

Declining Competition and Investment in the U.S.*

Germán Gutiérrez[†] and Thomas Philippon[‡]

November 2017

Abstract

We argue that the increasing concentration of US industries is not an efficient response to changes in technology and reflects instead decreasing domestic competition. Concentration has risen in the U.S. but not in Europe; concentration and productivity are negatively related; and industry leaders cut investment when concentration increases. We then establish the causal impact of competition on investment using Chinese competition in manufacturing, noisy entry in the late 1990s, and discrete jumps in concentration following large M&As. We find that more (less) competition causes more (less) investment, particularly in intangible assets and by industry leaders.

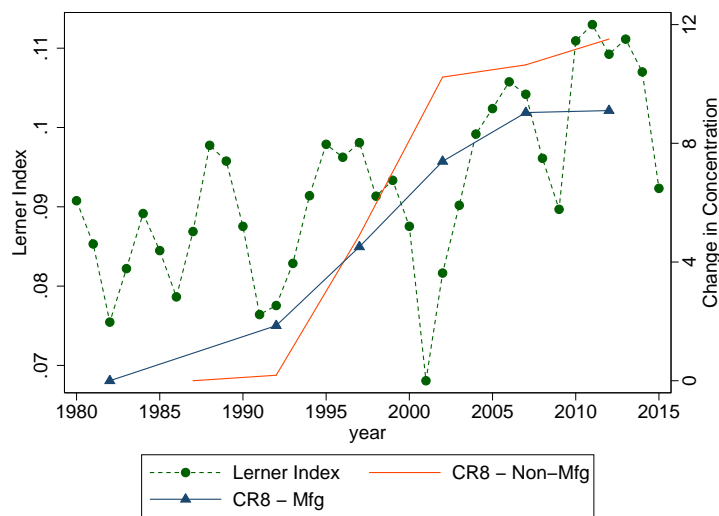
*We are grateful to Bob Hall, Janice Eberly, Steve Davis and Christopher House for their comments and discussions, as well as Viral Acharya, Manuel Adelino, Olivier Blanchard, Ricardo Caballero, Charles Calomiris, Alexandre Corhay, Emmanuel Farhi, Jason Furman, Xavier Gabaix, John Haltiwanger, Campbell Harvey, Glenn Hubbard, Ron Jarmin, Boyan Jovanovic, Sebnem Kalemli-Ozcan, Ralph Koijen, Howard Kung, Javier Miranda, Holger Mueller, Valerie Ramey, David Robinson, Tano Santos, René Stulz, Alexi Savov, Philipp Schnabl, Jose Scheinkman, Martin Schmalz, Lukas Schmid, Carolina Villegas-Sanchez, Johannes Wieland, Luigi Zingales, and seminar participants at NYU, ESSIM, Columbia University, University of Chicago, Harvard, Duke, NBER EFG and NBER ME meetings for stimulating discussions.

[†]New York University. ggutierr@stern.nyu.edu

[‡]New York University, CEPR and NBER. tphilipp@stern.nyu.edu

Two important stylized facts have emerged in recent years regarding the U.S. business sector. The first fact is that concentration and profitability have increased across most U.S. industries, as shown by Grullon et al. (2016). Figure 1 shows the aggregate Lerner index (operating income over sales) across all Compustat firms along with the change in weighted average 8-firm concentration ratio in manufacturing and non-manufacturing industries. Estimates of excess profits based on Barkai (2017) yield similar results (see Appendix).

Figure 1: Concentration and Mark-ups

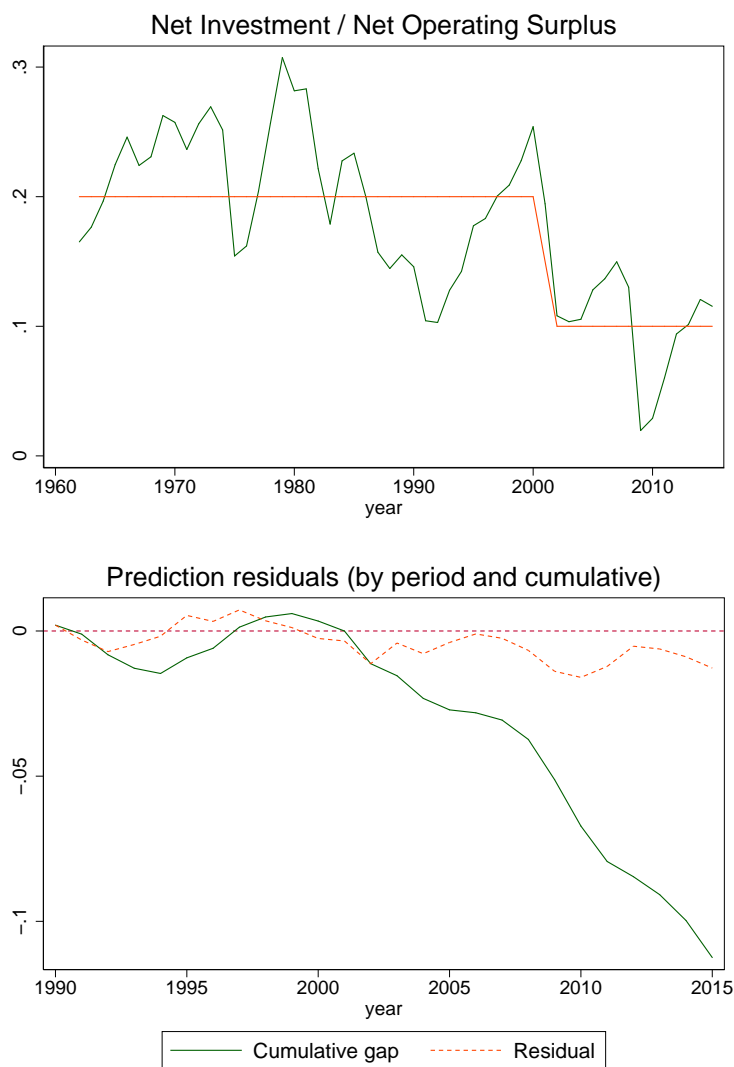


Notes: Lerner Index from Compustat, defined as operating income before depreciation minus depreciation divided by sales. 8-firm CR from Economic Census, defined as the market share (by sales) of the 8 largest firms in each industry. Data before 1992 based on SIC codes. Data after 1997 based on NAICS codes. Data for Manufacturing reported at NAICS Level 6 (SIC 4) because it is only available at that granularity in 1992. Data for Non-Manufacturing based on NAICS level 3 segments (SIC 2).

The second stylized fact is that business investment has been weak relative to measures of profitability, funding costs, and market values since the early 2000s. The top chart in Figure 2 shows the ratio of aggregate net investment to net operating surplus for the non financial business sector, from 1960 to 2015. The bottom chart shows the residuals (by year and cumulative) of a regression of net investment on (lagged) Q , estimated over 1990-2001. Both charts show that investment has been low relative to profits and Q in recent years. By 2015, the cumulative under-investment is large, around 10% of capital. Industry and firm level analyses suggest that this weakness starts around 2000 (see Alexander and Eberly 2016 and Gutiérrez and Philippon 2017b).

While these two stylized facts are well established (see references below), their interpretation remains controversial. There is little agreement about the causes of these evolutions, and even less about their consequences. For instance, Furman (2015) and CEA (2016) argue that the rise in concentration suggests “economic rents and barriers to competition”, while Autor et al. (2017a) argue almost exactly the opposite: they think 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.” Network effects and increasing differences in the

Figure 2: Net Investment, Profits and Q-Residuals



Notes: Annual data from US Flow of Funds accounts. Net investment, net operating surplus for Non Financial Business sector; Q for Non Financial Corporate sector.

productivity of Information Technology could also increase the efficient scale of operation of the top firms, leading to higher concentration. The key point of these later explanations is that concentration reflects an efficient increase in the scale of operation. For short, we will refer to this hypothesis as the efficient scale hypothesis (henceforth EFS).

The evolution of profits and investment could also be explained by intangible capital deepening, as discussed in Alexander and Eberly (2016). More precisely, an increase in the (intangible) capital share together with a downward bias in our traditional measures of intangible investment could lead, even in competitive markets, to an increase in profits (competitive payments for intangible services) and a decrease in (measured) investment. We will refer to this hypothesis as the intangible deepening hypothesis (henceforth INTAN). Finally, trade and globalization can explain some of the same facts (Feenstra and Weinstein, 2017). Foreign competition can lead to an increase in measured (domestic) concentration (e.g. textile industry), and a decoupling of firm value from the localization of its investments. We refer to this hypothesis as the globalization hypothesis (henceforth GLOBAL).¹

These hypotheses are not mutually exclusive. For instance, a combination of EFS, INTAN and GLOBAL is often heard in the discussion of internet giants Google, Amazon, Facebook, Apple and Microsoft. INTAN can also contribute to DDC since patents and intangible assets can create barriers to entry and increase the fixed costs associated with lobbying, compliance, and litigation.

The main contribution of our paper is to propose and test two hypothesis. We first argue that the rise in concentration in most industries reflects declining domestic competition (henceforth DDC) and not EFS. We then argue that the decline in competition is (partly) responsible for the decline in investment, after controlling for INTAN and GLOBAL. There are other technical contributions in the construction of various measures of competition and investment at the firm and industry levels, but we do not discuss them here.

Evidence that Concentration Reflects Decreasing Domestic Competition Let us start with DDC. We take into account GLOBAL by measuring separately sales, profits and investment at home and abroad, and we adjust our measures of concentration for foreign imports, following Feenstra and Weinstein (2017). The main alternative hypothesis to DDC is then EFS. We rule out EFS with three pieces of evidence. The first piece of evidence is a comparison with Europe. We consider industries with significant increases in concentration in the U.S., such as the Telecom industry, and we show that these same industries have not experienced similar increases in concentration and profit rates in Europe, even though they use the same technology and are exposed to the same foreign competition. Secondly, EFS predicts that concentration should lead to productivity gains at the industry level, as high productivity leaders expand. There is some evidence for EFS during the 1990s as the relationship between concentration and productivity was positive, but it is zero or negative in the 2000s. Thirdly, EFS predicts that leaders should increase investment and R&D in concentrating industries. We find the opposite: the relative investment of leaders is lower

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

in concentrated industries, in physical and intangible capital. We conclude that EFS cannot be the main explanation for concentration in most industries.

Evidence that DDC Causes Low Investment The second point of our paper is that DDC causes low investment. Even if we make a convincing argument that DDC explains the observed rise in concentration, it is not obvious how this should affect investment. Investment and concentration are jointly endogenous, and in models of innovation (Klette and Kortum, 2004), rents can encourage investment in innovation. The impact of competition on investment is therefore an empirical question.²

The first empirical challenge is to measure investment correctly and address the INTAN hypothesis. We build on Peters and Taylor (2016) and Alexander and Eberly (2016) to take into account intangible assets. We find that mismeasured intangible investment accounts for a quarter to a third of the apparent investment gap (Gutiérrez and Philippon, 2017b). This paper focuses on the remaining two thirds.

