratios. Compustat coverage as a share of the economy varies over time (as more firms go public) and across industries (depending on the nature of production); and the importance of foreign competition varies over time. To ensure CRs are stable over time and across industries, and account for imports we compute:

$$CRA_{jt} = \frac{\sum_{i \in \{j, \text{top4}\}} sale_{it}^{CPSTAT}}{s_{jt}^{CPSTAT}} \times c_{jt}^{MA}$$

where s_{it}^{CPSTAT} denotes sales for firm i which belongs to industry j and s_{jt}^{CPSTAT} denotes sales across all Compustat firms in industry j . c_{jt}^{MA} denotes the coverage adjustment, equal to a three-year centered moving average of the yearly coverage ratio ($c_{jt} = \frac{s_{jt}^{CPSTAT}}{s_{jt}^{BEA} + Imports_{jt}}$, where s_{jt}^{BEA} denotes gross output from the BEA and Imports denotes imports from Peter Schott's data). We use a moving average to smooth the impact of FX volatility given that Compustat sales include both domestic and foreign sales. c_{jt} can exceed 1 for exporting industries and may be affected by FX volatility even if 'real output' coverage remains flat, so we cap c_{jt}^{MA} at 1.25 (which assumes slightly higher domestic CR relative to global CRs). Last, to ensure the estimated CRs are robustly estimated, we include only industries where average database coverage after 2000 exceeds 10%. See replication code for details.

Other Definitions.

- **Market Value of Equity (ME):** ME is defined as the total number of common shares outstanding (item CSHO) times the closing stock price at the end of the fiscal year (item PRCC_F). When either CSHO or PRCC_F are missing in Compustat, we fill-in the value using CRSP. If ME is also missing in CRSP, we use PRCC_C x CSHO.
- **Market Value (MV):** MV is defined as the market value of equity (ME) plus total liabilities (LT) and preferred stock (PSTK)
- **Q:** firm-level Q is defined as the ratio of market value to total assets (AT). We cap Q at 10 and winsorize it at the 2% level, by year to mitigate the impact of outliers. See [Gutiérrez and Philippon \(2017b\)](#) for a discussion of alternate definitions of Tobin's Q .

³¹In some cases, Compustat NAICS codes contain fewer than six digits. In that case, we repeat the process using NAICS-5 to NAICS-2 codes. Firms that cannot be mapped to an ISIC segment (those with NAICS code 999 are excluded from industry-level analyses).

Table 10: Mapping of BEA industries to segments

BEA code	BEA Industry	Mapped segment
	Agriculture, forestry, fishing, and hunting	Omitted
1100	Farms	Agr_farm
1130	Forestry, fishing, and related activities	Agr_forest
	Mining	Omitted
2110	Oil and gas extraction	Min_oil_and_gas
2120	Mining, except oil and gas	Min_ex_oil
2130	Support activities for mining	Min_support
2200	Utilities	Utilities
2300	Construction	Construction
	Durable goods manufacturing	Omitted
3210	Wood products	Dur_wood
3270	Nonmetallic mineral products	Dur_nonmetal
3310	Primary metals	Dur_prim_metal
3320	Fabricated metal products	Dur_fab_metal
3330	Machinery	Dur_machinery
3340	Computer and electronic products	Dur_computer
3350	Electrical equipment, appliances, and components	Dur_electrical
3360	Motor vehicles, bodies and trailers, and parts	Dur_transp
3360	Other transportation equipment	Dur_transp
3370	Furniture and related products	Dur_furniture
3390	Miscellaneous manufacturing	Dur_misc
	Nondurable goods manufacturing	Omitted
3110	Food and beverage and tobacco products	Nondur_food
3130	Textile mills and textile product mills	Nondur_textile
3150	Apparel and leather and allied products	Nondur_apparel
3220	Paper products	Nondur_paper
3230	Printing and related support activities	Nondur_printing
3240	Petroleum and coal products	Nondur_petro
3250	Chemical products	Nondur_chemical
3260	Plastics and rubber products	Nondur_plastic
4200	Wholesale trade	Wholesale_trade
4400	Retail trade	Retail_trade
	Transportation and warehousing	Omitted
4810	Air transportation	Transp_air
4820	Railroad transportation	Transp_rail
4830	Water transportation	Transp_water
4840	Truck transportation	Transp_truck
4850	Transit and ground passenger transportation	Transp_passenger
4860	Pipeline transportation	Transp_pipeline
4870	Other transportation and support activities	Transp_other
4930	Warehousing and storage	Transp_storage

