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DECLINING COMPETITION AND INVESTMENT IN THE U.S.

Germán Gutiérrez
Thomas Philippon

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ABSTRACT

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Germán Gutiérrez
NYU Stern School of Business
44 West 4th Street
KMC 9-190
New York, NY 10012
ggutierr@stern.nyu.ed

Thomas Philippon
New York University
Stern School of Business
44 West 4th Street, Suite 9-190
New York, NY 10012-1126
and NBER
tphilipp@stern.nyu.edu

Declining Competition and Investment in the U.S.*

Germán Gutiérrez† and Thomas Philippon‡

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Abstract

The U.S. business sector has under-invested relative to Tobin's Q since the early 2000's. We argue that declining competition is partly responsible for this phenomenon. We use a combination of natural experiments and instrumental variables to establish a causal relationship between competition and investment. Within manufacturing, we show that industry leaders invest and innovate more in response to exogenous changes in Chinese competition. Beyond manufacturing we show that excess entry in the late 1990's, which is orthogonal to demand shocks in the 2000's, predicts higher industry investment given Q. Finally, we provide some evidence that the increase in concentration can be explained by increasing regulations.

Two important stylized facts have emerged in recent years regarding the U.S. corporate sector. The first fact is that there has been a broad decrease in turnover and a broad increase in concentration across most U.S. industries. This fact is illustrated in Figure 1. We discuss later how this fact was progressively uncovered by various researchers in the literature review. For now, we simply refer to Decker et al. (2014) for a discussion of the decline in turnover, and to CEA (2016) for a discussion of the increase in concentration. We also discuss the details of the data later in the paper and in the Appendix. The top chart in Figure 1 shows the decline in the establishment entry and exit rates as reported by the U.S. Census Bureau's Business Dynamics Statistics (BDS). Decker et al. (2015) show that the decline occurs across all sectors in the 2000's, including the traditionally high-growth information technology sector. The bottom chart in Figure 1 shows the average Herfindahl and Modified-Herfindahl (adjusted for common ownership, as defined in Salop and O'Brien (2000) and implemented by Azar et al. (2016)) across all BEA industries in Compustat. Concentration decreases in the early 1990's as more firms go public and enter Compustat. But it increases rapidly thereafter. The modified Herfindahl rises even faster than the traditional Herfindahl because of

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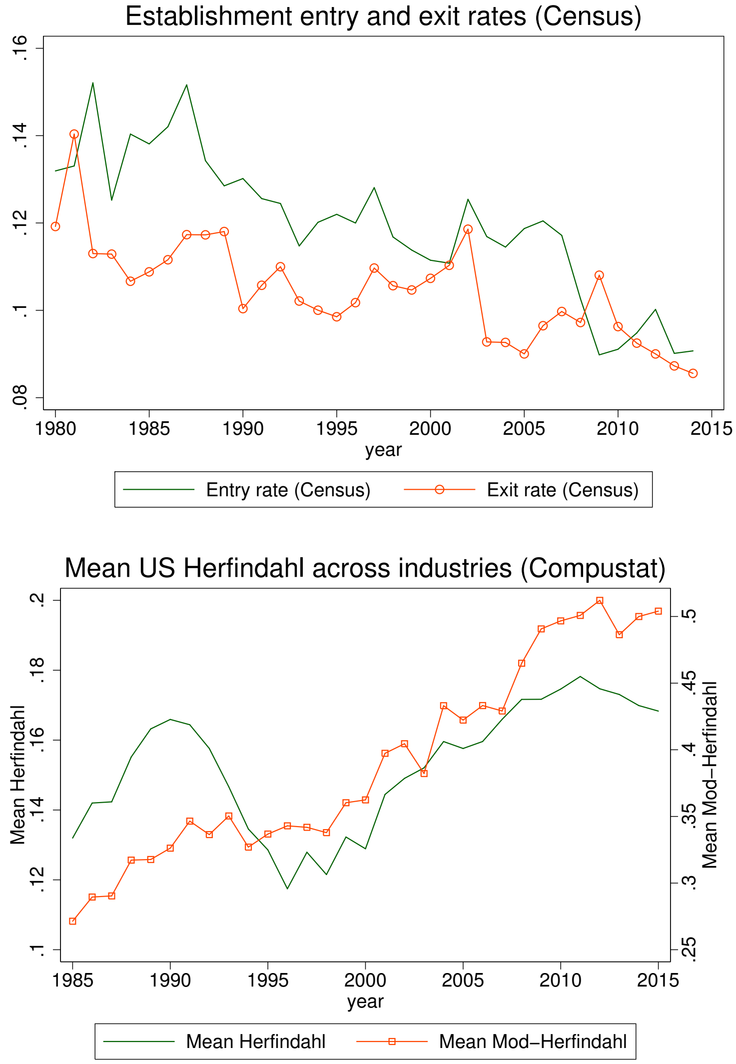
†New York University

‡New York University, CEPR and NBER

Figure 1: Firm entry, exit and concentration



Note: Annual data. Top chart based on U.S. Economic Census. Bottom chart based on Compustat.

the rapid increase in institutional ownership and increased concentration in the asset management industry.

The second stylized fact is that corporate investment has been unexpectedly weak in recent years. The top chart in Figure 2 shows the aggregate net investment rate for the non financial business sector along with the fitted value for a regression on (lagged) Q from 1990 to 2001. The bottom chart shows the regression residuals (by year and cumulative) from 1990 to 2015. Both charts show that investment has been low relative to Q since sometime in the early 2000's and by 2015, the cumulative under-investment is more than 10% of capital.[1]

[1] There are several ways to show the same fact. Gutiérrez and Philippon (2016) shows that investment is weak relative to profits, and also plot the yearly residual from cross-sectional investment regressions, using industry and firm level data. These show in a non-parametric way that investment has been weak relative to Q since the early 2000's. Jones and Philippon (2016) calibrate a standard macro-economic model assuming that the investment gap is

The weakness of investment does not only appear in the U.S. There is widespread agreement that investment, and investment growth, has decreased across Advanced Economies including Europe (IMF, 2014). The decline in investment has been discussed in academic and policy papers (e.g. Bussiere et al. 2015, Kose et al., 2017). The existing literature argues that low investment is explained by weak aggregate demand (Bussiere et al., 2015), or by financial constraints and increased uncertainty, particularly for stressed economies (Kalemli-Ozcan et al., 2015).

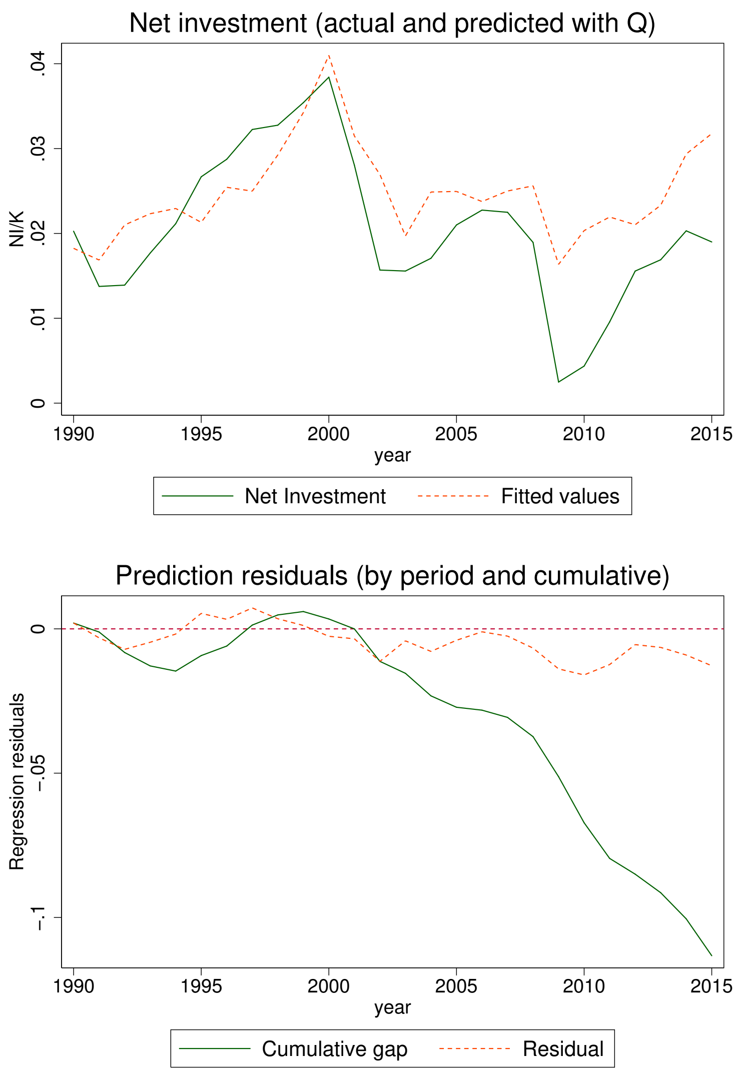
The goal of our paper is to propose and defend another explanation for the low investment rate in the U.S. We argue that increasing concentration and decreasing competition in many industries explains an important share of the decline in investment. Furman (2015) emphasizes the weakness of corporate fixed investment and discusses some selected components, such as drilling investment. He points out that low investment has coincided with high private returns to capital, implying an increase in the payout rate (dividends and shares buyback). He also argues that "the distribution of returns to capital has grown increasingly skewed and the high returns increasingly persistent. This potentially reflects the rising influence of economic rents and barriers to competition, as some corporations make substantial returns year after year." Gutiérrez and Philippon (2016) show that investment is weak relative to measures of profitability and valuation, and that this weakness starts in the early 2000's. Importantly, investment is not low *because* Tobin's Q is low, but rather *despite* high Q. This simple observation rules out a long list of potential explanations, including low expected productivity growth or low expected demand. Gutiérrez and Philippon (2016) also find that financial frictions, measurement errors (due to the rise of intangibles, etc.), or globalization do not fully explain the lack of investment. Lee et al. (2016) find that industries that receive more funds have a higher industry Q until the mid-1990's, but not since then.

These two stylized facts – the increase in concentration and relative weakness of corporate investment – are not controversial. But their interpretation and implications are. There is little agreement about the causes of these evolutions, and even less about their consequences. For instance, there is no paper showing that the rise in concentration has been detrimental to the real economy. The increase in concentration might not be large enough to matter in the aggregate, and it might be partly compensated by foreign competition such that domestic Herfindahl indexes might no longer meaningfully measure competition. Moreover, it is impossible to assess the welfare consequences of the decline in investment without understanding the cause of the decline. These issues also connect our work to the recent controversy regarding the impact of trade with China for the U.S. economy (Autor et al., 2013; Pierce and Schott, 2016; Feenstra et al., 2017), which we discuss in detail below.

The Competition Hypothesis In this paper, we argue that the two stylized facts are linked and we provide evidence on the underlying economic forces. More precisely, we argue that the rise in concentration is responsible for a significant part of the gap in corporate investment. Before diving into the data and identification issues, however, it is important to clarify some theoretical

driven by declining competition. They find that the capital stock is 5% to 10% lower than it should be. Hall (2015) studies deviations from prior trends following the Financial crisis. He estimates that the capital stock at the end of 2013 was 13.2% below trend (i.e., 13.2% below the expected level had the economy grown along the pre-crisis trend).

Figure 2: Net Investment vs. Q



Notes: Annual data. Net investment and Q for Non Financial Business sector from US Flow of Funds accounts.

predictions. Any model of investment and competition has to struggle with (at least) two complex issues: (i) the exact definition of investment, i.e., how to include intellectual property; and (ii) the details of imperfect competition, monopolistic or oligopolistic, with or without free entry, foreign versus domestic, etc. If we consider a neoclassical production function with constant returns to scale, it is rather straightforward to argue that capital demand decreases when competition decreases, in the same way labor demand or any other factor demand decreases. On the other hand, if we include R&D and other intangible investment, then we need to consider the relationship between competition and innovation. As Gilbert (2006) explains, this relationship 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). We argue that a fairly robust prediction in a broad class of models is that an increase in the competitiveness of domestic entrants increases industry investment by increasing neck-and-neck competition.

The analysis is more nuanced in an open economy, and it becomes crucial to distinguish between leaders and laggards. Consider an industry where leaders are significantly more productive than domestic laggards. As a result, they face weak domestic competition. Now imagine that there is entry of foreign firms. The laggards are likely to go out of business, or at least to shrink significantly. The leaders, on the other hand, might choose to invest and innovate more, rather than less, either because their customers now have better alternative options (the elasticity effect) or because they want to re-establish their leadership (the escape-competition effect). If we aggregate domestic firms, we can see that the impact of foreign competition on domestic investment is ambiguous, but that we can test the differential responses of leaders and laggards.