The second challenge for the DDC hypothesis is to establish a *causal* connection between competition and investment. The main identification issue is that firm entry and exit are endogenous. Consider an industry j where firms operate competitively under decreasing returns to scale. Suppose industry j receives the news at time t that the demand for its products will increase at some time $t + \tau$ in the future. There would be immediate entry of new firms in the industry. As a result, we would measure a decrease in concentration (or in Herfindahl indexes) followed and/or accompanied by an increase in investment. Anticipated demand (or productivity) shocks can thus explain why we see more investment in less concentrated industries even if it is not due to competition.

We construct three tests to show that DDC causes low investment, using changes in competition that are not driven by anticipated demand or supply shocks. We first consider industries exposed to Chinese competition. This is, in a sense, the exception that proves the rule. Unlike most others, these industries have experienced an overall increase in competition. Using the approach of Pierce and Schott (2016), we show that industry leaders react to exogenous changes in foreign competition by increasing their investment, in particular in R&D. This result is consistent with the recent work of Hombert and Matray (2015). Of course, foreign competition also drives out weak domestic firms, so the overall impact on domestic investment is ambiguous (marginally negative in our sample).

The Chinese natural experiment offers clean identification, but its external validity is problematic. It identifies an *increase* in competition for a particular sector and a limited set of firms, as opposed to a broad *decline* in domestic competition. The shock is only significant for half of the

²By contrast, the macroeconomics of imperfect competition are well understood (Rotemberg and Woodford, 1999) and other implications of DDC are straightforward: DDC predicts higher markups, higher profits, lower real wages, and a lower labor share. As Gilbert (2006) explains, the relationship between competition and investment is rather sensitive to the details of the environment, such as the extent of property rights (exclusive or not) or the nature of innovation (cost reduction versus new product). Looking at investment is also useful because it can help us distinguish the EFS and DDC hypotheses, as explained above. Finally, the welfare implications of a significant decline in the capital stock are large. For these three reasons, we argue that it is particularly important to understand the response of investment to DDC.

manufacturing sector, or about 10% of the non-financial private economy. For these reasons it is imperative to study the impact of DDC on the remaining 90% of the non-financial private economy.

Our second test relies on a model of noisy entry. Entry rates across industries depend on expected demand – the identification problem explained above – but also on noisy signals and on idiosyncratic entry opportunities. The variation in entry rates that is orthogonal to future demand and productivity is a valid instrument for competition. This “noisy” entry is usually small, which makes it difficult to identify the effect of competition. It turns out, however, that there is a major exception in the late 1990s. During that period, we document large variations in entry rates across industries that are uncorrelated with past and future sales growth, productivity growth, analysts’ forecasts, and Tobin’s Q . We discuss why the peculiar features of that period – especially during the second half of the 1990’s with extreme equity valuation and abundant capital funding – are likely to have created more than the usual amount of randomness in entry rates (Gordon, 2005; Anderson et al., 2010; Hogendorn, 2011; Doms, 2004). Using noisy entry as an instrument for differences in concentration across industries, we find that concentration lowers investment and causes a gap between Q and investment, as predicted by the theory. Moreover, consistent with our hypothesis and our previous evidence from manufacturing, the decline in investment comes mostly from industry leaders.

The third test is based on large mergers & acquisitions (M&A). This test is important because mergers are a significant contributor to the overall increase in concentration. It also offers a different identification strategy. The likelihood of a merger is endogenous to future demand since we expect consolidation in declining industries, but the actual realization of the transaction is (partly) random. The identification assumption here is that other factors are captured by smooth trends, while M&A transactions are lumpy. We show that, conditional on current measures of concentration and expected sales growth, a discrete increase in merger-related concentration leads to a decline in investment.

Overall, using three entirely different identification strategies, and using both firm-level and industry-level data, we find that competition encourages investment, particularly by industry leaders, and particularly in intangible assets.

Related Literature. Our paper is related to several strands of literature. There is a growing literature studying trends on competition, concentration, and entry. Davis et al. (2006) find a secular decline in job flows. They also show that much of the rise in publicly traded firm volatility during the 1990’s is a consequence of the boom in IPOs, both because young firms are more volatile, and because they challenge incumbents. Haltiwanger et al. (2011) find that “job creation and destruction both exhibit a downward trend over the past few decades.” Decker et al. (2015) argue that, whereas in the 1980’s and 1990’s declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000’s, including the traditionally high-growth information technology sector. Furman (2015) shows that “the distribution of returns to capital has grown increasingly skewed and the high returns increasingly persistent” and argues that it “poten-

tially reflects the rising influence of economic rents and barriers to competition.”³ CEA (2016) and Grullon et al. (2016) are the first papers to extensively document the broad increases in profits and concentration. Grullon et al. (2016) also show that firms in concentrating industries experience positive abnormal stock returns and more profitable M&A deals. Blonigen and Pierce (2016) find that M&As are associated with increases in average markups. Dottling et al. (2017) argue that low investment in Europe is well explained by low Q , unlike in the US. Faccio and Zingales (2017) show that competition in the mobile telecommunication industry is heavily influenced by political factors, and that, in recent years, many countries have adopted more competition-friendly policies than the US. Autor et al. (2017a) study the link between concentration and the labor share. An important issue in the literature is the measurement of markups and excess profits. The macroeconomic literature focuses on the cyclical behavior of markups (Rotemberg and Woodford, 1999; Nekarda and Ramey, 2013). Over long horizons, however, it is difficult to separate excess profits from changes in the capital share. De-Loecker and Eeckhout (2017) estimate markups using the ratio of sales to costs of goods sold, but in the long run this ratio depends on the share of intangible expenses, and the resulting markup does not directly provide a measure of market power. Barkai (2017), on the other hand, estimates the required return on capital and finds a significant increase in excess profits.

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

Last, our paper is related to the effect of foreign competition – particularly from China (see Bernard et al. (2012) for a review). Bernard et al. (2006) show that capital-intensive plants and industries are more likely to survive and grow in the wake of import competition. Bloom et al. (2015) argue that Chinese import competition leads to increased technical change within firms and a reallocation of employment towards more technologically advanced firms. Frésard and Valta (2015) find that tariff reductions lead to declines in investment in markets with competition in strategic

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

substitutes and low costs of entry. Within-industry, they find that investment declines primarily at financially constrained firms. The decline in investment is negligible for financially stable firms and firms in markets featuring competition in strategic complements. Hombert and Matray (2015) show that R&D-intensive firms were better able to cope with Chinese competition than low-R&D firms. They explain this result based on product differentiation, using the Hoberg and Phillips (2017) product similarity index. Autor et al. (2013); Pierce and Schott (2016); Autor et al. (2016); Feenstra et al. (2017) study the effects of Chinese import exposure on U.S. manufacturing employment. Feenstra and Weinstein (2017) estimate the impact of globalization on mark-ups, and conclude that mark-ups decreased in industries affected by foreign competition. Some of these papers find a reduction in investment for the ‘average’ firm, which is consistent with our results and highlights the importance of considering industry leaders and laggards separately.

The remainder of this paper is organized as follows. Section 1 discusses our dataset and shows that the investment gap is driven by industry leaders in concentrating industries. Section 2 provides evidence of declining domestic competition. Section 3 presents the tests and results used to establish causality between competition and investment. Section 4 concludes. Various Appendices provide details on the data, mark-up estimations and robustness checks.

1 Data and Stylized Facts

In this Section we summarize the data used throughout the paper, and we present two new stylized facts that are critical to understanding the dynamics of concentration and investment.

1.1 Data

We use a wide range of aggregate-, industry- and firm-level data, summarized in Table 1. We describe the treatment of intangible assets and the calculation of Herfindahls in the rest of this section. Further details on the datasets are relegated to Appendix B.

1.1.1 Intangible Assets

It is essential to account for intangible assets when measuring capital, investment and Q . It is not always possible to use exactly the same definitions in aggregate/industry datasets and in firm-level datasets.

Aggregate and Industry-level data. Aggregate and industry-level data are sourced from U.S. and European National Accounts. Since 2013, these accounts capitalize ‘identifiable’ intangible assets such as software, R&D, and entertainment, literary, and artistic originals. We use the corresponding measures of I and K in our analyses. When estimating Q , we follow the literature and measure the ratio of market value to the replacement cost of capital including intangibles (Gutiérrez and Philippon, 2017b).

Table 1: Summary of Key Data Sources

Data type	Key Data fields	Source	Region	Granularity
Aggregate/sector-level	$I, K, OS,$ and Q	Flow of Funds	US	Country and Sector (NFCB, NFNCB)
Industry-level data	I, K and OS	BEA	US	~NAICS L3
		OECD STAN	EU	ISIC Rev 4
Concentration Measures	Herfindahls and Concentration Ratios	Economic Census	US	NAICS L3-L6
		Compustat	US	BEA segments
		CompNET	EU	ISIC Rev 4
		BvD Amadeus	EU	ISIC Rev 4
Firm Financials	I, K, OS, Q and other controls	Compustat NA	US	Firm
		Compustat Global	EU	Firm
China	Import Exposure	UN Comtrade	Global	HS code
	NTR Gap and import value	Peter Schott's website	US	NAICS L6
Productivity & controls	TFP & Mfg Industry Controls	NBER-CES Database	US	NAICS L6
	TFP	BLS KLEMS	US	BEA segments
Other	Analyst Forecasts	I/B/E/S	US	Firm
	Intangible Capital	Peters & Taylor	US	Firm

Firm-level data. US firm-level data are sourced from Compustat and therefore follow GAAP. Under GAAP, firms report stock and flow measures of tangible capital in the Property, Plant and Equipment (PP&E) and Capital Expenditures (CAPX) line items. The treatment of intangible assets, however, is more nuanced. Internally created intangibles are expensed on the income statement and almost never appear on the balance sheet – these include R&D and advertising expenses, for example. Externally created (i.e., acquired) intangible assets are capitalized and reported in the Intangible Assets line item. These include Goodwill and Other (identifiable) Intangible Assets such as patents and software.

Peters and Taylor (2016) (PT for short) estimate firm-level intangible capital by combining estimates of internally and externally-created intangibles. For the former, they follow Corrado and Hulten (2010) in using granular investment and depreciation assumptions on the R&D and Sales, General & Administrative (SGA) line items to capitalize R&D as well as “expenditures on product design, marketing and customer support, and human capital and organizational development.” For the latter, they use the balance sheet measure of externally created intangibles directly.⁴ We use PT’s estimates of I and K in our firm-level analyses, and report results separately for tangible, intangible and total capital where appropriate. For Q , PT advocate a measure labeled ‘total Q ’ and defined as the ratio of market value of productive assets to tangible plus intangible capital. We deviate from this definition and instead estimate firm-level Q as the market-to-book ratio, in line with Gutiérrez and Philippon (2017b). Gutiérrez and Philippon (2017b) compare the distribution and performance of market-to-book and ‘total Q ’ and find that market-to-book is more stable over time and relies on fewer measurement assumptions. Nonetheless, we confirm that our results are robust to using ‘total Q ’.

1.1.2 Adjusted Herfindahls

Our ideal competition measure should cover the whole economy and take into account foreign competition (i.e., imports).