Table 10: Mapping of BEA industries to segments (cont'd)

BEA code	Sector/Industry	Mapped industry
	Information	Omitted
5110	Publishing industries (includes software)	Inf_publish
5120	Motion picture and sound recording industries	Inf_motion
5130	Broadcasting and telecommunications	Inf_telecom
5140	Information and data processing services	Inf_data
	Finance and insurance	Omitted
5210	Federal Reserve banks	Finance_banks
5210	Credit intermediation and related activities	Finance_banks
5230	Securities, commodity contracts, and investments	Finance_securities
5240	Insurance carriers and related activities	Insurance
5250	Funds, trusts, and other financial vehicles	Finance_funds
	Real estate and rental and leasing	Omitted
5310	Real estate	Omitted
5320	Rental and leasing services and lessors of intangible assets	Rental_leasing
	Professional, scientific, and technical services	Omitted
5411	Legal services	Legal_serv
5415	Computer systems design and related services	Computer_serv
5412	Miscellaneous professional, scientific, and technical services	Misc_serv
5500	Management of companies and enterprises	Omitted
	Administrative and waste management services	Omitted
5610	Administrative and support services	Adm_support
5620	Waste management and remediation services	Waste_mgmt
6100	Educational services	Educational
	Health care and social assistance	Omitted
6210	Ambulatory health care services	Health_ambulatory
6220	Hosp and nursing	Health_hospitals
6220	Hospitals	Omitted
6220	Nursing and residential care facilities	Omitted
6240	Social assistance	Health_social
	Arts, entertainment, and recreation	Omitted
7110	Performing arts, spectator sports, museums, and related activities	Arts_performing
7130	Amusements, gambling, and recreation industries	Arts_recreation
	Accommodation and food services	Omitted
7210	Accommodation	Acc_accomodation
7220	Food services and drinking places	Acc_food
8100	Other services, except government	Other_ex_gov

- **Total Capital (K^{PT}):** K^{PT} is set equal to PPEGT plus K_INT, where the former is included in Compustat and the latter is provided by [Peters and Taylor \(2016\)](#).
- **Firm Age:** Firm age is defined as the number of years over which a firm appears in Compustat, irrespective of whether the underlying data fields satisfy our exclusion restrictions (i.e., we measure age before imposing any exclusion restrictions).
- **Ratios:** We also compute a variety of ratios as described in the text (e.g., SALE/COGS, XSGA/XOPR). All of these ratios are winsorized at the 2% and 98% level, by year to mitigate the impact of outliers.

E.1.2 Compustat Global

Global concentration measures are based on Compustat Global, which includes most public firms across advanced economies. Data are available from 1987, but coverage is fairly thin until the late-1990s. We download tables g_funda, g_company and g_exrt_mth via WRDS. We apply the same screens as for the US (consol = “C”, indfmt = “INDL”, datafmt = “STD”, popsrc = “I”) and exclude firm-year observations with missing year, sales, assets, or *gvkey*.³² We use the exchange rates in exrt_mth to convert all financials to USD. For a few firms, currency codes and financials appear inconsistent – particularly when currency codes change. We therefore drop firms (gvkeys) entirely whenever sales or assets increase or decrease by a factor of 20 in the same year as the currency code changes. Firms are mapped to countries/regions using headquarter location (LOC). We then use the same definitions and mapping procedure as for the US.

E.1.3 Economic Census Concentration Ratios

Last, we obtain sales, employment and payroll data by industry from the US Economic Census’ Concentration accounts. The data include breakdowns for the top 4, 8, 20 and 50 firms in each industry along with industry totals, and are published every five years. All firms operating within a given SIC/NAICS category in the United States are included. See [link](#) for additional details.