In Section 1, we show that the investment gap is primarily driven by industry leaders. These firms exhibit higher profit margins but lower investment and lower capital. We then use a mixture of firm- and industry-level data to test the implications of higher U.S. and foreign competition on both leader and industry investment.

Identification Issue The challenge for the competition hypothesis that we put forward is to establish a *causal* connection between competition and investment. The main identification issue is that firm entry and exit are endogenous. We present later a model of entry and competition where we derive an explicit formula for the econometric bias as a function of the shocks and the structural parameters, but the intuition is simple enough that we can explain it here. 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. What would we expect to see? Presumably, there would be immediate entry of new firms in the industry. There would also be more investment for an extended period of time. As a result, we would measure a decrease in concentration (or in Herfindahl indexes) followed and/or accompanied by an increase in investment by all firms, both new entrants and incumbents. Anticipated demand shocks, then, could explain the cross sectional evidence in Gutiérrez and Philippon (2016). And similar explanations could arise from anticipated productivity shocks. The existing evidence is therefore fundamentally inconclusive.

Our identification strategy is based on a combination of natural experiments (with clean identification but limited scope) and instrumental variables (with weaker identification but applicable across all firms/industries). Our natural experiment is import competition from China, using either the import penetration measure of Autor et al. (2016) or the transition to Permanent Normal-Trade-Relations proposed by Pierce and Schott (2016). This allows us to test the effect of (foreign) competition on U.S. industry leaders. The results align well with the prediction of the models discussed above. On the one hand, Chinese competition leads to a decrease in the number of U.S. firms as the weaker ones exit. On the other hand, industry leaders *increase* investment and employment, and we observe some capital deepening. These two opposite forces produce an ambiguous effect on overall domestic investment.

The Chinese natural experiment offers clean identification, but its external validity is problematic. It identifies an *increase* in competition for particular sector and a limited set of firms, as opposed to a broad *decline* in competition for the whole economy. To identify the impact of competition more broadly, we need an instrument for industry concentration that is orthogonal to future demand and productivity shocks, as explained earlier. We argue that excess entry in the 1990's – defined as entry relative to current and expected fundamentals – satisfies this requirement. 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). We document extreme cross-sectional differences in entry rates and we show that our measure of excess entry is indeed orthogonal to shocks that occur in the 2000's. Using excess entry as an instrument for differences in concentration across industries, we find that concentration lowers investment and causes a gap between Q and investment.

Finally, we shed some light on why entry and exit have decreased and why concentration has risen over the past 20 years. There are three broad types of explanations: (i) this could represent a (potentially efficient) response to technological changes (IT,..) that increase the optimal scope of firms (winner-takes-all equilibrium,..) ; (ii) this could be due to demographic changes (aging,..) in the population of potential entrepreneurs; (iii) or this could be due to lax enforcement of anti-trust (merger approvals,..) or regulations that increase barriers to entry. We find support for the regulation hypothesis: increasing regulation predicts increasing concentration across time and industries. We find limited support for the superstar firm hypothesis and for the demographics hypothesis: concentration is somewhat correlated with future productivity, but not after 2000; and demographic measures do not yield robust relations.

Related Literature. Our paper is related to several strands of literature. We highlight the key references in this section; and discuss relevant facts throughout the paper.

Third, our paper is related to a growing literature studying recent trends on competition, concentration, and entry. There are many ways to think about competition and business dynamism, and it is difficult to figure out exactly who mentioned first a potential decline in these variables for the U.S. economy. Perhaps the earliest contribution to the debate came from the study of firm volatility, even though this research was initially not focused on competition in the goods market. In the late 1990's and early 2000's, researchers noticed increased volatility at the firm level. The trend was first discovered in stock returns, Campbell et al. (2001), and then in all kinds of real variables. Comin and Philippon (2005), for instance, find that "firm volatility increases after deregulation [and] is linked to research and development spending." However, just as these papers were being published, the trends started to reverse. Davis et al. (2006) find a secular decline in job flows. They also show that the rise in firm volatility is concentrated among publicly traded firms. Much of the rise in publicly traded firm volatility during the 1990's was a consequence of the boom in IPOs, both because young firms are more volatile, and because they challenge incumbents.

Then, using the Census data, researchers started to focus on the secular decline in job flows. Haltiwanger et al. (2011) write: "It is, however, noticeable that job creation and destruction both exhibit a downward trend over the past few decades." Decker et al. (2014) provide a fuller picture and conclude that business dynamism has been declining. The trend has been particularly severe in recent years. In fact, 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.

Moving from flows (firm volatility, entry, exit, IPOs, job creation and destruction,..) to stocks (concentration, Herfindahl,..) also happened in stages. The rise in concentration was first noted in industry studies (banking, agriculture, see CEA, 2016 for references). The first broad and systematic study appears to come from the Council of Economic Advisors CEA (2016) who document that the majority of industries have seen increases in the revenue share enjoyed by the 50 largest firms between 1997 and 2012. Similarly, Grullon et al. (2016) study changes in industry concentration. They find that "more than three-fourths of U.S. industries have experienced an increase in concentration levels over the last two decades;" and that firms in industries that have become more concentrated have enjoyed higher profit margins, positive abnormal stock returns, and more profitable M&A deals.Autor et al. (2017) link the increase in concentration with the rise of more productive, superstar firms. Mongey (2016); Bronnenberg et al. (2012) highlight concentration patterns at the product market level. And Nekarda and Ramey (2013) (and others) study increases in price-cost mark-ups over time. Last, Gutiérrez and Philippon (2017a) compare concentration trends between the U.S. and Europe. They find that concentration has increased in the U.S. while it has remained stable (or decreased) in Europe. They also find that industries that have concentrated in the U.S. decreased investment more than the corresponding industries in Europe. Faccio and Zingales (2017) show that competition in the mobile telecommunication industry is heavily influenced by political factors, and that, in recent years, many countries have adopted more competition-friendly policies than the U.S.

Second, our paper contributes to the growing literature studying the recent under-investment in the U.S. economy. We provide a brief summary of key papers, and refer the reader to Gutiérrez and Philippon

(2016) for a more comprehensive literature review. The decline in investment has been discussed in policy papers (Furman, 2015; IMF, 2014), especially in the context of a perceived decrease in competition in the goods market (CEA, 2016); as well as academic papers (see, for example, Hall (2015); Alexander and Eberly (2016)). Gutiérrez and Philippon (2016) show that the investment residuals – at the firm level and at the industry level – are well explained by measures of competition. Controlling for current market conditions, industries with less competition and more concentration (traditional or due to common ownership) invest less.[2]

Lee et al. (2016) find that industries that receive more funds have a higher industry Q until the mid-1990's, but not since then. The change in the allocation of capital is explained by a decrease in capital expenditures and an increase in stock repurchases by firms in high Q industries since the mid-1990's. Relatedly, Alexander and Eberly (2016) study the implications of the rise of intangibles on investment. And Jones and Philippon (2016) explore the macro-economic consequences of decreased competition in a DSGE model with time-varying parameters and an occasionally binding zero lower bound. Kose et al. (2017) study weak investment growth globally, including emerging markets. Several other papers study under-investment in Europe, including Bussiere et al. (2015); Buca and Vermeulen (2015); Gutiérrez and Philippon (2017a).

Third, this paper is related to a large literature that aims to explain the relationship between competition, innovation and investment. See Gilbert (2006) for a relatively recent survey. Of particular relevance to our paper, are Aghion et al. (2005, 2009); Aghion and Schankerman (2004). Aghion et al. (2009) introduces the Schumpeterian models of competition; and Aghion et al. (2009) study how foreign firm entry affects investment and innovation incentives of incumbent firms. Relatedly, Asturias et al. (2017) studies firm entry and exit patterns in periods of slow and high productivity growth; and 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.

Last, our paper is related to the effect of import exposure on employment and innovation – particularly from China. The literature is large, so we highlight the key papers. See Bernard et al. (2012) for a literature review. Bloom N and Reenen (2015) examine the impact of Chinese import competition on patenting, IT and TFP across twelve European countries. They argue that the absolute volume of innovation increases within the firms most affected by Chinese imports; and

[2] They also use industry- and firm-level data to test whether under-investment relative to Q is driven by (i) financial frictions, (ii) measurement error (due to the rise of intangibles, globalization, etc), (iii) decreased competition (due to technology or regulation), or (iv) tightened governance and/or increased short-termism. They find that proxies for competition and ownership explain the bulk of the investment gap, across industries and across firms. Measurement error due to the rise of intangibles explain some but not all patterns. Controlling for current market conditions, industries with less entry and more concentration (traditional or due to common ownership) invest less. Within each industry-year, the investment gap is driven by firms owned by quasi-indexers and located in industries with more concentration/more common ownership. These firms spend a disproportionate amount of free cash flows buying back their shares. We do not discuss governance here because the natural experiments and instruments that we use are focused on competition. One should keep in mind, however, that there are important interactions between governance and competition. For instance, Giroud and Mueller (2010) shows that the impact of governance is stronger in noncompetitive industries. A companion paper studies the causality between increased quasi-indexer ownership and investment; as well as the interaction between ownership and competition (Gutiérrez and Philippon, 2017b).

that Chinese import competition led to (i) increased technical change within firms and (ii) a re-allocation of employment towards more technologically advanced firms. Autor et al. (2016) study how rising import competition from China affected U.S. patenting activity. They control for secular trends in patenting activities, and find the opposite: that increased import exposure led to a reduction in patent production. Pierce and Schott (2016); Autor et al. (2016); Acemoglu et al. (2016); Autor et al. (2016); Feenstra et al. (2017) study the effects of Chinese import exposure on U.S. manufacturing employment. They show that a large portion of the reduction of U.S. manufacturing employment can be explained by Chinese import competition. Some of these papers briefly study capital and investment in addition to employment. Consistent with our results, they find that increased Chinese competition led to reductions in capital for the 'average' firm. Frésard and Valta (2015) study the effect of tariff reductions on capital expenditures, with a focus on market structure.[3] Feenstra and Weinstein (2010) estimate the impact of globalization on mark-ups, and conclude that mark-ups decreased in industries affected by foreign competition.

All of the above papers on import competition analyze the unconditional effect of trade shocks on firm and industry-level outcomes. By contrast, we focus on conditional outcomes – namely how increased Chinese competition affects leaders and laggards differently. To our knowledge, only Hombert and Matray (2015); Bernard and Schott (2006) and Amore and Zaldokas (2015) study conditional outcomes. Hombert and Matray (2015) show that R&D-intensive firms are better able to cope with Chinese competition: they exhibit higher sales growth, profitability and capital expenditures than low-R&D firms. Bernard and Schott (2006)show that capital-intensive plants and industries are more likely to survive and grow in the wake of import competition. And Amore and Zaldokas (2015) argue that firms with worse corporate governance are more affected by foreign competition.

The remainder of this paper is organized as follows. Section 1 discusses key empirical facts regarding competition and investment. It argues that the investment gap is largely explained by industry leaders. Section 2 presents a model of competition and discusses its implications for investment. Section 3 discusses our dataset. Section 4 presents the tests and results used to establish causality between competition and investment. Section 5 discusses some (correlation) analyses aimed at explaining the rise in Concentration. Section 6 concludes.

1 Three Facts about Concentration and Investment

This section presents three facts related to concentration, mark-ups and investment that help motivate our analysis.

[3] They consider U.S. tariff reductions between 1974 and 2015 for a variety of countries

1.1 Fact 1: Investment Gap Affects Primarily Concentrating Industries

Figure 3 shows that the capital gap is primarily driven by concentrating industries. Namely, we plot the coefficients $\alpha_{1,t}$ and $\alpha_{2,t}$ from the following industry-level regression

$$\begin{aligned} log\left(\frac{K_{j,t}}{K_{j,00}}\right) &= \beta_1 \overline{med\,Q_{j,00,t}} + \beta_2 Mean\,log(Age_{j,t-1}) \\ &+ \alpha_{1,t} 1\{\text{Top 5 }\Delta\text{Herfindahl}\} + \alpha_{2,t} 1\{\text{Bottom 5 }\Delta\text{Herfindahl}\} \end{aligned} \tag{1}$$

where $K_{j,t}$ denotes total capital in industry j at time t; $\overline{med\,Q_{j,00,t}}$ denotes the average value, by year, of the median Q across all firms in industry j from 2000 to time t; and $Mean\,log(Age_{j,t-1})$ denotes the average log-age across all firms in industry j at time t. Thus, $\alpha_{1,t}$ measures the capital gap (controlling for Q and average firm age) for the five industries that exhibit the largest increase in concentration; and $\alpha_{2,t}$ measures the capital gap for the five industries with the smallest increase in Herfindahl.[4] As shown, the capital gap against Q is strongly negative for industries that have become more concentrated and positive for industries that have become less concentrated. Granted, these results are subject to the identification issue listed above; and they may be affected by foreign competition. But they do suggest that the investment gap is driven by concentrating industries. The remainder of the paper aims to address the identification concerns.