For Manufacturing, Feenstra and Weinstein (2017) (FW for short) construct such a measure. They use Census Herfindahls for the U.S. and import data for foreign countries. The replication files available at the author’s website include Herfindahls at the country- and 4-digit Harmonized System (HS-4) level, from 1992 to 2005. We start from these Herfindahls, aggregate them and map them to BEA segments.⁵ We then extend the series to cover 1990 to 2015 by regressing FW Herfindahls on Compustat Herfindahls and share of sales.⁶ The detailed calculations are described

⁴Because it includes non-identifiable assets such as Goodwill, marketing and human capital, PT’s measure of intangible capital is broader than that of National Accounts. It results in higher capital estimates. Our conclusions are robust to excluding Goodwill from PT’s measure of intangible capital

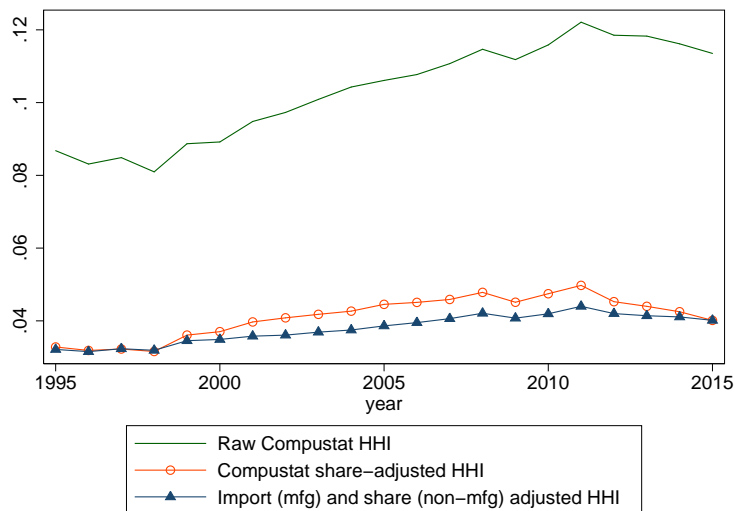
⁵First, we aggregate country-sector Herfindahls $HHI_t^{c,j}$ across countries c to obtain the *Overall Herfindahl Index* for HS-4 sector j (HHI_t^j). Next, we use the correspondence of Pierce and Schott (2012) to map HS-4 sectors to NAICS-6 sectors, which can then be mapped to BEA segments (which roughly correspond to ~NAICS-3 segments). Last, we aggregate Herfindahls across HS-4 segments j into BEA segments k , to obtain Herfindahls at the BEA segment k : HHI_t^k .

⁶FW Herfindahls are based on SIC segments before FW 1997 and NAICS segments afterwards, which results in a jump in HHI_t^k for some series. We control for the jump by subtracting the 1997 change in HHI_t^k from all HHI_t^k series

in the appendix.

Outside Manufacturing, neither Census nor foreign Herfindahls are available – so we have to use Compustat. We start with the “raw” Herfindahls from Compustat and adjust them to account for the domestic coverage of Compustat as well as the share of imports. Consider an industry with x firms in Compustat and N firms globally, all with equal shares of the U.S. market. The Compustat share of output is $s^{CP} = \frac{x}{N}$, and the Compustat-based Herfindahl $HHI^{CP} = \frac{1}{x}$. Under these assumptions, the adjusted Herfindahl can be computed as $HHI_t^k = \frac{1}{N} = HHI_{kt}^{CP} \times s_{kt}^{CP}$ where s_{kt}^{CP} is the share of Compustat sales in US output plus imports. We refer to this measure as the “Compustat share-adjusted” Herfindahl (HHI_{kt}^{CPadj}). For service sectors, import data is not available but these are typically small, so we set them to zero.

Figure 3: Weighted Average Herfindahls

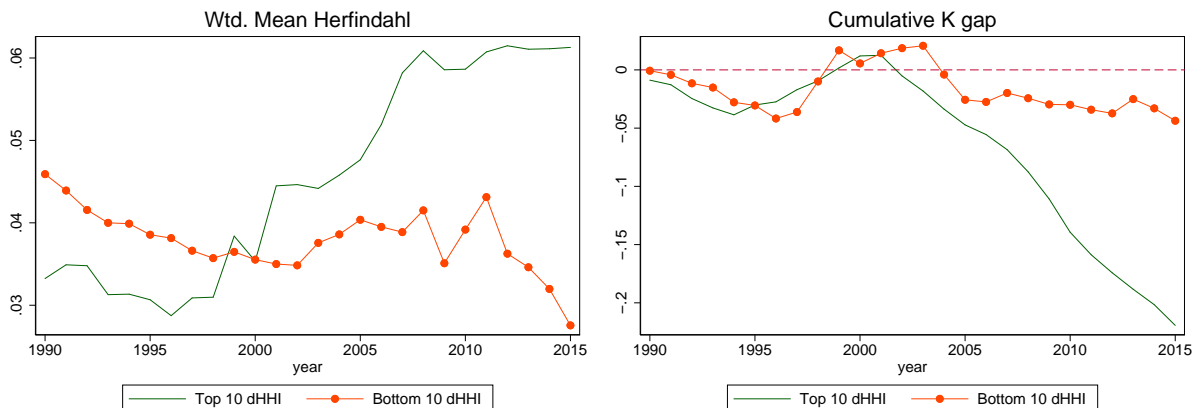


Notes: Annual data. Figure shows the weighted average of three measures of Herfindahls. The Raw Compustat HHI is the sum of squared Compustat market shares. The Compustat share-adjusted HHI adjusts for the Compustat share of sales. The Import and Share adjusted HHI is based on FW Herfindahls for Manufacturing and Compustat share-adjusted Herfindahls for non-manufacturing.

Figure 3 shows the impact of both adjustments sequentially. The Compustat share adjustment accounts for the share of Compustat sales in domestic output plus imports, while the import ad-

after 1998. We then extend the time series through a regression of the form $\log(HHI_t^k) = \log(HHI_t^{k,CPraw}) + \log(s_{kt}^{CP}) + \alpha^k + \varepsilon_{kt}$, where $HHI_t^{k,CP}$ denotes the Herfindahl from Compustat and s_{kt}^{CP} denotes the share of sales of Compustat firms as a percent of total US output plus imports. The Compustat Herfindahl ($HHI_t^{k,CP}$) is highly correlated with the FW Herfindahl (HHI_t^k) at the BEA segment-level, particularly once controlling for the share of Compustat sales. For instance, the R^2 of the regression above excluding fixed effects is 42% and including fixed effects is 95% – so the filled-in Herfindahls seem accurate. The level of HHI_t^k following FW tends to be lower than the level implied by Compustat. Most of our regressions include fixed effects, so this is not an issue. However, for columns 1-2 in Table 6 as well as some Figures, the level of the HHI_t^k matters. We therefore add a constant across all manufacturing segments, to match the average level of HHI_t^k to that of $HHI_t^{k,CP}$ across all manufacturing industries.

Figure 4: Cumulative Capital Gap for Concentrating and Non-Concentrating Industries



Notes: Annual data. Left plot shows the weighted average import adjusted Herfindahl for the 10 industries with the largest and smallest relative change in import-adjusted Herfindahl. Right plot shows the cumulative implied capital gap (as percent of capital stock) for the corresponding industries. See text for details.

justment accounts for the concentration of foreign firms. All three series have increased since 1995, by 30%, 22% and 25%, respectively. The increase is concentrated in non-manufacturing industries as shown in Appendix B.1.4.⁷

1.2 Two Stylized Facts

This section shows why it is critical to understand the dynamics of concentrating industries, and within industries, of the leading firms.

Fact 1: The Investment Gap Comes from Concentrating Industries. Figure 4 shows that the capital gap is coming from concentrating industries.⁸ The solid (dotted) line plots the implied capital gap relative to Q for the top (bottom) 10 concentrating industries. For each group, the capital gap is calculated based on the cumulative residuals of separate industry-level regressions

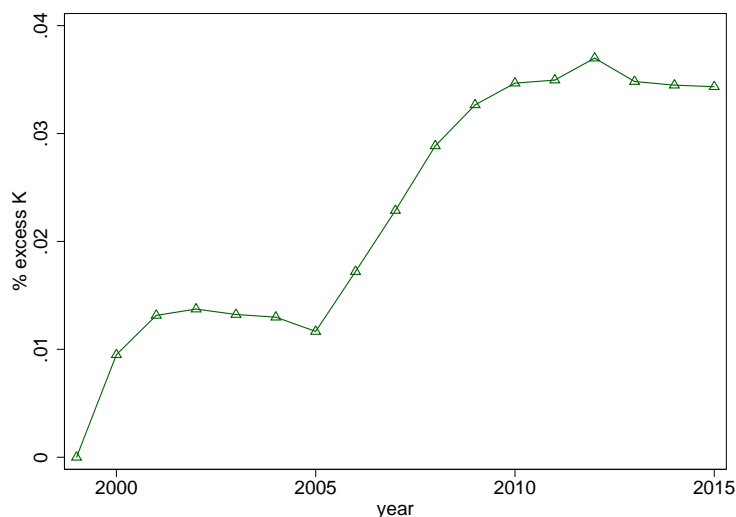
⁷We validate the use of Compustat in two ways. First, we compare the evolution of Herfindahls adjusted for the Compustat share of sales (HHI_{kt}^{CPadj}) to alternate Compustat- and FW-based Herfindahls, as described in Appendix B.1.4. HHI_{kt}^{CPadj} exhibits the highest correlation with FW-Herfindahls (81% in levels and 66% in changes). Second, we gather census CRs and use them to (i) test the robustness of key results to using Census CRs instead of import-adjusted Herfindahls; and (ii) compare Compustat CRs against Census CRs. Most of our results are robust to using Census CRs instead of import-adjusted Herfindahls (see Appendix C for details). In addition, Census and Compustat CRs are strongly correlated at the BEA segment-level (80% in levels and 56% in changes). We also perform extensive sensitivity analyses to adjustments in the calculation of import-adjusted Herfindahls (e.g., using s_{kt}^{BEA} instead of s_{kt}^{CP}). Appendix B.1.4 provides additional details on the tests and comparisons. See Davis et al. (2006) for additional discussion of the limitations in using Compustat to measure industry concentration

⁸We define concentrating industries based on the relative change in import adjusted Herfindahls from 2000 to 2015. The top 10 concentrating industries include Arts, Health other, Inf. motion, Inf. publish and software, Inf Telecom, Transp pipeline, Transp truck, Min exOil, Retail trade, Transp_air. We exclude Agriculture because Compustat provides limited coverage for this industry.

of net industry investment from the BEA on our measure of (lagged) industry Q from Compustat.⁹ The Herfindahl index for the bottom 10 turns out to be rather stable over time, and investment remains largely in line with Q for this group.

Fact 2: Industry Leaders Account for the Increased Profit Margins and for the Investment Gap. In Table 2 (see also Appendix Figure 9), we define leaders by constant shares of market value to ensure comparability over time.¹⁰ Capital K includes intangible capital as estimated by Peters and Taylor (2016). Table 2 shows that the leaders' share of investment and capital has decreased, while their profit margins have increased.