Data before 1992 is based on the SIC system. For manufacturing, we use the retrospective tabulation based on unified SIC codes published in the 1992 Economic Census. For non-manufacturing, we use the data as reported, which follows the 1987 SIC system in both 1987 and 1992, though there are small adjustments across years. Data after 1997 is based on NAICS, with each of the 1997, 2002, 2007 and 2012 reports using slightly different NAICS vintages. Like [Ganapati \(2018\)](#), we restrict our sample to consistently defined SIC/NAICS codes over each five-year period. Data for service industries are reported by tax-paying segments. We keep tax-payable firms because they are reported consistently over time and are closest to our analysis. Data for wholesale trade are reported as a total and by type of merchant (e.g., merchant wholesaler, manufacturer). We keep only the total.

Table 3 shows the coverage of the data. We restrict our sample to the post-1987 period, when concentration increased. There is continuous coverage for the manufacturing sector over the entire time period at the 4-digit SIC and 6-digit NAICS levels. Coverage for non-manufacturing sectors is spottier. Wholesale trade,

³²We also address selected data issues manually (e.g., outliers in sales growth, especially when reported currency changes). See replication code for details.

retail trade and services are covered since 1987, as well as some transportation and communication sectors. All major industries except agriculture, mining and construction are covered after 1997.

We use these data in four ways: first, we use the reported concentration ratios directly in some of our figures and/or regressions. Second, we compute census-based import-adjusted concentration as

$$CR8_{jt}^{IA} = CR8_{jt} \times \frac{sale_{jt}}{sale_{jt} + imp_{jt}} = CR8_{jt} \times US\ Share_{jt}$$

where $CR8_{jt}$ and $sale_{jt}$ are based on the US Economic Census; and $imports_{jt}$ is based on Peter Schott's data (set to zero when missing). Third, we aggregate census concentration ratios to BEA industries since 1997, for use in the PCA analysis. Census concentration measures follow the NAICS hierarchy, which almost always maps one-to-one to BEA industries. When this is not the case, we first aggregate (domestic) concentration ratios to BEA industries by taking a sales-weighted average; and then apply the import adjustment. For some regressions, we interpolate Census concentration measures between economic census years. Last, we combine the concentration data with price indices from the NBER-CES database for manufacturing and the BEA's detailed GDP by Industry accounts for our analyses of productivity and prices. See below for details.

E.2 Details on the Construction of Results

E.2.1 Introduction

Figures 2, Panel A: Profits. Profits rates are based on OECD table STANI4_2016, which follows ISIC Rev. 4 segments. Data are available for 37 countries. We focus on the nonagriculture business sector excluding real estate (D05T82X), and include only advanced economies for which gross profits data are available since 2000: the EU28 ex. BGR, CYP, HRV, MLT, ROU plus JPN, KOR, NOR, and the USA. AUS, CHE and CAN are excluded because data are available after 2005. We convert all nominal quantities to US dollars using the OECD's exchange rates, available at [link](#). We define the gross profit rate as the ratio of GOPS to PROD. We aggregate across countries by taking the production-weighted average.

Figure 2, Panel B. Concentration. We then measure concentration using the same calculation as for the US, with three exceptions: first, we do not adjust for imports. Second, we use the 27 industries defined in EU KLEMS, instead of BEA industries. Third, we use gross output data from OECD STAN to adjust for Compustat coverage, instead of BEA gross output data. To ensure consistency between STAN output and Compustat sales, we drop firms in country x industry x years where STAN data are not available. This means our EU-wide series includes 23 countries (EU28 ex Bulgaria, Croatia, Cyprus, Malta, Romania). Concentration is measured at the region x industry-level. We then compute changes since 2000, and aggregate across industries within a region, weighing by production in constant 2009 prices (STAN item PRDK). We use constant prices because variations in oil prices can introduce undue volatility to the weights of petroleum-dependent industries (see [Jones et al. \(2019\)](#)).

Figure 2, Panel C. Labor Share. Figures reports the value-added weighted average change in the labor share for the Market Economy based on EU KLEMS (KLEMS LAB/VA). Data for most countries are available since 1995, but we include countries for which data are available at least since 2000. Thus, the EU series includes EU28 ex. HRV, HUN, MLT, POL. We then compute changes since 2000, and aggregate across industries within a region, weighing by value added (EU KLEMS item va).