These results are consistent with Gutiérrez and Philippon (2017a), who compare investment patterns between the U.S. and Europe across industries that have become concentrated in the U.S. They find that investment in these industries decreased substantially more in the U.S. than in Europe.

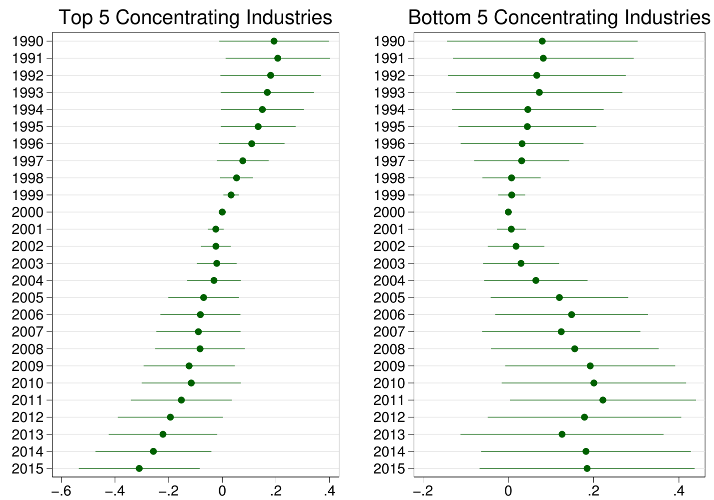
1.2 Fact 2: Profit Margins Have Increased for Industry Leaders

The second fact is that mark-ups have increased. This is true when measured using price-cost margins (also known as the Lerner Index) as well as estimating user cost of labor and capital. For instance, Figure 4 shows the aggregate Lerner index across all Compustat firms, along with the weighted average Modified-Herfindahl for the U.S. economy (weighted by industry sales). Like Grullon et al. (2016), we measure price-cost margins as the operating income before depreciation minus depreciation divided by sales. Beyond the clear cyclical patterns, the Lerner index exhibits a consistent upward trend that aligns with the rise in the Modified-Herfindahl.

Figure 5 shows the Lerner index of leaders and laggards separately. Leaders include those firms with the highest market value, which combined account for 33% of the market value in each industry and year. Laggards are those firms with the lowest market value that combined account for 33%

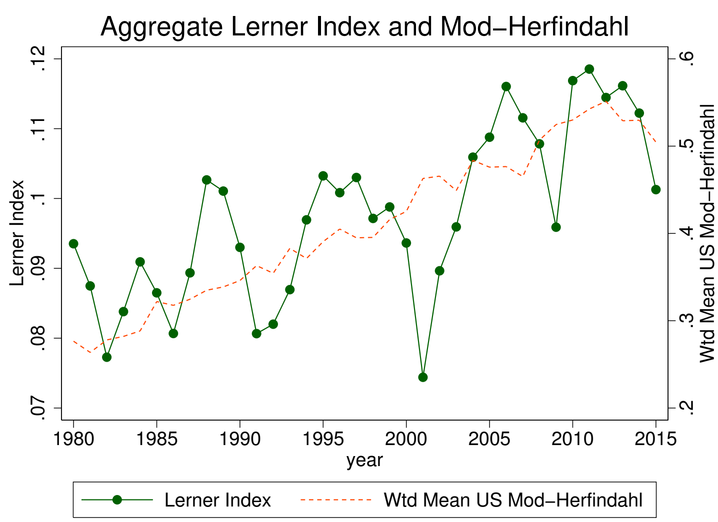
[4] We identify concentrating / non-concentrating industries based on the absolute change in Herfindahl from 2000 to 2015, but different definitions (e.g., based on relative changes) yield similar results. The top 5 concentrating industries include Agriculture, Inf. publishing, Nondurable Textile, Nondurable Printing and Inf. motion. The bottom 5 concentrating industries include Prof. services, Mining support, Nondurable Petroleum, Transportation pipeline and Educational Services. Results are robust (albeit less significant) to excluding Nondurable Textile from the set of concentrating industries given the influence of foreign competition.

Figure 3: Capital Gap for Concentrating Industries



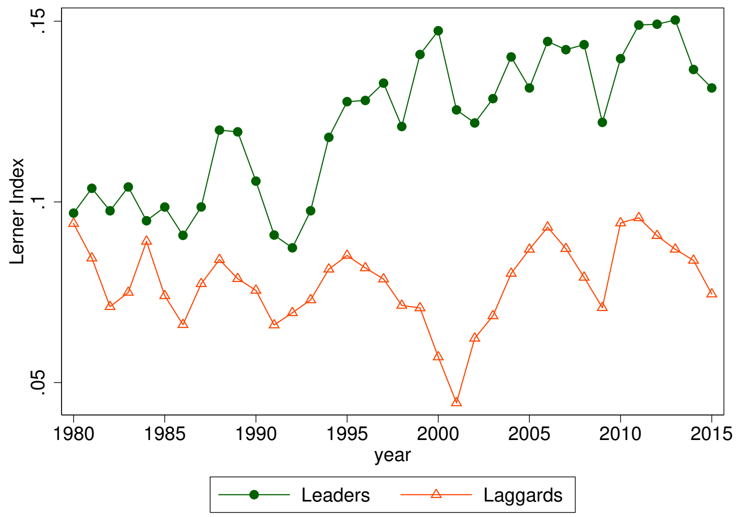
Notes: Annual data from BEA (capital stock) and Compustat (Q, age and Herfindahl). Left chart plots $\alpha_{1,t}$ as estimated from regression 1. It measures the capital gap (controlling for Q and average firm age) for the five industries that exhibit the largest increase in concentration. Right chart plots $\alpha_{2,t}$ which measures the capital gap for the five industries with the smallest increase in concentration. See text for additional details.

Figure 4: Lerner Index and Concentration



Notes: Annual data from Compustat.

Figure 5: Lerner Index: Leaders vs. Laggards



Notes: Annual data. Lerner Index defined as operating income before depreciation minus depreciation divided by sales. Leaders are defined as those firms with the highest market value that, combined, account for 33% of Market Value within each industry and year. Laggards account for the bottom 33% of Market Value.

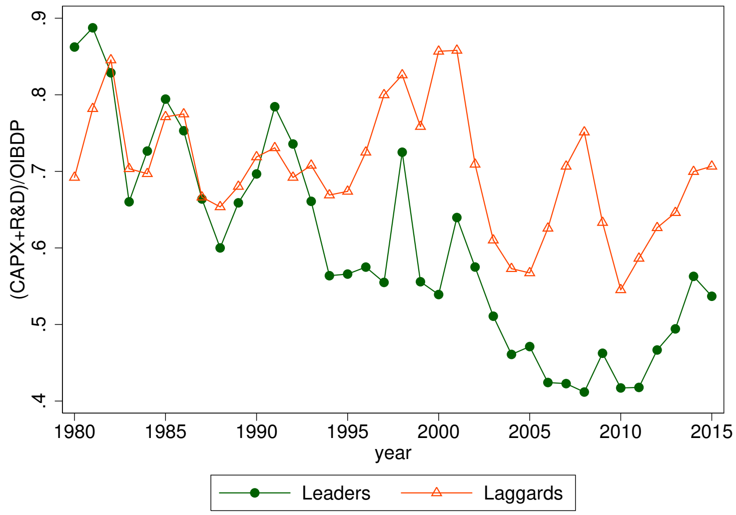
of industry market value in each year. As shown, the Lerner index of leaders started to increase in the mid-1990's and reached it's highest level in 2011-2013. The timing of rising mark-ups coincides with the rise in the U.S. Herfindahl. As shown in Figure 1, the Compustat-based U.S. Herfindahl reaches its lowest level in the mid-1990's and rises rapidly thereafter. By contrast, the Lerner index of Laggards has remained essentially stable over the past 35 years.

We must acknowledge that the Lerner index is not a perfect measure of mark-ups. In particular, it does not recognize that some of the deviation between prices and marginal costs may be due to either efficient use of scale or the need to cover fixed costs.[5] But other methods also suffer problems. For instance, methods following Hall (1988) (including recent methods such as De Loecker and Warzynski (2012)) struggle to account for changing capital shares – a substantial problem when considering long periods, including the recent shift towards intangible capital.

To address some of these weaknesses, we estimate an alternate measure of industry-level mark-ups that roughly follows Barkai (2017) and Caballero et al. (2017). In particular, we estimate the industry-level Equity Risk Premia using Analyst earnings projections; and use it to calculate the capital share of output. We then combine the estimated capital share and the labor share to obtain the profit share of output – a measure of average mark-ups. See Appendix for more details on this calculation. We find that the profit share increased more at industries that have become more concentrated – a finding consistent with Grullon et al. (2016), who show that the Lerner index increased more at industries that have become less competitive.

[5]See Elzinga and Mills (2011) for a discussion. Other key issues include the fact that the Lerner index ignores firms' exercise of monopsony power in factor markets and the effect of upstream market imperfections; the departures from cost-minimizing behavior due to, for example, governance problems; the effects of dynamic competition; and the departures from social optimum when a firm uses non-linear pricing tactics (e.g., bundling).

Figure 6: Gross Investment/Operating Income: Leaders vs. Laggards



Notes: Annual data from Compustat. Leaders (Laggards) include the firms with the highest (lowest) MV that combined account for ~33% of MV within each industry and year.

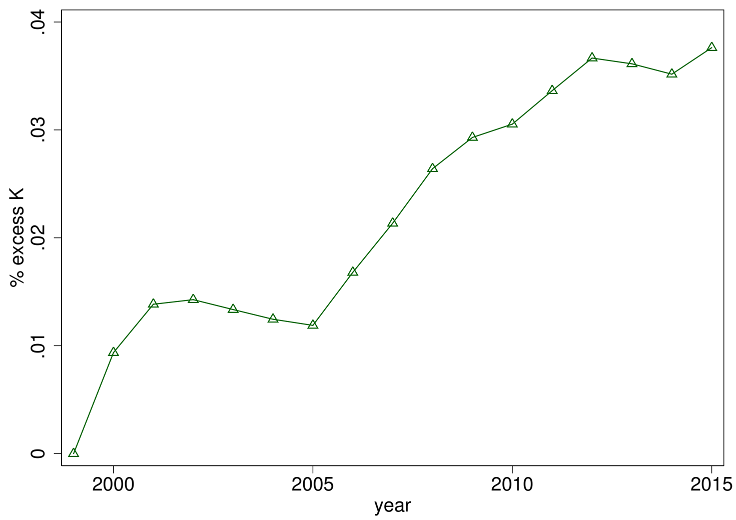
In the end, neither of these estimates is perfect. But they are still informative. And they both suggest that mark-ups increased more at industries that have become more concentrated.

1.3 Fact 3: Leaders Explain the Investment Gap

The third fact is that the investment gap appears to be concentrated at Leaders. Figure 6 shows the ratio of capital expenditures plus R&D divided by operating income before depreciation for leaders and laggards. As shown, the investment of leaders and laggards was largely similar in the 1980's and early 1990's, but starts to diverge thereafter. Investment decreases even further after 2000 reaching less than half it's 1980 level from 2004 to 2011. By contrast, laggards invested a relatively stable share of operating income through 2001. They decreased investment after 2000, but to a much lesser extent than leaders.

Table 1 shows a broader set of investment, capital and profitability measures separating leaders, average firms and laggards. The first row shows the average annual share of CAPX plus R&D contributed by leaders, as a percentage of total CAPX plus R&D across all firms in Compustat. As shown, leaders contributed 35% of CAPX plus R&D, on average, before 1995. Yet they contributed only 29% after 1996. The second row shows the ratio of CAPX plus R&D over operating income before depreciation (the same as Figure 6) for each group of firms; and rows 3 and 4 show the share of PP&E and capital held by the corresponding firms. Here, capital K is the estimated capital stock of Peters and Taylor (2016) which accounts for the value of intangibles. As shown, the share of PP&E and Capital held by leaders decreased by 4-6% from the pre-1995 to the post-1995 period. Row 5 shows that the share of profits received by leaders has remained stable, which combined with the lower share of capital implies a rise in the return on capital. This is shown in row 6. The excess

Figure 7: 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.

return on capital (defined as the ratio of operating income before depreciation to capital, minus the 1Y treasury rate) increased across all firms, but particularly for leaders.