Figure 5: Implied Gap in K due to Leader Under-Investment



Notes: Annual data. Figure shows the cumulative implied excess capital (as percent of total U.S. capital stock for the industries in our sample) assuming Compustat leaders continue to account for 35% of CAPX and R&D investment from 2000 onward. Non-leaders assumed to maintain their observed invest levels. Excess investment assumed to depreciate at the US-wide depreciation rate. US-wide capital and depreciation data from BEA.

Table 2 suggests that leaders are responsible for most of the decline in investment relative to profits. To quantify the implied capital gap, Figure 5 plots the percentage increase in the capital stock of the U.S. non-financial private sector assuming that Compustat leaders continued to invest 35% of CAPX plus R&D from 2000 onward, while the remaining groups invested as observed. The capital stock would be $\sim 3.5\%$ higher under the counter-factual. This is a large increase considering that our Compustat sample accounts for about half of investment (see Appendix B for details) and that the average annual net investment rate for the U.S. Non Financial Business sector has

⁹To be specific, each line is computed as follows: we first compute the residuals from separate industry-level regressions of net investment on (lagged) mean industry Q , from 1990 to 2001. Then, we average yearly residuals across the industries with the ten largest and ten smallest relative changes in import-adjusted Herfindahls from 2000 to 2015. Last, we compute the cumulative capital gap by adding residuals from 1990 to 2015, accounting for depreciation.

¹⁰OIBDP 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 2: Investment, Capital and Profits by Leaders and Laggards

Table shows the 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. Lerner Index defined as $(OIBDP - DP)/SALE$.

	1980-1995			1996-2015			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	0.33	0.34	0.33	0.33	0.33	0.33	0.00	0.00	0.00
Share of CAPX + R&D	0.35	0.32	0.34	0.29	0.32	0.39	-0.06	0.01	0.05
Share of PP&E	0.32	0.33	0.34	0.30	0.31	0.39	-0.02	-0.02	0.05
Share of K	0.31	0.33	0.36	0.27	0.33	0.39	-0.03	0.00	0.04
(CAPX+R&D)/OIBDP	0.71	0.67	0.71	0.52	0.57	0.70	-0.20	-0.10	-0.01
Lerner Index	0.10	0.09	0.07	0.13	0.11	0.07	0.02	0.02	0.001

been less than 2% since 2002. A macroeconomic simulation by Jones and Philippon (2016) (taking into account general equilibrium effects and monetary policy) based on our implied markup series suggests a shortfall of 5 to 10%.

2 Rising Concentration Reflects Decreasing Domestic Competition

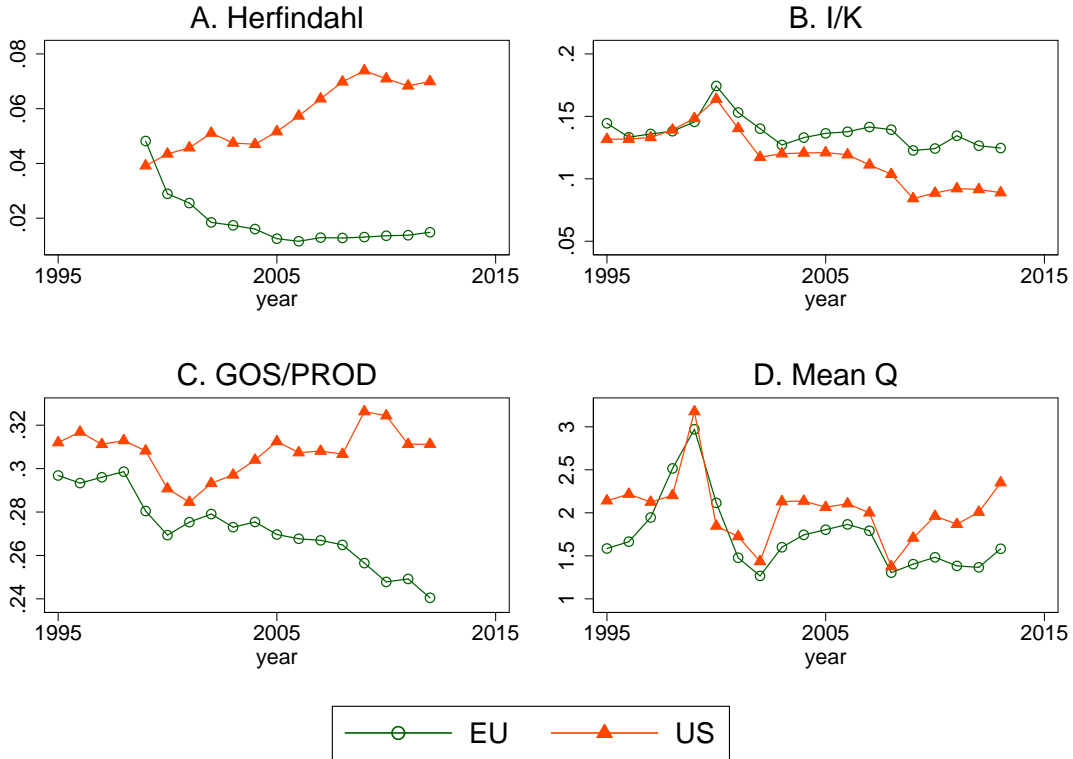
In this section we make the case that the increase in concentration reflects DDC. As explained above, we adjust our concentration measures to take into account foreign competition. The main alternative explanation is then EFS. The efficient scale argument is that technological change – information technology, networks, winner-take-all, etc – has increased the efficient relative size of the best firms in each industry. The key point here is that increasing skewness is an efficient response to changes in the environment. We present three pieces of evidence that are inconsistent with this interpretation but consistent with DDC.

2.1 US vs. Europe

The comparison with Europe is extremely data-intensive. We rely on the dataset of Dottling et al. (2017), which includes industry- and firm-level series of profit, investment and concentration for the U.S. and Europe under consistent industry segments.¹¹ We present only key comparisons of industries with significant increases in concentration in the U.S. (such as Telecom). Figure 6 compares the weighted average (domestic) Herfindahl, investment rate, operating margin and Q for the 5 industries that concentrate the most in the US. We exclude the Manufacturing - Textiles industry even though it exhibits a rise in domestic concentration because the increase is primarily due to foreign competition. Accounting for imports, the Herfindahl increased much less than for the remaining 5 concentrating industries.

¹¹Firm-level data is based on Compustat (NA and Global). Industry-data is based on the BEA, EU KLEMS and OECD STAN. Concentration measures are based on Compustat NA for the U.S. and BvD Orbis for Europe (given the larger presence of private firms in Europe). We are grateful to Sebnem Kalemli-Ozcan and Carolina Villegas-Sanchez for providing us with a historical time series of Herfindahls and Top-firm Market Shares computed based on the BvD Orbis merged vintage dataset of Kalemli-Ozcan et al. (2015). See Dottling et al. (2017) and Appendix B for additional details.

Figure 6: Comparison with EU for Top 5 Concentrating Industries in US



Notes: Figure based on the top 5 concentrating industries in the US. These industries are Information Telecom, Arts and Recreation, Wholesale and Retail trade, Other Services and Information Publishing (which includes software). Panel A plots the weighted average Herfindahl across these industries, weighted by sale. For the EU, each industry’s Herfindahl is the weighted average Herfindahl across countries. Panel B plots the weighted average investment rate, weighted by the capital stock. Panel C plots the the weighted average ratio of Gross Operating Surplus to Production. Last, Panel D plots the weighted average mean Q , by assets. All weights are based on the U.S. share of industries to control for differences in industry sizes across regions.

The series are aggregated across industries based on US share of sales, capital, output and assets (respectively) to ensure a common weighting across regions.¹² Concentration, profits and Q increased in the U.S., while investment decreased. By contrast, concentration decreased in Europe, and investment remained (relatively) stable despite lower profits and lower Q . This true even though these industries use the same technology and are exposed to the same foreign competition. As shown in the Appendix C.1.1, these conclusions remain when looking at the underlying industries – such as Telecom and Airlines.¹³ EFS, GLOBAL and INTAN therefore cannot explain the concentration in the US. On the other hand, these trends are consistent with DDC since antitrust enforcement has

¹²We present results using BvD Orbis Herfindahls, and also confirm that conclusions are robust to using Concentration Measures from the ECB’s CompNET (see Appendix C.1.1 for details).

¹³Airlines is not included in Figure 6 because EU KLEMS combines the entire Transportation and Storage sector, hence was combined in the analyses of Dottling et al. (2017). But we can compare concentration and mark-up trends using the ECB’s CompNET.

indeed become more aggressive in Europe than in the US in recent years (see Faccio and Zingales (2017) for Telecoms, Economist (2017) for Airlines, and Gutiérrez and Philippon (2017a) for all industries).

2.2 Concentration and TFP

According to the EFS hypothesis, concentration reflects an *efficient* increase in the scale of operation. A key prediction of the EFS hypothesis is therefore that concentration leads to productivity gains at the industry level, as high productivity leaders expand. It has happened before, for instance in Retail Trade during the 1990's.¹⁴ The question is whether EFS is the main driver of concentration over the past 20 years as hypothesized by Autor et al. (2017a). To test this idea, we study the relationship between changes in concentration and changes in industry TFP at two levels of granularity. First, we study the more granular NAICS Level 6 manufacturing industries using productivity measures from the 2017 release of the NBER-CES database (which contains data up to 2011). Next, we broaden the sample to all US industries by using KLEMS, at the expense of considering more aggregated \sim NAICS Level 3 industries.¹⁵ We only include industry segments that remain stable over each 5-year period in our regressions, so that no aggregation/mapping is necessary.

Table 3: Industry regressions: Concentration vs. TFP

Table shows the results of industry-level OLS regressions of contemporaneous changes in TFP and Concentration over the periods specified. Observations are weighted by value added. Columns 1-3 include NAICS-6 manufacturing industries, with TFP from NBER-CES database. Columns 4-5 include all industries in our sample, with TFP from U.S. KLEMS. Standard errors in brackets. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. † TFP change to 2011 in column 3, and to 2014 in the last 5Y period of column 5 due to data availability.

	(1)	(2)	(3)	(4)	(5)
	$\Delta\text{TFP}(t, t-5)$			$\Delta\text{TFP}(t, t-5)$	
	97-02	02-07	07-12 [†]	90-00	00-14 [†]
$\Delta\text{Census CR8}(t, t-5)$	1.456** [0.312]	0.237 [0.652]	-1.35 [0.871]		
$\Delta\text{CP CR8}(t, t-5)$				0.461* [0.198]	-0.208+ [0.115]
Sectors	Mfg			All	
Granularity	NAICS-6			KLEMS	
Observations	469	469	299	86	129
R^2	0.045	0	0.008	0.061	0.025

Table 3 shows that the relationship between concentration and TFP was positive in the 1990's but not after. In fact, the relationship is negative in the 2007 to 2012 period. Columns (1) to (3) focus on NAICS Level 6 manufacturing industries.¹⁶ Columns (4) and (5) show that the results

¹⁴The Retail Trade industry became substantially more concentrated – and more productive – over the 1990's. Lewis et al. (2001) find that over the 1995 to 2000 period, a quarter of the U.S. productivity growth is attributable to advances in the retail industry, and almost a sixth of that is attributable to Walmart.