E.2.2 Measurement Issues

Figure 6: Mark-up vs Profits. GOS/PROD for nonagriculture business sector excluding Real Estate from OECD STAN, as described above. Compustat series equal to the sales-weighted average of SALE/COGS across all Compustat firms in a given year x region, included in sample above. Data reported for EU since 1989, but note that a sizable portion of European firms report COGS only after ~ 2005 .

Table 7: Summary of Income Statement. Start from US Compustat sample described above. Keep firm x year pairs for neither SALE, COGS, SG&A, OIBDP, DP and OIADP are missing. Report the sales weighted average of the ratio of COGS/SALE, SG&A/SALE, etc across all firms and years in a given decade. All ratios are winsorized at the 2% level by year.

Figure 16: SALE/COGS vs. SG&A intensity for high-mark-up firms. Start from US Compustat sample described above. Drop firms with missing SALE/COGS or XSGA/XOPR. Identify firms in the top 25th percentile of the SALE/COGS distribution. Report a scatter plot of the sales-weighted average ratio of SALE/COGS and XSGA/XOPR across those firms, in each year. As above, SALE/COGS and XSGA/XOPR are winsorized at the 2% level by year.

Figure 4 and 5. All the analyses of mark-up measurement using the China Shock are based on NAICS-6 manufacturing industries. We complement Compustat with three additional datasets:

- **Import and Exports:** Import and export data are sourced from Peter Schott's [website](#) and was first used in [Schott \(2008\)](#). Data are available by HS-code x year from 1989 to 2017, but include a mapping to NAICS-6 industries which follows the concordance of [Pierce and Schott \(2012\)](#). We use these data to estimate import penetration and import-adjusted concentration at different levels of granularity (NAICS-6 as well as BEA industries).
- **NTR gap:** We also gather Non-Normal-Trade-Relations tariff gaps from the replication file of [Pierce and Schott \(2016\)](#). NTR gaps are defined for NAICS level 6 industries.³³
- **NBER-CES database:** Last, we use the NBER-CES database, which includes output and productivity data by NAICS Level 6 manufacturing industry from 1971 to 2011. It also includes measures of the production structure in each industry (such as production workers as a share of total employment, the log average wage, etc.), which are used as controls in regressions and to test alternate theories of concentration.

³³NTR gaps are available in file 'gaps_by_naics6_20150722_fam50', which includes NTR gaps for each NAICS Level 6 code.

These datasets are merged into the main Compustat sample by NAICS-6 industry x year, which includes the total capital estimates of [Peters and Taylor \(2016\)](#). See main text for details on the construction of each result.

E.2.3 Entry, Exit and Turnover

All figures are based on our main Compustat sample described above. See text for details.

E.2.4 Joint evolution of Concentration, TFP and prices

Table 2: Concentration, TFP, Prices and Mark-ups: BLS industries. Merge Compustat import-adjusted concentration measures with BLS KLEMS data on prices and productivity. Compute mark-ups and implement regression.

Table 3: Concentration vs Prices: Detailed industries. For manufacturing, we merge Economic Census concentration ratios with sales, prices, employment and payroll data from the NBER-CES database. The data are based on 4-digit SIC codes before 1997 and 6-digit NAICS after 1997. For non-manufacturing, merge sales, payroll, employment and concentration data from the Economic Census to prices from the BEA's detailed GDP by Industry accounts (files GDPbyInd_GO_NAICS_1997-2016.xlsx and GDPbyInd_GO_SIC.xlsx). These files include ~400 industries, with more than 200 corresponding to manufacturing industries. [Ganapati \(2018\)](#) uses more detailed accounts, but we focus on this higher level of aggregation because, even for these accounts, the BEA acknowledges that “the more detailed estimates are more likely to be either based on judgmental trends, on trends in the higher-level aggregate, or on less reliable source data.” Some of the BEA industries aggregate several NAICS codes. We manually map as many codes as possible, and aggregate concentration ratios by taking a weighted average when needed. We then compute quantities, labor productivity and mark-ups as defined in the text – and estimate the regressions.