To measure the capital gap due to leaders, Figure 7 shows the percentage increase in the aggregate U.S. capital stock assuming that Compustat leaders continued to invest 35% of CAPX plus R&D from 2000 onward, while the remaining groups invested as observed. As shown, the capital stock would be nearly 4% higher (after accounting for depreciation) today. This is a substantial increase considering that (i) our Compustat sample accounts for 20-25% of aggregate capital and 30-40% of investment for the industries in our sample (see Section 3 for details); and (ii) the average annual net investment rate for the U.S. Non Financial Business sector has been less than 2% since 2002. Indeed 4% accounts for a third of the ~12% gap estimated using the coarse analysis of Figure 2 and the 13.2% estimated by Hall (2015). Lower investment by private leaders, feedback effects from decreased leader investment to laggards, as well as other hypotheses such as governance and measurement error due to the rise of intangibles likely account for the difference.

2 Models of Competition and Investment

The main contribution of our paper is empirical, but we need a model to understand precisely what the endogeneity issue is, and exactly what a valid experiment or a valid instrument would be. In particular, we need a model to clarify the issues of endogenous entry, the timing of information, foreign demand, and the different responses we can expect from industry leaders and laggards in response to the same set of shocks.

Table 1: 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.

	Average from 1980-1995			**Average from 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 CAPX + R&D	**0.35**	0.31	0.34	**0.29**	0.31	0.40	**-0.06**	0.01	0.06
(CAPX+R&D)/OIBDP	0.72	0.67	0.72	0.51	0.57	0.69	**-0.20**	-0.10	-0.03
Share of PP&E	0.34	0.32	0.35	0.30	0.29	0.41	**-0.04**	-0.03	0.06
Share of K	0.33	0.32	0.35	0.27	0.32	0.40	**-0.06**	0.01	0.05
Share of OIBDP	0.35	0.32	0.33	0.34	0.32	0.34	**0.01**	0.00	-0.01
Return on K - 1Y Treas	0.12	0.11	0.10	0.19	0.15	0.12	**0.07**	0.04	0.03

2.1 Monopolistic Competition and Free Entry

Let us start with a discussion of the fundamental identification issue. We use here a simple model of industry equilibrium under monopolistic competition. In addition to clarifying the identification problem, the model illustrates the role of information and suggests a set of potential instruments. The model abstracts from strategic interactions and firm heterogeneity, which we discuss later.

Description of the Model. The model is basically the industry block of a standard macroeconomic model. Firms make entry, investment, and production decisions. The timing is as follows:

- Period $t-1$: pay fixed cost κ^e_{t-1} to become active (or not)
- Period t: active firms are indexed by $i \in [0, N_{t-1}]$
  - Invest $k_{i,t}$;
  - Produce $y_{i,t} = A_t k^{\alpha}_{i,t} l^{1-\alpha}_{i,t}$;

All active firms have the same production function where A_t is productivity and $l_{i,t}$ is the quantity of labor hired by the firm. In terms of interpretation, it is best to think of each period as a few years. We assume that "firms" live for one period, or, equivalently, that the fixed cost κ must be repaid at the end of each period if the firm wants to remain active. The industry demand curve is given by the schedule

$$Y^D_t = D_t P_t^{-\sigma} \tag{2}$$

where D_t is a (stochastic) demand shifter, P_t is the industry price index, and σ is the demand elasticity across industries, which we assume is weakly above unity: $\sigma \geq 1$. Industry output is a CES aggregate of firms' outputs

$$Y^S_t \equiv \left(\int_0^{N_{t-1}} y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{3}$$

where ϵ is the elasticity of substitution across firms within the same industry. It is larger than the between-industry elasticity: $\epsilon > \sigma \geq 1$.[6] The standard Dixit-Stiglitz CES aggregator takes ϵ as an exogenous parameter. It is straightforward to consider a model where ϵ is an increasing function of N_{t-1}, as in Feenstra (2003) for instance. This only reinforces the consequences of entry that we analyze below. For ease of exposition we treat ϵ as a parameter, and we simply point out in the discussion where endogenous firm-level markups matter. The price index is then defined in the usual way as

$$P_t \equiv \left(\int_0^{N_{t-1}} p_{i,t}^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}, \tag{4}$$

and we impose the market clearing condition $Y^D_t = Y^S_t$.

[6] A standard calibration of the New Keynesian model is $\epsilon = 6$, chosen to deliver a steady state markup of 20% (Gali, 2008). The value of σ depends on the level of aggregation. In models with two sectors, home and foreign for instance, it is typical to use σ close to 1. With finer industry definitions σ should be higher, as assumed here.

The Firm's Problem. Let ρ_t be the user cost of capital at time t (i.e., the depreciation rate plus the rate of time preference).[7] The firm's problem is

$$\max_{k_{i,t},l_{i,t},p_{i,t}} p_{i,t}y_{i,t} - w_t l_{i,t} - \rho_t k_{i,t},$$
$$\text{s.t. } y_{i,t} = \left(\frac{p_{i,t}}{P_t}\right)^{-\epsilon} Y_t,$$
$$\text{and } y_{i,t} = A_t k_{i,t}^{\alpha} l_{i,t}^{1-\alpha}.$$

The solution to the pricing problem is to set a fixed markup over marginal cost $p_{i,t} = \mu\chi_t$, where the markup is $\mu \equiv \frac{\epsilon}{\epsilon-1}$ and the marginal cost is $\chi_t \equiv \frac{1}{A_t}\left(\frac{\rho_t}{\alpha}\right)^{\alpha}\left(\frac{w_t}{1-\alpha}\right)^{1-\alpha}$. In equilibrium, all firms set the same price and have the same size; which yields the industry price index (4) is $P_t = \mu\chi_t N_{t-1}^{\frac{-1}{\epsilon-1}}$.

The key point is that a larger number of firms implies a lower price index. The quantity index (3) becomes $Y_t^S = y_t N_{t-1}^{\frac{\epsilon}{\epsilon-1}}$. It increases with average firm output y_t, and with the number of firms because of the taste for variety. The industry equilibrium condition $Y_t^D = Y_t^S$ then implies $y_t = (\mu\chi_t)^{-\sigma} D_t N_{t-1}^{\frac{\sigma-\epsilon}{\epsilon-1}}$. Since $\epsilon > \sigma$, firm output is a decreasing function of the number of active firms, conditional on the demand shifter D_t. Investment is proportional to output: $k_t = \frac{\alpha}{r_t+\delta}\chi_t y_t$. Aggregating across firms we have $K_t = N_{t-1}k_t$, so industry investment is

$$K_t = \alpha\mu^{-\sigma}\frac{\chi_t^{1-\sigma}}{\rho_t} D_t N_{t-1}^{\frac{\sigma-1}{\epsilon-1}}. \tag{5}$$

We can summarize our results as follows:

Lemma 1. *Investment per firm and total industry investment both increase with demand D_t and decrease with the user cost $r_t + \delta$. Industry investment increases with the number of firms N_{t-1}, while investment per firm decreases.*

All firms have the same market share $\frac{1}{N_{t-1}}$ so the Herfindahl is predetermined and equal to the inverse of the number of firms:

$$H_t = \sum_{1}^{N_{t-1}} \left(\frac{1}{N_{t-1}}\right)^2 = \frac{1}{N_{t-1}} \tag{6}$$

The last step is to consider the entry decision of firms at time $t-1$.

Entry Decisions. The free entry condition is $\mathbb{E}_{t-1}\left[(\mu-1)\chi_t y_t\right] = (1+r_{t-1})\kappa_{t-1}^e$ where r_{t-1} is the required return on entry costs, taking into account the risk of failure as well as risk premia.

[7] Formally, the firm's problem has two stages. At the production stage, the firm solves $\pi_{i,t}(k_{i,t}) \equiv \max_{l_{i,t},p_{i,t}} p_{i,t}y_{i,t} - w_t l_{i,t}$, subject to the production function and the demand curve $y_{i,t} = \left({p_{i,t}}/{P_t}\right)^{-\epsilon} Y_t$. At the investment stage it solves $\max_{k_{i,t}} \mathbb{E}_t\left[\pi_{i,t}(k_{i,t})\right] - \rho_t k_{i,t}$. Assuming that D_t is known at the beginning of time t, when $k_{i,t}$ is chosen, we can collapse the two stages into one.

Expected profits have to cover the entry cost. Note that the free entry condition essentially pins down expected firm output.[8] This is a typical property of expanding variety models. This free entry condition together with the equilibrium production derived earlier, pins down the number of firms:

$$N_{t-1}^{\frac{\epsilon-\sigma}{\epsilon-1}} = \frac{(\mu-1)\,\mu^{-\sigma}}{\kappa^e} \frac{\mathbb{E}_{t-1}\left[\chi_t^{1-\sigma} D_t\right]}{1+r_{t-1}}. \tag{7}$$

The number of active firms depends on expected demand, expected productivity (as long as $\sigma > 1$), and the cost of creating a firm. We now discuss the endogeneity issue. To make the point as clearly as possible, consider the following definition of a competitive economy.

Definition 1. *The competitive limit (denoted by c) with finite entry corresponds to $\epsilon \to \infty$ and $\kappa^e \to 0$, holding constant the ratio $\psi \equiv \frac{\mu-1}{\kappa^e}$.*

In the competitive limit, the markup μ converges to 1, and the entry cost converges to zero.[9] In the limit, we see from equation (5) that industry investment is independent from the number of firms

$$K_t^c = \frac{\alpha \chi_t^{1-\sigma}}{\rho_t} D_t, \tag{8}$$

and the industry price level equals the marginal cost, $P_t^c = \chi_t$, also independently from N_{t-1}.

Identification Problem. The competitive limit allows us to illustrate the endogeneity issue. By definition, market power is irrelevant in the competitive limit. Yet we will show that a regression of investment on standard measures of concentration would likely produce negative coefficients. To be more precise, consider an economy with competitive industries indexed by $j = 1..J$ subject to industry-specific demand shocks $D_{j,t}$. The aggregate economy is non-stochastic, and factors prices – w_t, ρ_t, and thus χ_t – are also non-stochastic. Investment in industry j is determined by equation (8) as $K_{j,t}^c = \frac{\alpha \chi_t^{1-\sigma}}{\rho_t} D_{j,t}$ and we specify the random demand shocks as

$$D_{j,t} = \bar{D} e^{d_{j,t-1}} e^{\nu_{j,t}}$$

where $\mathbb{E}_{t-1}\left[e^{\nu_{j,t}}\right] = 1$, and $d_{j,t-1}$ is known at time $t-1$ and has strictly positive cross-sectional variance: $VAR^{(j)}\left(d_{j,t-1}\right) > 0$. Suppose an econometrician runs cross-industry regressions (or panels regressions with time fixed effects) in order to determine the impact of concentration on investment. The proposition below explains the source of the bias.

Proposition 1. ***Fundamental Endogeneity Issue**. In the competitive limit with anticipated demand shocks, the cross-industry OLS regression of log-investment on log-Herfindahl gives a slope of minus one.*

[8] So long as we abstract from the covariance between χ_t and y_t.

[9] What happens to the number of firms depends on the limit of the ratio ψ. A realistic benchmark is to have the ratio converge to a finite value. If the convergence of the markup to 1 is slower than that of the entry cost to 0 then N goes to infinity. The results below do not depend on having a "finite" number of firms, but it makes the exposition a lot simpler.

Proof. In the competitive limit with deterministic factor prices we have $\log N^c_{j,t-1} = \log \frac{\psi\chi_t^{1-\sigma}}{1+r_{t-1}} + \log \mathbb{E}_{t-1}[D_{j,t}]$, therefore $\log H_{j,t} = -\log \frac{\psi\chi_t^{1-\sigma}}{1+r_{t-1}} - \log \bar{D} - d_{j,t-1}$. The cross sectional variance of the Herfindahl is simply $VAR^{(j)}(\log H_{j,t}) = VAR^{(j)}(d_{j,t-1})$ On the other hand, we have $\log K^c_{j,t} = \log \frac{\alpha\chi_t^{1-\sigma}}{\rho_t} + \log \bar{D} + d_{j,t-1} + \nu_{j,t}$ therefore, using the Herfindahl index, $\log K_{j,t} = -\log H_{j,t} + \eta_t$ where η_t is a time fixed effect. This implies $COV^{(j)}\left(\log K^c_{j,t}, \log H_{j,t}\right) = -VAR^{(j)}(\log H_{j,t})$ and therefore the OLS slope is -1. □

This is an extreme example of omitted variable bias. There is in fact no economic connection between the number of firms and industry-level investment, as we can see from equation (8), but the econometrician would recover a coefficient of -1. The R^2 would depend on the variance of unexpected demand shocks $\nu_{j,t}$. A similar issue arises if we consider industry-specific productivity shocks $A_{j,t}$.