¹⁵When necessary, we use the sales-weighted average to aggregate concentration ratios across NAICS Level 3 segments to match the granularity of KLEMS.

¹⁶The number of observations decreases in column 3 due to substantial changes to NAICS Level 6 categories

are similar (and more significant) when we broaden the scope to all industries in our sample. The positive relationship at the beginning of the sample is consistent with the results in Autor et al. (2017b), but the results in the 2000’s are not. To be clear, Autor et al. (2017b) make two points. The first is that economic activity has shifted towards firms with lower labor shares, a fact also documented by Kehrig and Vincent (2017) and that we replicate in our data. The second point is that the concentration is explained by EFS. We find some evidence in favor of EFS in the 1990s, but evidence against it in the 2000s.

2.3 Investment by Leaders

According to the EFS hypothesis, leaders should increase investment in concentrating industries, reflecting their increasing relative productivity. We test this at the firm-level, by performing the following regression for firm i that belongs to BEA segment k :

$$\begin{aligned} \Delta \log(K_{it}) = & \beta_1 Q_{it-1} + \beta_2 HHI_{t-1}^k \times Leader_{it-1}^k + \beta_3 HHI_{t-1}^k \\ & + \beta_4 Leader_{it-1}^k + \beta_5 \log(Age_{it-1}) + \eta_t + \mu_i + \varepsilon_{it}, \end{aligned} \quad (1)$$

where K_{it} is firm capital (PP&E, Intangibles, or Total), HHI_t^k the import-adjusted Herfindahl, and $Leader_{it}^k$ is an indicator for a firm having a market value in the top quartile of segment k . We include Q_{it-1} and $\log(Age_{it-1})$ as controls, along with firm and year fixed effects (η_t and μ_i). β_2 is the coefficient of interest. Table 4 shows that leaders in concentrated industries under-invest. The under-investment is apparent in tangible assets as well as intangible assets. This is inconsistent with EFS and consistent with DDC. Appendix C.1.2 reports results using Census-based measures of concentration, and including the Noisy Entry instrument (defined below) instead of Herfindahls as an exogenous measure of competition. In unreported tests, we confirm that results are robust considering manufacturing and non-manufacturing industries separately.

between NAICS 2007 and NAICS 2012. Results before 2007 are robust to considering only those industries with consistent segments from 1997 to 2012. In unreported tests, we find a negative and significant coefficient when considering the 10Y period from 2002 to 2012. In unreported tests, we find positive correlations between concentration and value-added per worker, but this would be true under any model of increasing market power irrespective of productivity.

Table 4: Investment by Leaders

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 Herfindahls. Regression from 2000 to 2015, following equation (1). We consider three measures of capital: PP&E, intangibles defined as in Peters and Taylor (2016) and their sum (total). Leaders measured as the two-year moving average of an indicator for a firm having market value in the top quartile of the corresponding BEA segment k . 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. + $p < 0.10$, * $p < 0.05$, ** $p < .01$.

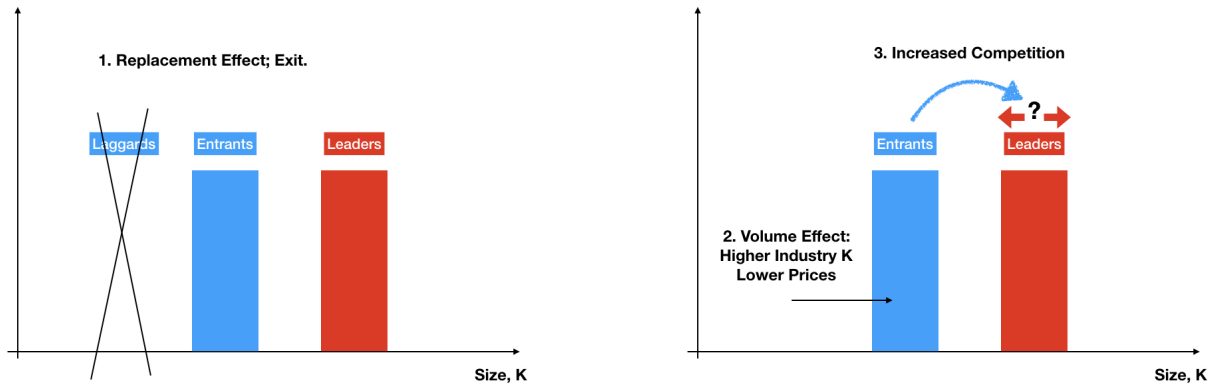
	(1)	(2)	(3)
	$\Delta \log(PPE)^a$	$\Delta \log(Int_{PT})^b$	$\Delta \log(K_{PT})^{a+b}$
	≥ 2000	≥ 2000	≥ 2000
Q_{it-1}	6.84**	3.38**	4.01**
	[0.24]	[0.13]	[0.13]
HHI_{t-1}^k	15.82	11.25	21.32*
	[14.43]	[9.40]	[9.44]
$Leader_{it-1}^k$	0.91	0.37	0.22
	[1.16]	[0.96]	[0.85]
$HHI_{t-1}^k \times Leader_{it-1}^k$	-34.41*	-24.43+	-29.28**
	[13.92]	[12.89]	[11.20]
$\log(Age_{it-1})$	-6.10**	-14.02**	-12.52**
	[1.38]	[0.89]	[0.87]
Observations	59361	56472	56704
R^2	0.06	0.08	0.09
Year FE	YES	YES	YES
Firm FE	YES	YES	YES

3 Competition Encourages Investment

The previous section has shown that international, industry, and firm level evidence is inconsistent with EFS and consistent with DDC in the US. We now make the case that competition increases investment, and therefore that DDC has caused a shortfall in business investment. Establishing causality is challenging because entry, exit – and therefore concentration – are endogenous. We thus propose three different identification strategies. Figure 7 summarizes the testable predictions. Consider an industry, initially in equilibrium with some leaders and some laggards, but disrupted by entrants that are more productive than the current laggards. There is first a replacement effect, as the laggards are forced out. Then, because the entrants are productive, industry output expands and prices fall. Finally, the leaders react. This third effect is theoretically ambiguous, as discussed at length in the literature (Gilbert, 2006). In non-strategic models (Klette and Kortum 2004, monopolistic competition with iso-elastic demand curves, etc.), leaders would cut investment. In strategic models (entry deterrence, neck-and-neck competition, etc.) leaders could increase investment and innovation.

Which of these predictions we can test depends on the context. If competition is domestic, we can test the industry level response of investment, as well as the response of leaders. If entrants are

Figure 7: Testable Predictions



foreign competitors we can only test the investment response of the leaders since we do not measure investment by foreign competitors.

3.1 Evidence from Chinese Competition

Our first test is based on increased competition from China during the 2000's, following Autor et al. (2016) and Pierce and Schott (2016). Pierce and Schott (2016) exploit changes in barriers to trade following the United States granting Permanent Normal Trade Relations (PNTR) to China. PNTR became effective on December 2001 as China entered the WTO. We find that the impact of Chinese competition is consistent with the theoretical predictions of Figure 7 with strategic responses by the leaders.

Figure 8 shows a strong replacement effect. It plots the normalized number of firms in industries with high and low Chinese exposure. Both groups have the same pre-existing trends, including during the dot-com boom, but start to diverge after 2000.

Using actual import penetration as a measure of exposure raises endogeneity issues. In our regressions and in the next figure we therefore use the instrument proposed by Pierce and Schott (2016). Before PNTR, China was considered a non-market economy which, under the Smoot-Hawley Tariff Act of 1930, are subject to relatively high tariff rates (known as "Non-Normal Trade Relations" tariffs or "non-NTR rates"). From 1980 onward, U.S. 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 U.S. and Chinese firms (see Pierce and Schott (2016) for a wide range of anecdotal and news-based evidence). This ended in 2000, when the U.S. granted PNTR to China. The granting of PNTR removed uncertainty around tariffs, leading to an increase in competition. Pierce and Schott (2016) show that industries facing a larger NTR gap experienced a larger increase in Chinese imports and a larger decrease in U.S. employment.

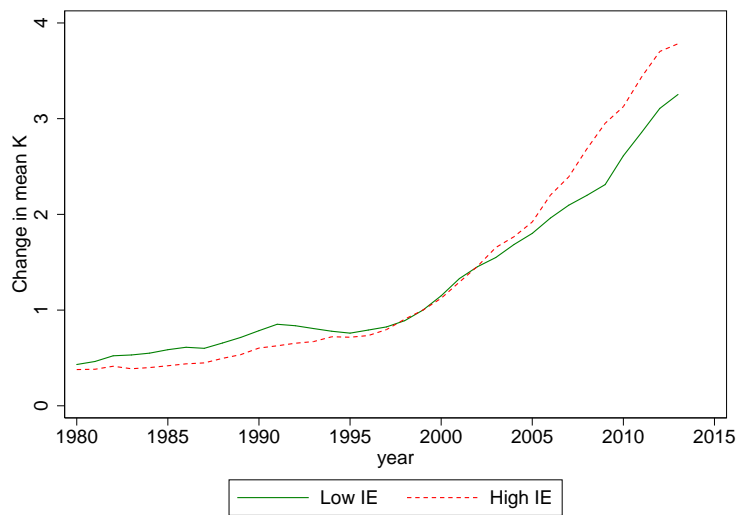
Figure 8: Number of firms by Chinese exposure (1991 = 1)



Notes: Annual data. Firm data from Compustat; import data from UN Comtrade. Manufacturing industries only, split into ‘high’ (above-median) and ‘low’ (below-median) exposure based on import penetration from 1991 to 2011.

Figure 9 focuses on *surviving* firms. It shows that K per existing firm increases *faster* in high exposure industries than in low exposure industries following China’s entry into the WTO. Moreover, the increase within high exposure industries is concentrated among leaders (Figure 15 in the Appendix).

Figure 9: K^{PT} per Existing Firms, by Chinese Exposure (1999 = 1)



Notes: Annual data. US incorporated firms in manufacturing industries only. In each year we sum capital across all firms and divide by the number of firms. Industries assigned to high (low) exposure if they have above (below) median NTR gap (see below for definition). Similar patterns for PP&E and Intangibles.

We 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 tariff rate that was locked in by PNTR

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

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. We then examine the link between increased competition and investment (by leaders and laggards) using a generalized difference-in-differences (DiD) specification:

$$\begin{aligned} \log(K_{i,j,t}) = & \beta_1 Post - 2001 \times NTRGap_j \times \overline{\Delta IP_t^{US}} \\ & + \beta_2 Post - 2001 \times NTRGap_j \times \overline{\Delta IP_t^{US}} \times Leader_{i,j,0} \\ & + Post - 2001 \times X_{j,91}'\gamma + \eta_t + \mu_i + \varepsilon_{it}, \end{aligned} \quad (2)$$

where the dependent variable is a given measure of capital for firm i in industry j during year t .¹⁷ $\overline{\Delta IP_t^{US}}$ captures time-series variation in Chinese competition averaged across all industries.¹⁸ The first two terms on the right-hand side are the DiD terms of interest. The first one is an interaction between the NTR gap and $\overline{\Delta IP_t^{US}}$ 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 interacts the post-PNTR dummy with time-invariant industry characteristics such as initial capital and skill intensity.¹⁹ We include year and firm fixed effects η_t and μ_i . Our main sample for this analysis includes all U.S. incorporated manufacturing firms in Compustat over the 1991 to 2015 period, but we also report results only with continuing firms (i.e., firms that were in the sample before 1995 and after 2009).