E.2.5 Investment and Profits by Leaders vs. Laggards

Table 4: Investment, Capital and Profits by Leaders and Laggards. Rank firms by market value. Define a firm as leader if it is the top firm in a given industry or the cumulative market value up to and including this firm is below 33% of the industry market value. Repeat the exercise for mid-performers (33-66% of MV) and the bottom 33%. Next, compute the total OIBDP, CAPX + R&D, PP&E and Capital K (including intangibles as estimated by [Peters and Taylor \(2016\)](#)) by year and by MV group x year. Estimate the share of a given measure – say OIBDP – as the ratio of leader OIBDP to total OIBDP in a given year. Because firms are discrete, the actual share of market value in each grouping varies from year to year. To improve comparability, re-scale shares by the ratio of 33.33% to the share of market value. Report the average across all years in a given period.

Table 5: Investment by Leaders We start from our base Compustat sample, mapped to BEA industries. Deflate capital stock using the industry-level price of capital reported in the BEA's fixed assets tables (see

below for a description). Compute yearly change in (deflated) capital stock and winsorize at the 2% and 98% level by year. Include only firm-year pairs with non-missing PPEGT, K_INT and K_PT. Define leaders as firms with market value in the top quantile by BEA industry and year. Estimate regression as reported in the text.

E.2.6 PCA

Our PCA analysis is based on the BEA industries described in Table 10. We define the data sources and definitions for all measures included in the analysis. The rest of the details are provided in the text.

- **Census Concentration (cr4_cen and Dcr4_cen):** The level in census concentration, as described in Section E.1 as well as the change since 2007
- **BEA Intangible Capital Share (intan_kshare_bea and Dintan_kshare_bea):** ratio of intellectual property capital to total capital as measured in Section 3 of the BEA Fixed Assets tables, available at [link](#); as well as the change since 1997
- **Intangible Capital Share (intan_kshare_med_pt):** Define the firm-level intangible capital share as the ratio of internally-developed intangibles K_INT - INTAN (from [Peters and Taylor \(2016\)](#)) to total capital (K_INT + PPEGT). Compute the median across all firms in a given industry x year. Similar results including externally developed intangibles.
- **Import share (import_share):** ratio of imports from Peter Schott's data to the sum of gross output and imports.
- **BEA Profit Margin (profit_margin_bea):** ratio of net operating surplus to gross output as measured by the BEA's GDP by Industry accounts (file [GDPbyInd_GO_1947-2017](#)).
- **Compustat Median Profit Margin (profit_margin_med_cp):** Define firm-level profit margin as the ratio of operating income after depreciation to sales (OIADP/SALE). Compute the median across all firms in a given industry x year.
- **US KLEMS inputs:**
 - Labor Share (ls_kl) defined as the ratio of total labor expenses to gross output minus intermediate inputs.
 - TFP growth (dtfp_kl) equals the five-year log-change in a given industry's multifactor productivity index (MFP)
 - Price, ULC and Mark-up growth (Dlogp_kl, Dlogulc_kl and Dlogmu_kl, respectively) defined as described in section E.2.4 above.
- **Leader Turnover (lead_turnover_mv):** market-value based turnover rate, as defined in section XX above.

- **Compustat firm-level leader investment gap (ikgap_cp):** we roughly follow [Crouzet and Eberly \(2018\)](#). Define the net investment rate for firm i in industry j as the log-change in (deflated) total capital, $\Delta \log(K_{ijt}^{PT})$, using the industry-level deflator from the BEA's fixed assets tables. Then, estimate $\Delta \log(K_{ijt}^{PT}) = \beta \bar{Q}_{jt} + \beta_2 \log(Age_{ijt}) + \delta_i + \gamma_t + \varepsilon_{ijt}$, where we control for firm-age, industry average Q as well as firm and year fixed effects. The year fixed effects measure the annual investment gap.

Table 11: *Mapping of BEA industries to segments*

	1987	1992	1997	2002	2007	2012
Sector	SIC		NAICS			
Agriculture						
Mining						
Construction						
Manufacturing	X	X	X	X	X	X
Transportation	Partial		X	X	X	X
Communication	Partial		X	X	X	X
Utilities				X	X	X
Wholesale Trade	X	X	X	X	X	X
Retail Trade	X	X	X	X	X	X
FIRE				X	X	X
Services	X	X	X	X	X	X