Corollary 1. *Industry-specific productivity shocks $A_{j,t}$ creates biases similar to the ones highlighted in Proposition 1.*

With industry productivity shocks, we have $\log H_{j,t} = -\log\left(\mathbb{E}_{t-1}\left[\chi_{j,t}^{1-\sigma}\right]\right) + ...$, and predictable cross-sectional variation in industry-level marginal cost, $\chi_{j,t}$, leads to biases as long as $\sigma > 1$, which is the realistic case.

Instruments and Natural Experiments. There are two ways to avoid the omitted variable bias. One solution would be to control for the demand shifter D_t. The problem is that D_t is not observable. We can only measure nominal sales P_tY_t, which depend on both supply and demand factors.[10]

The other solution is to use natural experiments and/or instruments. The model can help us think about potential experiments and instruments. A good instrument in our model is a shock that randomly changes the opportunity cost of entry across industries. Let us consider the general model as a system of equations, where, as above, $j = 1..J$ indexes the industry:

$$\log K_{j,t} = \log \alpha \frac{\chi_{j,t}^{1-\sigma}}{\rho_t} + \log D_{j,t} - \sigma \log \mu_j + \frac{\sigma - 1}{\epsilon_j - 1} \log N_{j,t-1}$$

$$\frac{\epsilon_j - \sigma}{\epsilon_j - 1} \log N_{t-1} = \log(\mu_j - 1)\mu_j^{-\sigma} + \log \mathbb{E}_{t-1}\left[\chi_{j,t}^{1-\sigma} D_t\right] - \log(1 + r_{t-1})\kappa^e_{j,t-1}$$

This system makes it clear that random shocks to the entry cost κ^e_j could be used as instruments. More formally, we can state the following proposition.

Proposition 2. *Variation in entry costs κ^e_j that are uncorrelated with future demand $D_{j,t}$ and productivity $A_{j,t}$ would be valid instruments to assess the impact of concentration on investment.*

[10] The exception is when $\sigma = 1$ (i.e., log-preferences for consumers) where nominal sales are exogenous from industry-level supply shocks, but this is not an assumption we can defend empirically.

We will argue that the peculiar dynamics of entry in the late 1990's offer such an instrument. Essentially, we will document large cross-sectional variation in entry rates across industries, that do not predict future demand or productivity, but are driven by the willingness of investors (venture capitalists, or market participants in general) to fund risky ventures.[11]

A good natural experiment would be a change in the number of firms that is independent from future demand. Following the literature, we will argue that the increase in Chinese competition; and particularly the formal entry of China in the WTO provides such an experiment. It comes, however, with two important caveats: first, it affects only manufacturing, which raises issues of external validity; second, it is a foreign competition shock, so it is unclear which prediction we can test using data on domestic investment. Interpreting the China shock therefore requires a model with firm heterogeneity, strategic competition, and foreign entry. We now discuss such a model.

2.2 Heterogeneity and Foreign Competition

The model presented above allows us to interpret industry level data under domestic competition. Unfortunately, the cleanest large scale experiment that we have to test our hypothesis is the entry of China in the WTO. To discuss its implications, we need to focus on firm level strategic responses. Our goal here is to provide the simplest model that allows us to explain our empirical approach. The most important feature of the micro data that we need to capture is the heterogeneity of firms in terms of size and apparent productivity. We therefore consider a model of vertical differentiation in the spirit of Shaked and Sutton (1982; 1983). Consumers can purchase one unit of an indivisible good. A consumer of type θ purchasing one unit of quality z at price p receives utility

$$u = \theta z - p$$

Consumer types are distributed over $[0, \infty)$ according to the cumulative density function $F(\theta)$. We make a mild technical assumption about the distribution F.[12] The industry is populated by a leader (indexed by 2) and a competitive fringe (indexed by 1). The Appendix describes the case of a duopoly instead of a competitive fringe. Firms have Cobb-Douglass production functions as before (or any other constant return function), but the leader is more efficient in terms of quality z and marginal cost χ: $z_2 > z_1$ and $\chi_2 \leq \chi_1$. In other words, the leader has access to a technology set $\{\chi, z\}$ that strictly dominates the technology set of the fringe. Firms compete à la Bertrand. Since the fringe is competitive, it prices at marginal cost: $p_1 = \chi_1$. We now need to derive the demand curves. There are two marginal consumer types to consider. Type θ_1 is indifferent between buying

[11] It does not matter for us 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). At the end of the day, all that really matters is that these factors created variation in entry rates across industries (say in 1999) that turn out to be orthogonal to future demand (say in 2005).

[12] The distribution F is such that, for all θ, $2f(\theta) + f'(\theta)\frac{1-F(\theta)}{f(\theta)} \geq 0$. This condition holds for all the distributions used in the literature: exponential, normal, log-normal, Pareto, Weibull, inverse Gaussian, gamma, and Kumaraswamy distributions.

from 1 and not buying at all, so $\theta_1 z_1 - p_1 = 0$. Type θ_2 is indifferent between buying from 1 and buying from 2, so $\theta_2 z_1 - p_1 = \theta_2 z_2 - p_2$, which we write as

$$\theta_2 = \frac{p_2 - p_1}{z_2 - z_1}. \tag{9}$$

Consumers in the range $[0, \theta_1]$ are priced out, those in $[\theta_1, \theta_2]$ buy quality z_1 from the competitive fringe, and those in $[\theta_2, \infty)$ buy the high quality good from firm 2. We consider the case where the competitive fringe is active so we assume that the parameters are such that $\theta_1 < \theta_2$ (see the Appendix for primitive conditions). Notice the key property that the price elasticity of $\partial\theta_2/\partial p_2$ increases when the gap in quality $z_2 - z_1$ decreases. The profits of firm 2 are $\pi_2 = (p_2 - \chi_2)(1 - F(\theta_2))$.[13] The first order condition for the optimal pricing by the leader is

$$p_2 - \chi_2 = \frac{1 - F(\theta_2)}{f(\theta_2)}(z_2 - z_1). \tag{10}$$

The leader prices with a markup over its marginal cost, and the markup reflects the quality advantage of the leader, $z_2 - z_1$. We can consider two types of competitive pressures from the competitive fringe: quality competition ($z_1 \nearrow$), and cost competition ($\chi_1 \searrow$). Competition always increases production and investment at the industry level, but what is does to the leader depends on the initial conditions and on the nature of competition. We summarize the key results in the following proposition.[14]

Proposition 3. *A more efficient leader is more likely to react to competition by increasing production and investment. With respect to quality competition,* $\frac{\partial\theta_2}{\partial z_1} < 0$*. With respect to cost competition* $\frac{\partial\theta_2}{\partial\chi_1} < 0$ *but the magnitude decreases with* $z_2 - z_1$*.*

Proof. All the properties can be derived from the equilibrium condition that combines the definition of θ_2 in (9) with optimal pricing condition (10):

$$\frac{1 - F(\theta_2)}{f(\theta_2)} - \theta_2 = \frac{\chi_1 - \chi_2}{z_2 - z_1}$$

Under the technical assumption A1, the left hand side is a decreasing function of θ_2. See the Appendix for details. □

To understand the results, one should remember that there are two effects of an increase in competition. The direct effect, holding p_2 constant, is to steal market share from the leader, i.e., to increase θ_2. As one can see from (9), a decrease in p_1 or an increase in z_1 both increase θ_2 if p_2 does not change. The other effect of competition is to change the elasticity of θ_2 to p_2, which changes the optimal markup and therefore the price p_2. The leader responds to competition by lowering its price

[13]It is straightforward to generalize to N firms. In that case we have $\pi_i = (p_i - c)(F(\theta_{i+1}) - F(\theta_i))$ with the convention that $\theta_{N+1} = \infty$.

[14]The Appendix presents the case where, instead of a competitive fringe, we have duopoly between the leader and a dominated competitor.

p_2, thereby undoing some of the initial impact on its sales. Which effect dominates depends on the nature of the competition shock and on the initial conditions. With quality-based competition, the second effect dominates and a dominating incumbent (remember that $\chi_2 \leq \chi_1$) increases its sales in response to competition. With cost-based competition, the first effect dominates and incumbent sales decline, but the decline is weaker when the incumbent dominates more in the quality dimension ($z_2 - z_1$ is large). Of course, the neat dichotomy between quality and cost only exists in the stylized model. In reality, competition is always a mix of cost and quality. Overall, the key prediction is that competition is more likely to stimulate investment by the leader when the leader is more efficient. This result echoes the ones emphasized in the Schumpeterian innovation literature discussed below.

The theoretical results above do not depend on whether competition comes from domestic or from foreign firms. The empirical tests, however, depend on the geographic origin of competition. We only measure domestic investment at the industry level. Therefore we cannot test the most basic prediction that competition increases aggregate (industry) investment because we do not measure investment by foreign firms. The predictions regarding industry investment are ambiguous, so we focus on the firm-level predictions in our tests.

Corollary 2. *Consider an industry disrupted by a foreign entrant with marginal cost χ_1 and quality $z^f \in (z_1, z_2)$. Investment by the industry leader increases but the impact on domestic industry investment is ambiguous.*

The impact on domestic industry investment is ambiguous because the competitive fringe of inefficient firms might be wiped out by the foreign entrant. On the other hand, the industry leader reacts by being more aggressive. We test this proposition using the surge in Chinese import competition into the U.S. as a natural experiment.[15]

2.3 Innovation and Dynamic Competition

So far we have framed our discussion in the context of a neoclassical production function, where capital k is simply an input in production. There is, however, a large literature that focuses on the link between competition and innovation. At some level, this is just a relabeling of the variables. We can define k either as capital expenditure or as R&D. But there is a quantitative difference. The benchmark model presented earlier uses a constant return to scale production function. The innovation literature, on the other hand, focuses on factors that increase productivity in the long run and typically create increasing returns over some range.

A large literature has studied the link between competition, investment, and innovation (see Gilbert (2006) for a recent survey). From a theoretical perspective, we know that the relationship is non-monotonic because of a trade-off between average and marginal profits. Competition reduces the level of profits, but it also makes them more elastic to innovation, i.e., it can increase the difference

[15]Note that the predictions are less clear if the foreign entrant also has a lower marginal cost. In that case the leader would still always lower its price, but it is unclear what would happen to its market share. So we are not predicting that leaders always and everywhere react by investing more. Rather, we emphasize that the ones that enjoy a quiet life because of their dominant position are more likely to do so.

between the profits a firm earns if it innovates and the profits it earns if it does not innovate. The theoretical point is straightforward, but as Richard Gilbert states, *"differences in market structure, the characteristics of innovations, and the dynamics of discovery lead to seemingly endless variations in the theoretical relationship between competition and [innovation]".*

The point we wish to emphasize is that, broadly speaking, the theoretical predictions and the empirical evidence line up with our results in Proposition 3 above. For the UK, Aghion et al. (2009) find that the threat of entry spurs innovation incentives in sectors close to the technology frontier, but discourages innovation in laggard sectors. One interpretation is that advanced incumbents can innovate to escape competition, while laggards simply see their rents competed away. These effects can be modeled in a simple way using a dynamic duopoly, as in Aghion et al. (2014). In this class of models, there is an escape competition effect and a Schumpeterian effect. The former increases investment when industries face more neck-and-neck competition. The latter may lower incentives to invest in the presence of leaders and laggards. As a result, the threat of technologically advanced foreign entry affects firms differently: it spurs investment by domestic leaders, but discourages investment among laggards. It may lead to a lower entry rate, or a higher exit rate, which ultimately results in fewer, but larger firms.

2.4 Summary of Testable Predictions

Consider firm i in industry j and write it's investment as

$$k_{i,j,t} = F\left(C_{j,t}, X_{i,j,t}, Y_{i,j,t}\right)$$

where C_j measures competition in industry j, $X_{i,j}$ are observable determinants of investment and $Y_{i,j}$ are unobservable ones. Aggregating across firms, industry investment is

$$\bar{K}_{j,t} = \sum_{i=1}^{N_{j,t-1}} k_{i,j,t}.$$

Our tests allow us to study two hypotheses:

- **H1: industry investment increases with competition, $\frac{\partial \bar{K}_j}{\partial C_j} > 0$.** This is true in standard models including CES/monopoly, oligopoly, etc. It might not be true in some models of "innovation" because of the business stealing/Schumpeterian effect.