Table 5 shows that leaders increase investment in response to exogenous changes in foreign competition. We consider three different measures of capital: PP&E, Intangibles (measured as in PT) and total capital (equal to the sum of PP&E and Intangibles).²⁰ This supports a strategic interaction/neck-to-neck competition model, where leaders invest more to deter entry, while laggards

¹⁷We interpret the China shock as a permanent shock to competition. The correct test is then to look at the cumulative response of investment, i.e., the capital stock (or its log-change). Later on we consider more transitory shocks and we look at investment rates. Of course all our results hold if we cumulate the investment rates over time.

¹⁸The appendix presents results excluding $\overline{\Delta IP_{j,t}^{US}}$ 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 ($\Delta IP_{j,t}^{OC}$). $\Delta IP_{j,t}^{US}$ is defined in the Appendix, following Autor et al. (2016).

¹⁹These industry characteristics are sourced from the NBER-CES database. They include initial year (1991) (i) percent of production workers, (ii) ratio of capital to employment; (iii) ratio of capital to value added; (iv) average wage; (v) average production wage; and (vi) an indicator for advanced technology industries.

²⁰In unreported robustness tests, we confirm that our results are robust to including only balance sheet intangibles or excluding goodwill in the PT measure.

Table 5: Chinese Competition: $\log(K_t)$ results based on $NTRGap_j \times \overline{\Delta IP_{j,t}^{US}}$

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 (2). We consider three measures of capital: PP&E, intangibles defined as in Peters and Taylor (2016) and their sum (total). Regression over 1991 - 2015 period. Leaders defined as firms with MV in top quartile as of 1999 within each NAICS Level 6 industry. Industry controls include measures of industry-level production structure (e.g., PPE/Emp). Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. Standard errors in brackets, clustered at the industry-level. + $p < 0.10$, * $p < 0.05$, ** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(PPE_t)^a$	$\log(Int_t^{PT})^b$	$\log(k_t^{PT})^{a+b}$	$\log(PPE_t)^a$	$\log(Int_t^{PT})^b$	$\log(k_t^{PT})^{a+b}$
$Post01 \times NTRGap$	-7.136** [2.56]	-1.096 [1.99]	-1.223 [1.61]	-6.901* [2.75]	-2.236 [1.87]	-2.075 [1.56]
$Post01 \times NTRGap \times Lead_{99}$	7.251** [2.22]	6.143** [1.31]	5.795** [1.33]	5.848* [2.31]	7.097** [1.58]	6.469** [1.55]
Observations	29854	29980	29982	13988	14009	14021
R^2	0.088	0.508	0.46	0.131	0.541	0.496
Industry controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Sample	All firms			Continuing firms		

reduce investment or exit. Columns 4 to 6 focus on continuing firms; and show that leaders invested more than laggards, even when compared only 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) study 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 Appendix C.2.1 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.

3.2 Evidence from Noisy Entry

The China shock provides clean identification, but it does not have clear external validity for the entire US economy. It identifies an *increase* in competition for a particular sector (manufacturing) and a limited set of firms which account for about 10% of the non-financial private economy. This section presents our second test, which broadens the sample to the entire non-financial private

economy, while considering both *increases* and *decreases* in competition.

Our identification is based on the idea of noisy entry. Appendix D presents a formal model that can be summarized as follows:

$$\begin{aligned} I_t/K_t &= F(D_t, N_t) \\ N_t &= (1 - \delta) N_{t-1} + \gamma(D_t + u_t) + \epsilon_t \end{aligned}$$

where I_t/K_t is the investment rate, D_t is industry demand, N_t is the number of firms active at t , the shocks u_t and ϵ_t are uncorrelated with D_t and the function F is increasing in both arguments. The impact of competition on investment is measured by $\partial F/\partial N$. The term $\gamma(D_t + u_t)$ captures strategic entry which is increasing in a noisy signal of (future) demand. The term ϵ_t captures other random changes in entry costs.²¹ The second equation makes it clear that running an OLS regression of investment on the number of firms (or any other measure of concentration) leads to (upwardly) biased estimates (since γ is positive). On the other hand, both u and ϵ would be valid instruments for N in the investment equation.

Measuring Noisy Entry Noisy signals (u_t) and idiosyncratic entry opportunities (ϵ_t) represent temporary shocks (too much or too little realized entry) that dissipate over time, generating an impulse response structure. Consistent with overall efficiency, we find that noisy entry is usually small, and realized entry is typically consistent with (past and future) sales and productivity growth. However, there is an interesting exception in the late 1990s. During that period, we find large residuals in realized entry rates, controlling for fundamentals. In particular, we let noisy entry during the 1990's be the residuals from a regression of $\Delta \log N_{j,91-00}$ on observables:

$$\begin{aligned} \Delta \log N_{j,91-00} &= \beta_0 + \beta_1 \text{Med } Q_{j,91-00} + \beta_2 \text{Med } \Delta \log \text{Sales}_{j,91-00} \\ &+ \beta_3 \text{OS}/K_{j,91-00} + \beta_4 \text{CF}/\text{Assets}_{j,91-00} + \beta_5 \text{Med } \text{EPS } \text{Fcst}_{j,00} \\ &+ \beta_7 \Delta \text{IP}_{j,91,99}^{US} + \beta_8 \text{Mean firm assets}_{90} + \beta_9 \text{Mean firm age}_{90} + \varepsilon_j \end{aligned}$$

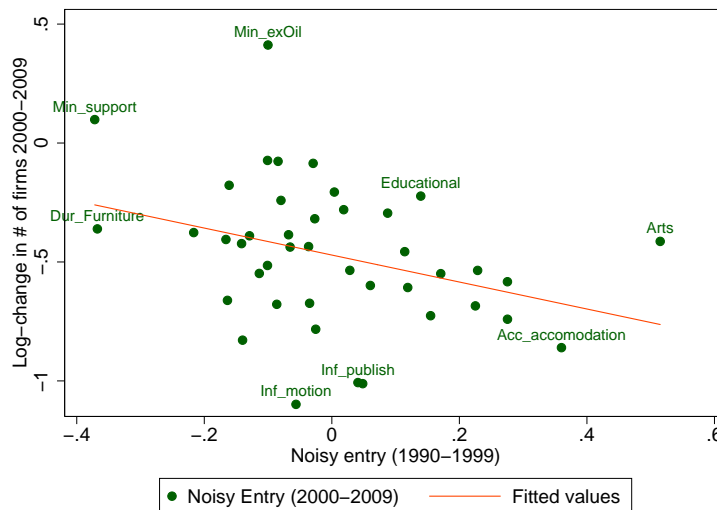
where we include measures of (past and projected) profitability, sales growth, import competition, cash flow and Q , among others. The sub-index 91-00 denotes the average value from 1991 to 2000; and $\text{Med } \text{EPS } \text{Fcst}_{j,00}$ denotes the median analyst-projected long term growth in Earnings-Per-Share across all firms in industry j as of 2000.²²

Figure 10 plots $\text{Noisy Entry}_{j,90-99}$ (x-axis) against the log-change in the number of firms in the 2000's (y-axis). As shown, we find large – positive and negative – variation in noisy entry across

²¹There is a long literature showing that early entry is strategically important, in particular because of brand preferences. See Bronnenberg et al. (2012). Therefore firms have strong incentives to make risky entry decisions. See also Mongey (2016) for a model of cross-regional variation in market concentration. One can formally compute the impulse response of investment to entry in standard DSGE models such as Corhay et al. (2017).

²²All variables our are based on Compustat, except for OS/K which is based on BEA figures. This regression yields an R^2 of 70%. We also considered absolute changes in the number of firms during the 1990's and found largely consistent results. Long term growth forecasts are often interpreted as 5-year growth forecasts.

Figure 10: Change in # of firms post-2000 vs. Noisy entry pre-2000



Notes: Annual data from Compustat. See text for details on noisy entry measure.

industries. Some industries, like ‘Arts’ and ‘Accommodation’ experienced substantially more entry than predicted by fundamentals. Other industries (e.g., Mining - Support) experienced too little entry. Consistent with the impulse response structure, we find mean reversion in concentration: industries that experienced more noisy entry also experienced more net exit in the 2000’s. Perhaps more importantly, noisy entry does not predict future demand or productivity. The coefficient is close to zero, insignificant, and in fact slightly negative (Appendix Table 11). Combined, these results suggest that our measure of noisy entry is consistent with the corresponding models; and is therefore a valid instrument for concentration.²³

²³The presence of noisy entry is documented for specific industries in several papers. For instance, Doms (2004) studies noisy entry and investment in the IT sector broadly – and the corresponding sub-sectors. He concludes that a “reason for the high growth rates in IT investment was that expectations were too high, especially in two sectors of the economy, telecommunications services and the dot-com sector.” And Hogendorn (2011) documents excessive entry in parts of the Telecom sector.

We do not need to take a stand on whether the exuberance of the late 1990’s was rational or not. Perhaps there were Bayesian mistakes, perhaps there were overly-optimistic forecasts, perhaps there were bubbles driven by the option to re-sell to future optimistic investors as in Scheinkman and Xiong (2003). All that matters for us is that these factors created variation in entry rates across industries (say in 2000) that turn out to be orthogonal to future demand (say in 2005). However, it is perhaps not surprising that we find noisy entry in the 1990s.

One explanation is potential variations in the willingness of investors (venture capitalists, or market participants in general) to fund risky ventures. This is particularly true given the optimistic environment in the late 1990’s and the large inflows into Venture Capital (VC). According to the National Venture Capital Association, annual VC commitments surged during the bubble period, growing from about \$10 billion in 1995 to more than \$100 billion in 2000. They then receded to about \$30 billion/year for the next decade (NVCA (2010)). According to Gompers and Lerner (2001), about 60 percent of VC funding in 1999 went to information technology industries, especially communications and networking, software, and information services. About 10 percent went into life sciences and medical companies, and the rest is spread over all other types of companies. Obviously, not all entry is funded by VC firms, so this can only explain a portion of the variation in entry rates – but the wide dispersion, and strong industry focus highlights the differential impact of the dot-com bubble across industries.

Another explanation is the presence of large stock market variations across most industries, as documented by Anderson et al. (2010). These extreme valuations translated into noisy entry – especially because firm entry increases precisely during periods of high-growth such as the late 1990’s (Asturias et al. (2017); Hobijn and Jovanovic (2001)).