- **H2: investment by leading firms increases with competition, $\frac{\partial k_{lead,j}}{\partial C_j} > 0$.** This is not true in symmetric CES (because there are no leaders, so $\frac{K_j}{N_j}$ decreases even though K_j increases with competition). But it is true in many models of vertical differentiation and innovation with "escape competition" effects.

Three observations are in order: first, in all models we have studied, H1 is weaker than H2, so testing H2 is the more demanding test. Second, an instrument for C_j is required to test either of these hypotheses because, as discussed above, C_j is correlated with $Y_{i,j}$. Third, we can test H1 or

Table 2: Summary of Tests, Hypotheses and Results

Tests	**Hypothesis tested**	dC_j (average)	**Estimated slope**	
China	H2	>0	0.29	of $K_{lead,j}$ on ΔIP^{US}
Excess Entry	H1	both	-0.55 to -0.7	of $\Delta log(K_j)$ on HHI^{US}
Regulation	H1	<0	-0.72	of $\Delta log(K_j)$ on HHI^{US}

H2 using either an increase or a decrease in C_j – both are valid tests. It is important to distinguish this point from the fact that, overall, we have witnessed an decrease in competition in recent years. More precisely, we perform the following tests:

1. Chinese competition allows us to test H2 in the case where $dC_j > 0$ on average.

2. Excess entry allows us to test H1 with $dC_j > 0$ (in the cross-section, immediately following the 1990's) and $dC_j < 0$ (in the time series, as 'excess firms' exit)

3. Regulation allows us to test H1, with $dC_j < 0$[16]

The following table summarizes our tests, and the associated hypotheses and average changes in competition dC_j. As a preview of results, we also include the estimated coefficients.

3 Data

Testing our hypothesis in detail requires the use of micro-data. We start from the same dataset as Gutiérrez and Philippon (2016) and append data on import exposure. The final dataset includes a wide range of aggregate-, industry- and firm-level data. The data fields and data sources are summarized in Table 3. Sections 3.1 and 3.2 discuss the aggregate and industry datasets, respectively. Section 3.3 discusses the firm-level dataset, including key definitions. Section 3.4 discusses the import dataset; and Section 3.5 discusses data on Regulation import dataset.

Firm- and industry-data are not readily comparable; they differ in their definitions of investment and capital, and in their coverage. As a result, we spent a fair amount of time simply reconciling the various data sources. We refer the reader to Gutiérrez and Philippon (2016) for details on the reconciliation and validation exercises.

3.1 Aggregate data

Aggregate data on funding costs, profitability, investment and market value for the U.S. Economy and the non financial sector is gathered from the U.S. Flow of Funds accounts through FRED. These data are used in the aggregate analyses discussed in the introduction; and to reconcile and ensure the accuracy of more granular data.

[16]Note that Regulation also is a potential explanation for why the average $dC_j < 0$

Table 3: Summary of Data Sources

Data fields	Source	Granularity
Aggregate investment and Q	Flow of Funds	US
Industry-level investment and operating surplus	BEA	~NAICS L3
Firm-level financials	Compustat	Firm
China import exposure	UN Comtrade	HS code
NTR Gap	Peter Schott's website	NAICS L6
Mercatus RegIndex	Regdata.org	NAICS L3

3.2 Industry data

Industry-level investment and profitability data – including measures of private fixed assets (current-cost and chained values for the net stock of capital, depreciation and investment) and value added (gross operating surplus, compensation and taxes) – are gathered from the Bureau of Economic Analysis (BEA). Note that BEA I and K include intangible assets (i.e., software, R&D, and some intellectual property), not just tangible capital.

Investment and profitability data are available at the sector (19 groups) and detailed industry (63 groups) level, in a similar categorization as the 2007 NAICS Level 3. We start with the 63 detailed industries and group them into 47 industry groupings to ensure investment, entry and concentration measures are stable over time. In particular, we group detailed industries to ensure each group has at least ~10 firms, on average, from 1990 - 2015 and it contributes a material share of investment (see Gutiérrez and Philippon (2016) for details on the investment dataset). We exclude Financials and Real Estate; and also exclude Utilities given the influence of government actions in their investment and their unique experience after the crisis (e.g., they exhibit decreasing operating surplus since 2000). Last, we exclude Management because there are no companies in Compustat that map to this category. This leaves 43 industry groupings for our analyses. All other datasets are mapped into these 43 industry groupings using the NAICS Level 3 mapping outlined by the BEA.

We define industry-level gross investment rates as the ratio of 'Investment in Private Fixed Assets' to lagged 'Net Stock of Private Fixed Assets'; depreciation rates as the ratio of 'Depreciation of Private Fixed Assets' to lagged 'Net Stock of Private Fixed Assets'; and net investment rates as the gross investment rate minus the depreciation rate. Both Current-Cost and Chained-Value investment/depreciation rates are available. We use current-cost amounts to compute Net Investment Rates, and chained quantity indices for industry-level regressions of $log(K)$.[17] Investment rates are computed across all asset types, as well as separating intellectual property from structures and equipment.

[17] Our results are generally robust to using chained quantity indices instead of current costs when computing net investment rates

3.3 Firm-level data

3.3.1 Dataset

Firm-level data is primarily sourced from Compustat, which includes all public firms in the U.S. Data is available from 1950 through 2016, but coverage is fairly thin until the 1970's. We exclude firm-year observations with assets under \$1 million; with negative book or market value; or with missing year, assets, Q, or book liabilities.[18] In order to more closely mirror the aggregate and industry figures, we exclude utilities (SIC codes 4900 through 4999), real estate (SIC codes 5300 through 5399) and financial firms (SIC codes 6000 through 6999); and focus on U.S. incorporated firms.

We supplement Compustat with three sources, all available through WRDS:

1. Execucomp: We gather CEO age from Execucomp, and use it to test theories of concentration in Section 5[19]

2. I/B/E/S: We gather EPS analyst forecasts from I/B/E/S. Forecasts are used to (i) control for projected growth in our excess entry estimate and (ii) estimate the cost of capital in the mark-up estimates reported in the Appendix [20]

3. Intangible Capital Estimates: Last, we gather firm-level intangible capital estimates as defined in Peters and Taylor (2016). Peters and Taylor (2016) rely on detailed investment and depreciation assumptions by intangible asset type to estimate firm-level (on- and off-balance sheet) intangible capital. They capitalize R&D as well as a portion of SG&A; and back-fill investment whenever data is not available (e.g., before firms become public). We use these figures in firm-level regressions with the China shock.

Firms are mapped to BEA industry segments using 'Level 3' NAICS codes, as defined by the BEA. When NAICS codes are not available, firms are mapped to the most common NAICS category among those firms that share the same SIC code and have NAICS codes available. Firms with an 'other' SIC code (SIC codes 9000 to 9999) are excluded from industry-level analyses because they cannot be mapped to an industry.

Firm-level data is used for two purposes:

- First, we aggregate firm-level data into industry-level metrics and use the aggregated quantities to explain industry-level investment behavior . We consider the aggregate (i.e., weighted

[18] These exclusion rules are applied for all measures except firm age, which starts on the first year in which the firm appears in Compustat irrespective of data coverage

[19] Execucomp data is already mapped to Compustat in WRDS.

[20] IBES provides the consensus of all available forecasts as of the middle (the Thursday following the second Friday) of each month. IBES data is mapped to Compustat GVKEY through a two-step approach. First, we use the header map between GVKEY and IBES Ticker provided in the Compustat Security table (IBTIC variable). Then, for those GVKEYs that have missing IBTIC in Compustat and have a valid PERMNO, the link is supplemented with additional historical GVKEY-IBES ticker links as follows: we first merge the rest of GVKEYS with PERMNOs on a historical basis using CRSP-Compustat Merged Database. Then, we bring in additional IBES Tickers from the IBES-PERMNO link (we use the WRDS ICLINK and CIBESLINK applications).

average), the mean and the median for all quantities, and use the specification that exhibits the highest statistical significance. We require at least 5 firms in a given industry-year pair to include a given observation in industry-level analyses (all firms are included in firm-level analyses, irrespective of the number of firms in a given industry-year).

- Second, we use firm-level data to analyze the determinants of firm-level investment through panel regressions. We compute a wide range of financial measures, including investment, cash flow, operating surplus, etc. The main variables are discussed in the following section; with additional details on the sample selection, variable definitions and data quality tests available in Gutiérrez and Philippon (2016).

3.3.2 Firm-level Definitions

Capital. We consider three measures of capital: net Property, Plant and Equipment (item PPENT), Intangible capital at replacement cost (item K_INT from Peters and Taylor (2016)) and total capital (PPENT + K_INT).

Employment. We use Compustat field EMP as a measure of employment

Entry and Exit. Entry is defined as the first year in which a firm (GVKEY) appears in Compustat and does not violate our exclusion restrictions. Enforcing exclusion restrictions has a minimal effect on our results, and ensures that our entry/exit rates map to all other analyses. Exit is defined as the last year available for a given GVKEY. We differentiate across exit types using field DLRSN, which is equal to 1 when a firm exits due to M&A.

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.

Q. Firm-level Q is defined as the ratio of market value to total assets (AT). We compute market value as the market value of equity (ME) plus total liabilities (LT) and preferred stock (PSTK), where the market value of equity (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). The resulting aggregate and mean Q from Compustat closely mirror the Flow of Funds Q.

Competition. Measures of competition aim to measure business dynamism, concentration and/or market power. We compute (i) the log-change in the number of firms in a given industry as a measure of entry and exit; (ii) the share of sales and market value held by the top 4, 8 and 20 firms in each industry; (iii) sales and market value Herfindahls as measures of concentration; and (iv) the common ownership-adjusted Herfindahl defined in Salop and O'Brien (2000) and implemented by Azar et al. (2016). The definition of items (i) to (iii) is standard. For (iv), we refer the reader to Gutiérrez and Philippon (2016) for details on the calculation.

We use Compustat item SALE for measures of sales concentration and market value as defined in the computation of Q above for measures of market value concentration. We use the sales Herfindahl as our primary measure of competition because it exhibits a higher correlation with investment as discussed in Gutiérrez and Philippon (2016).

In addition to the above US-focused measures, we compute an import-adjusted Herfindahl HHI^{IA} that aims to account for foreign competition. Due to data limitations, we only observe the total U.S. imports – not the number of firms they originate from. We therefore use HHI^{US} to estimate HHI^{IA} as follows: consider an industry with x firms in the U.S. and N firms globally, all with equal shares of the U.S. market. The U.S. share of output is $s = \frac{x}{N}$, and the US-based Herfindahl $HHI^{US} = \frac{1}{x}$. Under these assumptions, the import-adjusted Herfindahl could then be computed as

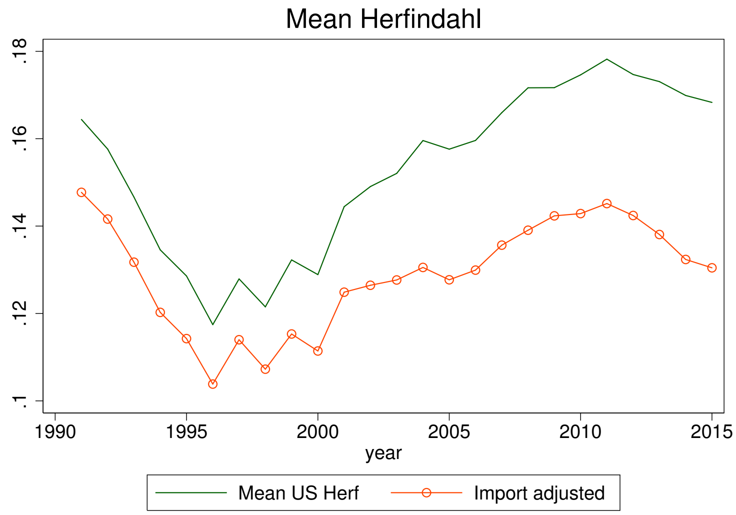
$$\begin{aligned} HHI^{IA} &= \frac{1}{N} \\ &= HHI^{US} \times s \end{aligned}$$

which is true as long as the concentration of foreign firms is the same as the concentration in the U.S. This is a strong assumption – but it is hard to justify a different one. We therefore assume this holds across all industries.

Figure 8 plots the average U.S. and import-adjusted Herfindahl across all industries in our sample. As shown, the two are fairly close together through 2000 but start to diverge thereafter. By 2015, the import-adjusted Herfindahl is much lower than the U.S. Herfindahl – but it still exhibits a substantial increase from 1995 to 2010. [21]

[21] It is worth noting that the number of U.S. firms in industries most affected by foreign competition has decreased drastically in the last few years (e.g., for the Non-Durable Textile industry, the Herfindahl increased from 0.08 in 2000 to 0.5 in 2015). Assuming that the concentration of foreign firms is the same as U.S. concentration does not appear appropriate for these industries. For some tests (particularly the Regulation tests), we therefore assume that foreign firms are perfectly competitive when computing the import-adjusted Herfindahl.

Figure 8: Mean Herfindahl: U.S. and Import-Adjusted



Notes: Annual data from Compustat. Total imports from Peter Schott's website. Import adjusted Herfindahl computed as described in the text.

The benefit from using Compustat to compute measures of Competition is that they are available every year. But this introduces two limitations: (i) Compustat covers only a portion of each industry, which under-states competition and (ii) a portion of sales by US-incorporated firms may be realized abroad, such that we over-state U.S. sales. To complement these measures, we gather industry measures of sales and market value concentration from the Economic Census – these measures cover the entire U.S. economy, and consider only US-sales. Other benefits of census-based measures are described in Grullon et al. (2016)Economic Census measures include the share of sales held by the top 4, 8, 20 and 50 firms in each industry. They are available for a subset of NAICS industries for 1997, 2002, 2007 and 2012. We aggregate concentration ratios to our 43 industry groupings by taking the average and/or weighted average across industries.

Mark-ups. Our primary measure of mark-ups is the price-cost ratio (also known as the Lerner index). The Lerner index differs from the Herfindahl and Concentration ratios because it does not rely on precise definitions of geographic and product markets; rather it aims to measure a firm's ability to extract rents from the market. We followGrullon et al. (2016) and define the Lerner Index as operating income before depreciation minus depreciation divided by sales.

3.4 China import-competition data

Data on international trade is sourced from the UN Comtrade Database[22] and Peter Schott's website.

UN Comtrade data is used by Autor et al. (2016) (among others) and includes bilateral imports by six-digit Harmonized Commodity Description and Coding System (HS) products. Data for a consistent set of countries is available from 1991 to 2014. We map these data to six-digit NAICS

[22] http://comtrade.un.org/db/default.aspx

codes by applying the crosswalk in Pierce and Schott (2012), which maps 10-digit HS products to six-digit NAICS industries. We also obtain Normal-Trade-Relations tariff gaps from Peter Schott's website. These tariff gaps are used in Pierce and Schott (2016) and are defined for NAICS level 6 industries.[23]

We supplement the import competition data with the NBER-CES Manufacturing Industry Database, which includes output data by NAICS Level 6 manufacturing industry from 1971 to 2009. 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. These datasets are discussed extensively in other papers so we refer the reader to Pierce and Schott (2016); Schott (2008) and Autor et al. (2016) for additional details.

3.5 Regulation data

As a measure of the amount and change in regulations affecting a particular industry, we gather the Regulation index published by the Mercatus Center at George Mason University. The index relies on text analysis to count the number of relevant restrictions for each NAICS Level 3 industry from 1970 to 2014. Note that most, but not all industries are covered by the index. See Al-Ubaydli and McLaughlin (2015) for additional details. When necessary, we aggregate the regulation index from NAICS level 3 industries into BEA industries by taking the median number of restrictions across all firms in an industry.[24]

4 Empirical tests and results

To establish causality between competition and investment, we perform two analyses. First, we use import exposure to China as an experiment for increased competition; and find that leaders in manufacturing industries more exposed to Chinese competition increased investment more. This analysis provides clean identification but applies only to manufacturing industries. To improve external validity, we use excess entry in the 1990's (relative to entry predicted using Q, sales, profitability, etc.) as an instrumental variable for concentration. We find that industries with higher excess entry, and therefore less concentration/more competition, invested more in the 2000's. The increase in investment is temporary and decreases over time as the number of 'excess' firms in an industry decreases. This latter analysis – discussed in Section 4.2– has weaker identification, but applies across all firms/industries.

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

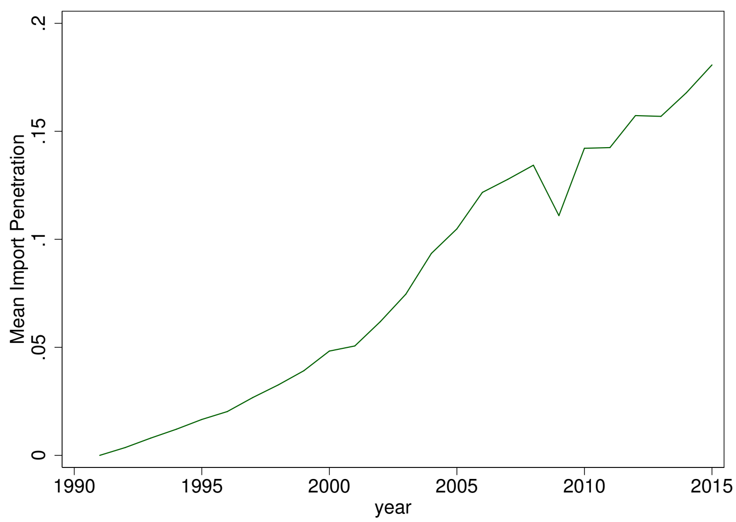
[24] We also considered the weighted mean by assets, but the median exhibits higher predictive power

4.1 China Import Competition

4.1.1 Empirical Strategy.

We use the growth of China and associated import exposure as a natural experiment for competition in U.S. manufacturing industries. As shown in Figure 9, imports from China started to increase in the early 1990's, and experienced a very rapid rise after 2000. The 'China shock' has been used in a variety of studies, including Acemoglu et al. (2016); Autor et al. (2016); Pierce and Schott (2016), among others. As discussed in Autor et al. (2016), three features of China's rise support its use as a natural experiment: (i) the unexpected nature of China's export growth, which was anticipated by very few observers; (b) China's substantial isolation under Mao, which created abundant opportunities for later catch up; and (c) China's distinctive comparative advantage in Manufacturing, which generated a material global supply shock.

Figure 9: Mean Import Exposure for Manufacturing Industries



Notes: Annual data for Manufacturing industries only. Mean import exposure across NAICS level 6 industries, based on data from UN Comtrade. Import penetration is constructed by dividing U.S. manufacturing imports from China by U.S. domestic manufacturing absorption as of 1991. Industry absorption is defined as U.S. domestic manufacturing output plus imports less exports.

Following Autor et al. (2016), we define import penetration ratio for industry j:

$$\Delta IP_{jt}^{US} = \frac{\Delta M_{jt}^{US}}{Y_{j,91} + M_{j,91} - E_{j,91}} \tag{11}$$

where $\Delta M_{j\tau}^{US}$ denotes the change in 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 sourced from the UN Comtrade Database (and measure U.S. imports and exports with the rest of the world). Only

NAICS level 6 industries where data is available across all sources are included in the analyses.[25] We use 1991 as our benchmark year because data is available across a broad sample of countries starting that year.

As explained in Propositions 1 and 2, we need to worry about changes in competition that are driven by future demand or productivity. We use two instrumental approaches. The first instrument, based on Acemoglu et al. (2016) uses import from China to eight other high-income countries. In particular, we compute

$$\Delta IP^{OC}_{jt} = \frac{\Delta M^{OC}_{j\tau}}{Y_{j,91} + M_{j,91} - E_{j,91}}$$

where $\Delta M^{OC}_{j\tau}$ denotes the change in imports from China in industry j during year t to eight other high-income countries; while the denominator is the same as above.[26] This instrument is valid if relative demand shocks between two industries are uncorrelated between the U.S. and the 8 other countries. The second instrument uses the reduction in tariff rate uncertainty from the U.S. granting PNTR to China, as in Pierce and Schott (2016). We discuss this second instrument later.

Armed with the above measure of trade exposure, we examine the link between increased competition from China and investment using a generalized OLS difference-in-differences (DID) specification:

$$log(k_{i,j,t}) = \beta_1 \widehat{\Delta IP^{US}_{j,t}} + \beta_2 \Delta IP^{\widehat{US}}_{jt} \widehat{\times Leader} + \boldsymbol{X'_{j,t-1}}\lambda + \boldsymbol{X'_{i,t-1}}\gamma + \eta_t + \mu_i + \alpha + \varepsilon_{it} \qquad (12)$$

where $\widehat{\Delta IP^{US}_{j,t}}$ and $\Delta IP^{\widehat{US}}_{jt} \widehat{\times Leader}$ are instrumented using ΔIP^{OC}_{jt} and $\Delta IP^{OC}_{jt} \times Leader$. The dependent variable is a given measure of capital (e.g., PP&E, Intangible capital, etc.) for firm i in industry j during year t. The first two terms on the right-hand side are the DID terms of interest. The first one measures the unconditional effect of Chinese competition. The second term adds an indicator for leader firms[27], to capture differences in investment between leaders and laggards. The remaining terms are controls. They include time-varying industry ($\boldsymbol{X'_{j,t-1}}\lambda$) and firm characteristics ($\boldsymbol{X'_{i,t-1}}\gamma$), as well as a constant, year and firm fixed effects (α, η_t and μ_i , respectively). In particular, we include the lagged firm age as a firm-level control, and the following

[25] The main concern with this is that some industry segments in the NBER-CES have no representation in Compustat and/or no import data from UN Comtrade. To mitigate this, we repeat all tests using an alternate measure of import penetration that does not rely on the NBER-CES database: the ratio of changes in Chinese imports to total U.S. imports as of 1991 $\left(\Delta IP^2_{j\tau} = \frac{\Delta M^{UC}_{j\tau}}{M_{j,91}}\right)$; and exclude all industry-level controls which are sourced from the NBER-CES database. We find consistent – and in some cases more significant – results when using this broader sample, which suggests that omitted industries due to data availability are not driving our results.

[26] Following Acemoglu et al. (2016), we use Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland as our benchmark countries. We use 1991 as the benchmark year in the denominator instead of 1988 as used by Acemoglu et al. (2016) because import and export data for the U.S. following HS codes is available only since 1991 in UN Comtrade. Prior to 1991, data is based on SITC codes; which would require an additional mapping to NAICS codes. Moreover, our focus is on the post-2000 period, so 1991 already embeds a lag to reduce endogeneity concerns.

[27] Defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry

industry-level controls sourced from the NBER-CES database: (i) the percent of production workers, (ii) the ratio of capital to employment; (iii) the ratio of capital to value added; (iv) the average wage; (v) the average production wage; and (vi) an indicator for advanced technology industries. We tested several other controls and neither affected the results. The remaining time-invariant characteristics are captured by the firm fixed effects; and year fixed effects account for aggregate shocks that affect all firms equally.

Our main sample for this analysis includes annual firm-level data from 1991 to 2015. We include all manufacturing firms, irrespective of entry/exit dates in our baseline specification; but also report results including only continuing firms [28] to capture differences in investment between firms that eventually exit (exiters) and incumbents that survive.

Several items about this specification warrant additional discussion. First, we focus on the level or (cumulative) changes in k as opposed to net investment to directly test model predictions. Investment rates are interesting in their own right, but are harder to measure and often far more volatile. They are heavily affected by movements in the depreciation rate. The level of k also incorporates alternate capital-building activities such as M&A and outright purchases/sales of fixed assets which correspond to investment decisions as defined in the model.

Second, we use a generalized DID specification because it allows us to differentiate the behavior of incumbents that survive, from that of exiters and new entrants. By contrast, regressing cumulative changes in K as in Autor et al. (2016) restricts the sample to continuing firms, and therefore limits our ability to contrast investment by laggards and leaders. This is particularly critical because, as documented in several papers, the China shock had material implications for the number of firms and the level of employment and capital in U.S. manufacturing industries. For instance,Pierce and Schott (2016) and Autor et al. (2016) show that employment decreased in industries more exposed to the China shock: a lot of firms were forced to shrink/exit and local entry likely decreased. Indeed our results are consistent with those of Pierce and Schott (2016) and Autor et al. (2016): if we consider all firms simultaneously, we find that capital decreases with import penetration. This is not surprising. Theoretical models do not imply that a given firm's or even the aggregate domestic investment / capital should increase with competition. Laggards may reduce investment until they exit, while leaders may increase investment in order to remain competitive/escape competition. It is therefore critical to differentiate the behavior among these groups; and this specification allows us to do so.