Empirical Results We estimate the effect of competition on investment with the following industry-level panel regressions:

$$HHI_{j,t-1} = \theta_0 + \theta_1 Noisy\ Entry_{j,90-99} + \theta_2 Mean\ Q_{j,t-1} + \theta_3 Excess\ Inv_{j,90-99} + \varepsilon_{1,jt}, \quad (3)$$

and

$$\frac{NI_{jt}}{K_{j,t-1}} = \beta_0 + \beta_1 \widehat{HHI}_{j,t-1} + \beta_2 Mean\ Q_{j,t-1} + \beta_3 Excess\ Inv_{j,90-99} + \varepsilon_{2,jt}. \quad (4)$$

We use noisy entry during the 1990's as an instrument for the industry-level (import adjusted) Herfindahl. We expect θ_1 to be negative because more entry leads to a lower Herfindahl. If competition (i.e., lower Herfindahl) increases investment β_1 should be negative.²⁴ Columns 1 and 2 of Table 6 show that, indeed, the coefficient on noisy entry and HHI are both negative and significant.

Equation (4) excludes industry and year fixed effects because it uses noisy entry as a purely cross-sectional measure. However, we can take advantage of the impulse response-structure of noisy entry to construct two additional time-varying tests. First, because noisy entry is temporary and expected to revert, its effect on industry investment should decrease over time. We test this by studying the behavior of γ_1 in separate year-by-year regressions of net investment on noisy entry:

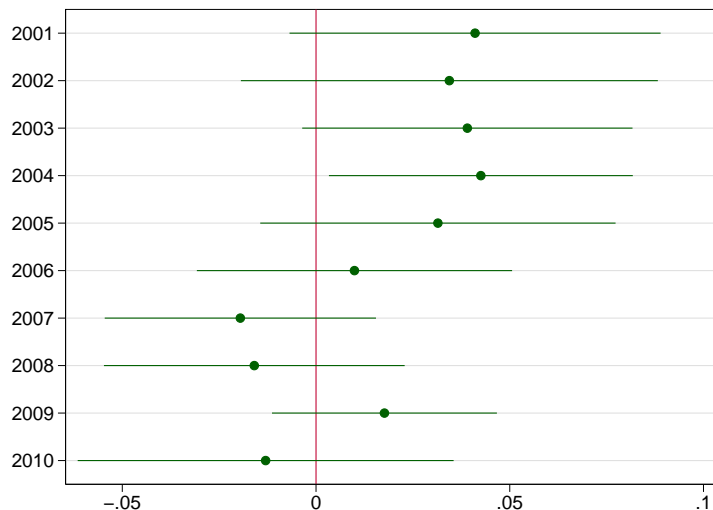
$$\frac{NI_{j,t}}{K_{j,t-1}} = \gamma_0 + \gamma_{1t} Noisy\ Entry_{j,90-99} + \gamma_{2t} Mean\ Q_{j,t-1} + \gamma_{3t} Excess\ Inv_{j,90-99} + \varepsilon_{jt}. \quad (5)$$

Figure 11 plots coefficients γ_1 from year-by-year regressions following equation (5). We include 10% confidence intervals. Consistent with the impulse response structure, Noisy Entry predicts substantially higher investment until approximately 2005 but not after. Coefficients are not always significant, but this is mostly due to the limited number of observations when running year-by-year regressions.²⁵

²⁴A potential concern is that optimistic valuations may have led to excess investment among existing firms. This could bias *against* finding an impact of competition since investment would then be lower in industries with a lot of entry. We control for industry-level excess investment in the 1990's, constructed by regressing net investment on industry Q , age and size. Our results hold with or without this control.

²⁵Appendix Figure 18 shows analogous results using changes in $\log(K)$ instead of I/K .

Figure 11: Noisy entry coefficient



Notes: Figure plots the coefficient of separate year-by-year regressions of net investment on noisy entry following equation (5). Observations are weighted by the stock of capital. As shown, industries with higher noisy entry experience a temporary increase in investment. 10% confidence intervals are shown.

Second, industries with more noisy entry in the 1990's start from low concentration but experience a stronger increase in concentration. Noisy entry should therefore predict not only the initial (or average) Herfindahl but also its change over time. We test this by interacting the sales-weighted average Herfindahl across all industries (time varying) with industry-level noisy entry (cross-sectional) in equation (4). We can then add industry and year fixed effects. Columns 3 and 4 of Table 6 interact the weighted average Herfindahl across all industries with industry-level noisy entry. This allows us to include industry and year fixed effects. As expected, industries with more noisy entry are more sensitive to aggregate concentration trends, which in turn lead to a larger reduction in investment.

Table 6: Noisy Entry: NI/K Regression Results

Table shows the results of industry-level 2SLS regressions of net investment on Herfindahls, instrumented by noisy entry. Columns 1 and 2 focus on cross-sectional variation. Industries with higher noisy entry exhibit lower Herfindahls and higher investment. Columns 3 to 4 study time series variation and include time and industry fixed effects. They interact noisy entry with aggregate series of concentration and excess investment, and use the interactions to predict industry concentration and investment. Standard errors in brackets clustered at the industry-level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	(1)	(2)	(3)	(4)
	1st St.	2nd St.	1st St.	2nd St.
	$HHI_{j,t}$	Net I/K	$HHI_{j,t}$	Net I/K
	01-05		01-15	
Mean Q (t-1)	0.02	0.025**	0.01	0.027+
	[.018]	[0.01]	[.01]	[0.01]
$Excess\ Inv_{90-99}$	-0.55	0.057		
	[1.03]	[0.45]		
$Excess\ Inv_{90-99}(i) \times NIK_{t-1}^{US}$			12.02	49.696**
			[14.33]	[16.73]
$Noisy\ Entry_{j,90-99}(i)$	-0.15**			
	[.046]			
$Noisy\ Entry_{90-99}(i) \times Wtm\ HHI_t$			4.41+	
			[2.28]	
$HHI_{i,t}$		-0.243*		-1.278**
		[0.10]		[0.45]
Year FE		No		Yes
Industry FE		No		Yes
Observations		210		630
RMSE		0.038		0.031
F-stat		10.652		3.752

The nice features of these regressions is that we use industry investment directly from the BEA. The source of our investment measure is thus completely independent from our measure of concentration from Compustat. It is also useful to focus on leaders. Appendix Table 12 performs a related analysis at the firm-level. Consistent with our hypothesis and our previous evidence from manufacturing, the increase in investment following noisy entry comes from industry leaders.²⁶

3.3 Evidence from M&A's

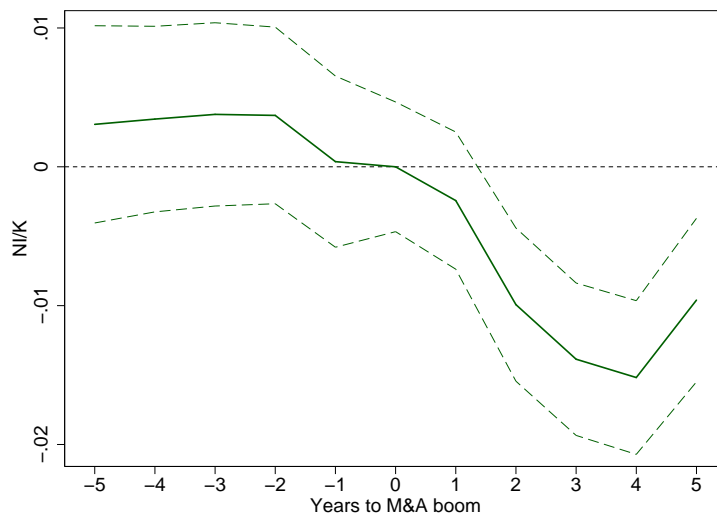
The third test is based on large mergers & acquisitions (M&A). As documented by prior work, merger activity is endogenous to industry dynamics. It sometimes drives consolidation in declining industries. Other times it plays an “expansionary” role following technological or regulatory shocks

²⁶Back of the envelope estimates of the implied sensitivity of investment to changes in import penetration implied by China regressions and to noisy entry suggest that they are similar. In unreported tests, we also confirm that results are robust to including only non-manufacturing industries, for which import adjustments are less material.

(Andrade and Stafford, 2004; Kaplan, 2000). The fact that M&As are endogenous is a challenge for identification. Nonetheless, the actual realization of large M&A transactions is (partly) random. M&A typically occurs in waves, that cluster through time and across industries (Andrade et al., 2001). We can thus use the discrete occurrence of M&A for identification. The identification assumption behind our test is that the omitted variables that cause the identification problem – particularly changes in demand and technology – are slow moving compared to lumpy M&A transactions. In other words, M&A waves result in sharp changes to the Herfindahl, which can identify the effect of concentration on investment without being affected by smooth changes in demand and technology.

We identify M&A booms as years in which firms accounting for more than 10% of sales in Compustat exit the database for M&A. This threshold selects roughly 5% of industry-year observations, mostly concentrated around M&A waves (the late 1980's, late 1990's and mid 2000's). We then study the behavior of investment around these periods. Figure 12 plots the weighted-average absolute change in the Net Investment rate over the five years before and after M&A booms, along with the corresponding 95% confidence interval. The period $t = 0$ corresponds to the fiscal year in which M&A transactions occur, so that $t = 1$ is the first complete fiscal year in which the merged firms no longer exist. As shown, the investment residual oscillates around zero before the M&A booms, but decreases sharply thereafter. The delay in the decline is consistent with slow adjustments to investment policies; while the sharpness of the decline suggests that M&A has a discrete effect on investment, compared to (relatively) smooth changes in demand and productivity.

Figure 12: Investment Following Large M&A



Notes: Average NI/K around M&A booms, normalized by subtracting NI/K at year of M&A boom. $t = 0$ denotes the year of acquisitions. Observations weighted by deflated capital stock.

Table 7 confirms these results through regressions.²⁷ Column 1 shows that M&A booms lead to increased (domestic) concentration. Columns 2 and 3 show that, conditional on measures of

²⁷As explained earlier, the China shock is permanent and can be tested using changes in K . Noisy entry is

Table 7: M&A and NI/K

Table shows the results of industry-level OLS regressions of Net I/K on measures of M&A booms, controlling for past concentration and output growth. NI/K in percentage points. M&A boom = 1 if firms accounting for >10% of sales exit Compustat for M&A during that year. Post M&A indicator defined as years 3-5 following an M&A boom. Standard errors in brackets clustered at the industry-level. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	(1)	(2)	(3)	(4)
	$Herf_j^{CP}(t)$	Net I/K (All)		
	≥ 1980	≥ 1980	≥ 1980	≥ 2000
$Mean Q_j(t-1)$		2.462**	2.468**	2.017**
		[0.66]	[0.66]	[0.48]
$Herf_j^{CP}(t-4)$	0.752**	-1.63	-1.493	
	[0.09]	[1.06]	[1.06]	
$Herf_j(t-4)$				5.707
				[4.28]
$\Delta \log(Output)_j(t-4)$		5.886**	5.834**	2.709**
		[0.97]	[0.96]	[0.91]
M&A boom(t-3)	0.025**	-0.546+		
	[0.01]	[0.32]		
Post-M&A indicator			-0.594*	-0.669+
			[0.25]	[0.33]
Age controls	Yes		Yes	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
Observations	1530	1529	1529	688
Within R^2	0.543	0.279	0.281	0.284

(domestic) concentration as well as expected sales growth at the time of M&A, large mergers result in lower investment. Column 2 measures M&A booms with an indicator, while column 3 considers years 3 to 5 following M&A booms – consistent with a relatively long-term effect of M&A on K . We use the Compustat Herfindahl – as opposed to the import-adjusted Herfindahl – to include the 1980's M&A wave and because domestic M&A deals affect domestic concentration.²⁸ We lag M&A booms (and concentration/sales measures) to account for the year of M&A completion and the (relatively) slow adjustment of investment policies. Column 4 shows that results are robust over the more recent period, while controlling for import adjusted Herfindahls available in more recent years.

temporary and must be tested using investment. M&As are somewhere in between. While merger deals may be permanent, ongoing entry and growth of new firms may offset the effects on concentration. To be consistent, we thus consider I/K over a multi-year period following M&A booms.

²⁸We cannot use census-based measures of concentration because they are available only every five years, and we are interested in sharp changes to concentration in the years surrounding M&A booms.

4 Conclusion

US industries have become more concentrated. We argue that rising concentration in the U.S. reflects declining domestic competition (DDC) – not increasing efficient scale (EFS) – and that DDC is (partly) responsible for the low rate of investment in the U.S. Our argument for DDC rests on three pieces of evidence. First, industry-level concentration, profitability and investment trends in Europe differ from those in the US, despite the use of similar technologies across the regions, and consistent with differential anti-trust enforcement. Second, the relationship between concentration and industry productivity has been zero or negative in the 2000s. Finally, leaders invest less in physical and intangible assets in concentrated industries.

We then show that competition – actual or via the threat of entry – has a positive causal impact on investment, in particular by industry leaders. We test this idea using the well-known China Shock, as well as a model of noisy entry. We find that leaders react to exogenous increases in competition by increasing investment, or, reciprocally, that leaders decrease investment when competition decreases. Finally, we show that, controlling for smooth industry trends, investment decreases sharply following bursts of M&A activity.

If these conclusions are correct, they carry significant welfare implications. Decreasing competition leads to higher markups, lower real wages, and a lower labor share. In macro-economic models, the welfare losses from an investment gap driven by decreasing competition can be large. For instance, Jones and Philippon (2016) calibrate a standard DSGE model to study the macro-economic effects of declining competition during the 2000's. They find that the capital stock is 5% to 10% lower and that the Zero Lower Bound (ZLB) binds for 2 more years than under constant competition.

References

- Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl (2009, feb). The effects of entry on incumbent innovation and productivity. *Review of Economics and Statistics* 91(1), 20–32.
- Alexander, L. and J. Eberly (2016). Investment hollowing out. *Working Paper*.
- Anderson, K., C. Brooks, and A. Katsaris (2010, jun). Speculative bubbles in the s&p 500: Was the tech bubble confined to the tech sector? *Journal of Empirical Finance* 17(3), 345–361.
- Andrade, G., M. Mitchell, and E. Stafford (2001, may). New evidence and perspectives on mergers. *Journal of Economic Perspectives* 15(2), 103–120.
- Andrade, G. and E. Stafford (2004, jan). Investigating the economic role of mergers. *Journal of Corporate Finance* 10(1), 1–36.
- Asturias, J., S. Hur, T. Kehoe, and K. Ruhl (2017, feb). Firm entry and exit and aggregate growth. Technical report, Mimeo.
- Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu (2016, December). Foreign competition and domestic innovation: Evidence from u.s. patents. Working Paper 22879, National Bureau of Economic Research.
- Autor, D., D. Dorn, L. Katz, C. Patterson, and J. V. Reenen (2017a, jan). Concentrating on the fall of the labor share. Technical report, mimeo.
- Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. V. Reenen (2017b, May). The fall of the labor share and the rise of superstar firms. Working Paper 23396, National Bureau of Economic Research.
- Autor, D. H., D. Dorn, and G. H. Hanson (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review* 103(6), 2121–2168.
- Autor, D. H., D. Dorn, and G. H. Hanson (2016, oct). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics* 8(1), 205–240.
- Barkai, S. (2017). Declining labor and capital shares. University of Chicago.
- Bernard, A., J. B. Jensen, and P. K. Schott (2006). Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of us manufacturing plants. *Journal of International Economics*.
- Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2012). The empirics of firm heterogeneity and international trade. *Annual Review of Economics* Vol. 4(1), 283–313.
- Blonigen, B. A. and J. R. Pierce (2016, October). Evidence for the effects of mergers on market power and efficiency. Working Paper 22750, National Bureau of Economic Research.

- Bloom, N., M. Draca, and J. Van Reenen (2015). Trade induced technical change: The impact of chinese imports on innovation, diffusion and productivity. *Review of Economic Studies*.
- Bronnenberg, B. J., J.-P. H. Dubé, and M. Gentzkow (2012, oct). The evolution of brand preferences: Evidence from consumer migration. *American Economic Review* 102(6), 2472–2508.
- CEA (2016, April). Benefits of competition and indicators of market power. Issue Brief.
- Comin, D. and T. Philippon (2005). The rise in firm-level volatility: Causes and consequences. In M. Gertler and K. Rogoff (Eds.), *Macroeconomics Annual*, Cambridge. NBER.
- Corhay, A., H. Kung, and L. Schmid (2017). Competition, markups and predictable returns. Working Paper.
- Corrado, C. A. and C. R. Hulten (2010, May). How do you measure a "technological revolution"? *American Economic Review* 100(2), 99–104.
- Davis, S., J. Haltiwanger, R. Jarmin, and J. Miranda (2006). Volatility and dispersion in business growth rates: Publicly traded versus privately held firms. In D. Acemoglu, K. Rogoff, and M. Woodford (Eds.), *Macroeconomics Annual*, Cambridge. NBER.
- De-Loecker, J. and J. Eeckhout (2017). The rise of market power and the macroeconomic implications.
- Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2015, November). Where has all the skewness gone? the decline in high-growth (young) firms in the u.s. Working Papers 15-43, Center for Economic Studies, U.S. Census Bureau.
- Doms, M. C. (2004). The boom and bust in information technology investment. *Economic Review*, 19–34.
- Dotting, R., G. Gutiérrez, and T. Philippon (2017). Is there an investment gap in advanced economies? if so, why? mimeo.
- Economist, T. (2017). A lack of competition explains the flaws in american aviation.
- Faccio, M. and L. Zingales (2017, January). Political determinants of competition in the mobile telecommunication industry. Working Paper 23041, National Bureau of Economic Research.
- Feenstra, R., H. Ma, and Y. Xu (2017, March). The china syndrome: Local labor market effects of import competition in the united states: Comment. Working paper.
- Feenstra, R. C. and D. E. Weinstein (2017). Globalization, markups and u.s. welfare. *Journal of Political Economy*.
- Fernald, J. G., R. E. Hall, J. H. Stock, and M. W. Watson (2017, 2017). The disappointing recovery of output after 2009. *Brookings Papers on Economic Activity*.

- Frésard, L. and P. Valta (2015). How does corporate investment respond to increased entry threat? *The Review of Corporate Finance Studies*.
- Furman, J. (2015). Business investment in the united states: Facts, explanations, puzzles, and policies. Technical report, Council of Economic Advisers.
- Gilbert, R. (2006). Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate? In *Innovation Policy and the Economy, Volume 6*, NBER Chapters, pp. 159–215. National Bureau of Economic Research, Inc.
- Gompers, P. and J. Lerner (2001, may). The venture capital revolution. *Journal of Economic Perspectives* 15(2), 145–168.
- Gordon, R. (2005, nov). The 1920s and the 1990s in mutual reflection. Technical report.
- Grullon, G., Y. Larkin, and R. Michaely (2016). Are us industries becoming more concentrated. Technical report, Working paper.
- Gutiérrez, G. and T. Philippon (2017a). How the us lost its competitive edge.
- Gutiérrez, G. and T. Philippon (2017b). Investment-less growth: An empirical investigation. *Brookings Papers on Economic Activity Fall*.
- Hall, R. E. (2015, jan). Quantifying the lasting harm to the US economy from the financial crisis. *NBER Macroeconomics Annual* 29(1), 71–128.
- Haltiwanger, J., R. Jarmin, and J. Miranda (2011, March). Historically large decline in job creation from startup and existing firms in the 2008–2009 recession. Census Bureau Report.
- Hoberg, G. and G. Phillips (2017). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*.
- Hobijn, B. and B. Jovanovic (2001, dec). The information-technology revolution and the stock market: Evidence. *American Economic Review* 91(5), 1203–1220.
- Hogendorn, C. (2011, dec). Excessive(?) entry of national telecom networks, 1990–2001. *Telecommunications Policy* 35(11), 920–932.
- Hombert, J. and A. Matray (2015). Can innovation help u.s. manufacturing firms escape import competition from china? Technical report, HEC Paris Research Paper No. FIN-2015-1075.
- IMF (2014). Private investment: What’s the holdup? *Chapter 4, World Economic Outlook*.
- Jones, C. and T. Philippon (2016). The secular stagnation of investment?
- Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2015). How to construct nationally representative firm level data from the orbis global database. Technical report, National Bureau of Economic Research.

- Kaplan, S. N. (2000). *Introduction to Mergers and Productivity*.
- Kehrig, M. and N. Vincent (2017). Growing productivity without growing wages: The micro-level anatomy of the aggregate labor share decline. *Unpublished*.
- Klette, T. J. and S. Kortum (2004). Innovating firms and aggregate innovation. *Journal of Political Economy* 112(5), 986–1018.
- Lee, D. W., H.-H. Shin, and R. M. Stulz (2016, September). Why does capital no longer flow more to the industries with the best growth opportunities? *Fisher College of Business Working Paper 2016(15)*.
- Lewis, B., A. Augereau, M. Cho, B. Johnson, B. Neiman, G. Olazabal, M. Sandler, S. Schrauf, K. Stange, A. Tilton, E. Xin, B. Regout, A. Webb, M. Nevens, L. Mendonca, V. Palmade, G. Hughes, and J. Manyika (2001). Us productivity growth, 1995 - 2000.
- Mongey, S. (2016). Market structure and monetary non-neutrality. *Working paper*.
- Nekarda, C. and V. Ramey (2013, jun). The cyclical behavior of the price-cost markup. Technical report, NBER Working paper.
- NVCA (2010). The economic importance of venture capital backed companies to the u.s. economy. Technical report, National Venture Capital Association, Thomson Reuters.
- Peters, R. H. and L. A. Taylor (2016). Intangible capital and the investment-q relation. *Journal of Financial Economics*.
- Pierce, J. R. and P. K. Schott (2012). A concordance between ten-digit u.s. harmonized system codes and sic/naics product classes and industries.
- Pierce, J. R. and P. K. Schott (2016, jul). The surprisingly swift decline of US manufacturing employment. *American Economic Review* 106(7), 1632–1662.
- Rotemberg, J. and M. Woodford (1999). The cyclical behavior of prices and costs. In J. B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, Volume 1B. Elsevier Science, North Holland.
- Scheinkman, J. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of Political Economy* 111, 1183–1219.
- Varela, L. (2017). Reallocation, competition and productivity: Evidence from a financial liberalization episode. Working Papers 2015-042-23, Department of Economics, University of Houston.