PNTR Instrument. We use $\Delta IP^{US}_{j,91-11}$ (instrumented by $\Delta IP^{OC}_{j\tau}$) as the basis of our analyses because it is a more direct measure of foreign competition. However, one could argue that demand shocks across advanced economies are highly correlated. In that case, $\Delta IP^{OC}_{j\tau}$ is not a valid instrument and regression results may be biased. To mitigate this concern, we study an alternative source of variation in China's import penetration: changes in barriers to trade following the United States granting Permanent Normal Trade Relations (PNTR) to China in 2000 and the associated accession of China into the WTO in 2001.

[28]Defined as firms that existed prior to 1995 and remain in the sample after 2009

In particular, we follow Pierce and Schott (2016) and exploit the reduction in tariff rate uncertainty from the U.S. granting PNTR to China. Before then, China was considered a non-market economy, which under the Smoot-Hawley Tariff Act of 1930 are subject to relatively high tariff rates. Such high tariff rates for non-market economies are known as "Non-Normal Trade Relations tariff" (non-NTR). From 1980 onward, U.S. Presidents began granting NTR tariff rates to China, but such waivers required annual approval by congress. This introduced substantial uncertainty around future tariff rates that limited investment by both U.S. and Chinese firms (see Pierce and Schott (2016) for a wide range of anecdotal and news-based evidence).

In 2000, the U.S. granted PNTR to China, which became effective on December 2001. The granting of PNTR removed uncertainty around tariffs, which led 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. Like Pierce and Schott (2016), we quantify the impact of 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

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

The change in U.S. policy is expected to have a larger effect on industries with larger NTR gaps. This measure is plausibly exogenous to competition after 2000: the vast majority of the variation in NTR gaps across industries arises from variation in non-NTR rates set 70 years prior to passage of PNTR. See Pierce and Schott (2016) for additional discussion. Using this exogenous measure of competition, we again examine the link between increased competition and investment using a generalized OLS difference-in-differences (DID) specification:

$$\begin{aligned} log(k_{i,j,t}) = \beta_1 Post - 2001 \times NTR\,Gap_j + \beta_2 Post - 2001 \times NTR\,Gap_j \times Leader \\ + +\boldsymbol{Post - 2001} \times \boldsymbol{X_{j,91}}'\boldsymbol{\gamma} + \boldsymbol{X'_{i,t-1}}\boldsymbol{\lambda} + \eta_t + \mu_i + \alpha + \varepsilon_{it} \end{aligned} \tag{13}$$

where the dependent variable is a given measure of capital (e.g., total assets, PP&E, etc.) for firm i in industry j during year t. 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 an indicator for the post-2001 period. The second term adds an indicator for leader firms, to capture differences in investment between leaders and laggards. The remaining terms are controls. $\boldsymbol{X_{j,91}}$ includes the initial year (1991) value of the industry characteristics included in 12 as controls; and $\boldsymbol{X_{i,t-1}}$ includes firm-age.

Note that $NTR\,Gap_j$ provides no time-series variation: it estimates a change in the average level of capital following 2002. In unreported tests, we interact $NTR\,Gap_j$with the mean import exposure $\overline{\Delta IP^{US}_{j,t}}$ and and use it to predict the time series of capital and K/Emp – first by interacting it with the post-2001 dummy and using equation 13; and then by instrumenting $\Delta IP^{US}_{j,t}$ with $NTR\,Gap_j \times \overline{\Delta IP^{US}_{j,t}}$. All conclusions remain consistent, although coefficients are more noisy.

4.1.2 Exploratory data analysis.

We begin by discussing broad trends in firm entry, firm exit, and investment for high- and low-exposure industries that lend support to our identification strategy and results. The following sub-section includes formal regression results. Throughout this section, we separate industries with 'high' (above-median) and 'low' (below-median) changes in Chinese import penetration from 1991 to 2011, $\Delta IP^{US}_{j,11}$.

Number of firms, entry and exit rates. Figure 10 shows the change in total number of firms in industries with high and low Chinese import penetration. We normalize the number of firms to 1995. As shown, both sectors exhibit roughly the same patterns before the rise of China: the number of firms was largely flat in the 1980's, increased rapidly in the 1990's and decreased with the dot-com bubble. The patterns diverge, however, starting in the mid 2000's. The number of firms in industries with high import penetration decreased much faster than the number of firms in industries with low import penetration. Today, there are half as many firms as there were in 1995 in high-exposure industries, against nearly 80% as many in low-exposure industries

Figure 10: Number of firms by Chinese exposure (1995 = 1)

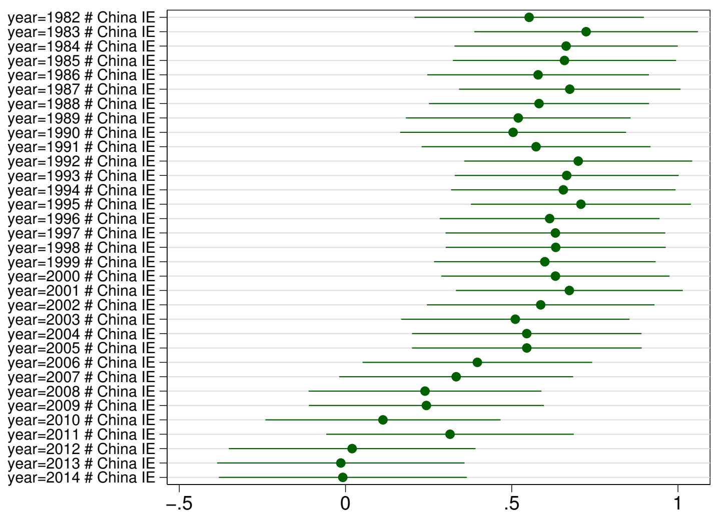
Notes: Annual data. Firm data from Compustat; import data from UN Comtrade. Manufacturing industries only, split into 'high' (above-median) and 'low' (below-median) exposure based on import penetration from 1991 to 2011.

To test the statistical significance of changes in the number of firms, we perform the following regression

$$log(N_{j,t}) = \mu_j + \eta_t + \beta_t \Delta IP_{j,99-11} \times 1\{year\} + \varepsilon_{j,t}$$

where $log(N_{j,t})$ denotes the log-number of firms in industry i at time t; μ_j and η_t denote industry and time fixed effects; and $\Delta IP_{j,99-11} \times 1\{year\}$ denotes the interaction between Chinese import penetration from 1999 to 2011 and an indicator for each year. If Chinese competition leads to a reduction in the number of firms, we should find stable coefficients on the interaction term (β_t) before 2000; and decreasing coefficients thereafter. Figure 11 shows the results, which support our hypothesis. Chinese competition appears to have led to a statistically significant reduction in the number of firms.

Figure 11: Number of Firms vs. Import exposure



Notes: Figure shows the coefficients β_t from regressing $log(N_{j,t}) = \mu_j + \eta_t + \beta_t \Delta IP_{j,99-11} \times 1\{year\} + \varepsilon_{j,t}$. As shown, increased Chinese competition leads to a reduction in the number of firms. Annual data. Firm data from Compustat; import data from UN Comtrade. Includes only manufacturing industries.

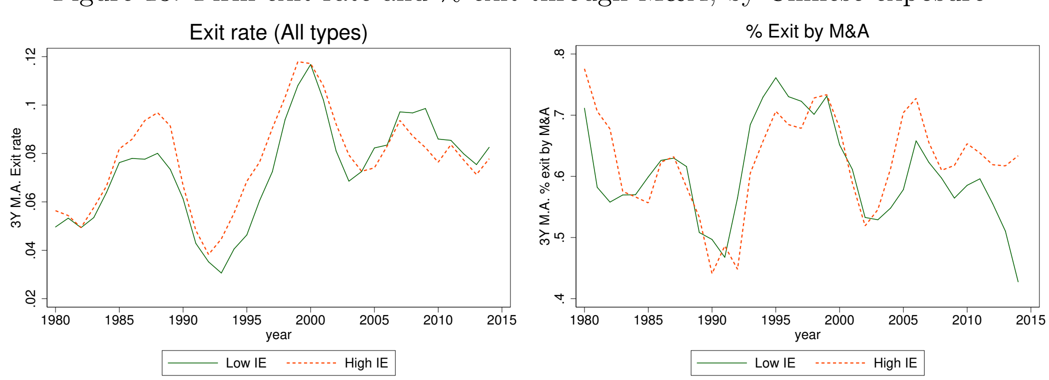
Is the decline in the number of firms due to lower entry or higher exit? As shown in Figures 12 and 13, primarily lower entry. In particular, Figure 12 shows the 3-year moving average aggregate entry rate across high and low exposure industries. High exposure industries had traditionally higher entry rates than low exposure industries. But this pattern flipped in the early 2000's. Entry into high-exposure industries decreased drastically and has remained well-below entry into low-exposure industries since 2003. By contrast, entry into low-exposure industries appears to have remained stable – affected primarily by the business cycle.

Figure 12: Firm entry rate by Chinese exposure

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 13 shows the 3-year moving average aggregate exit rates, and the percent exit rate through M&A, by level of import exposure. The total exit rates appear roughly similar across segments. That said, exit through M&A increased drastically for high exposure firms since the mid-2000's. Diving into industry-level exit rates also highlights some differences. In un-reported tests, we find that mean industry exit rate from 2000 to 2009 increases (significantly) with import exposure from 1991 to 2011. Thus, the substantially lower number of firms in high exposure industries appears to be primarily driven by lower entry, but also affected by higher exit and higher M&A activity.

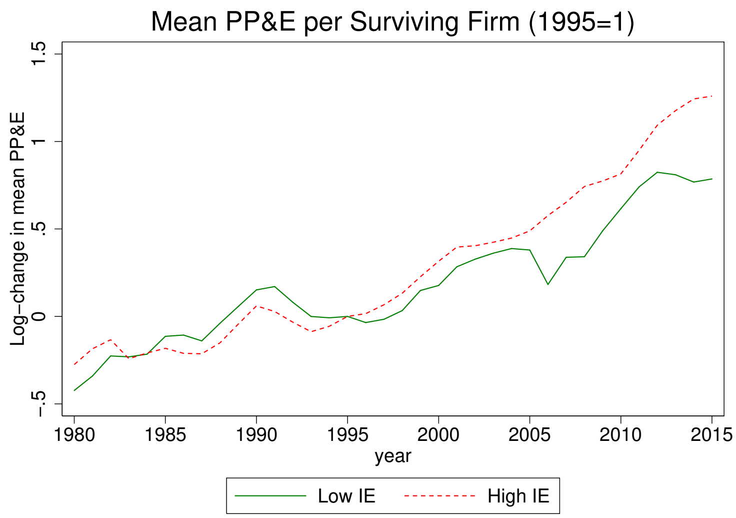
Figure 13: Firm exit rate and % exit through M&A, by Chinese exposure



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.

Firm investment. The number of firms in high-exposure industries decreased. Did the capital also decreased? No: as shown in Figure 14 the mean PP&E of firms in Compustat increased substantially faster in high exposure industries than low exposure industries. In other words, fewer firms remained, but they were substantially bigger.

Figure 14: Log-change in PP&E by Chinese Exposure

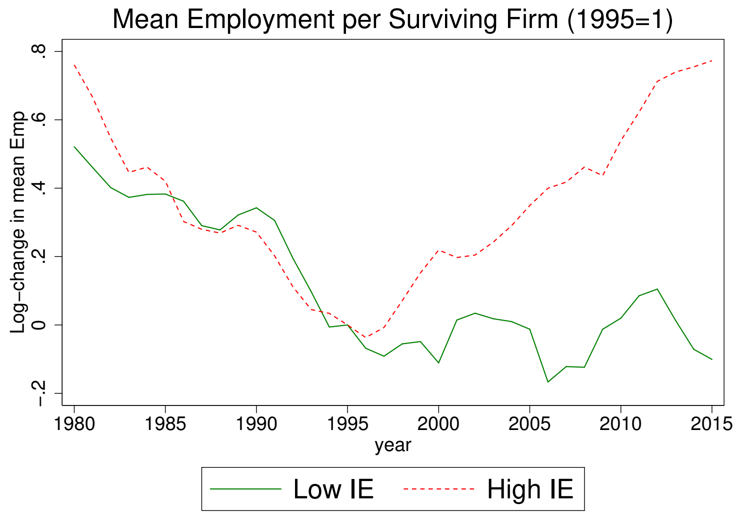


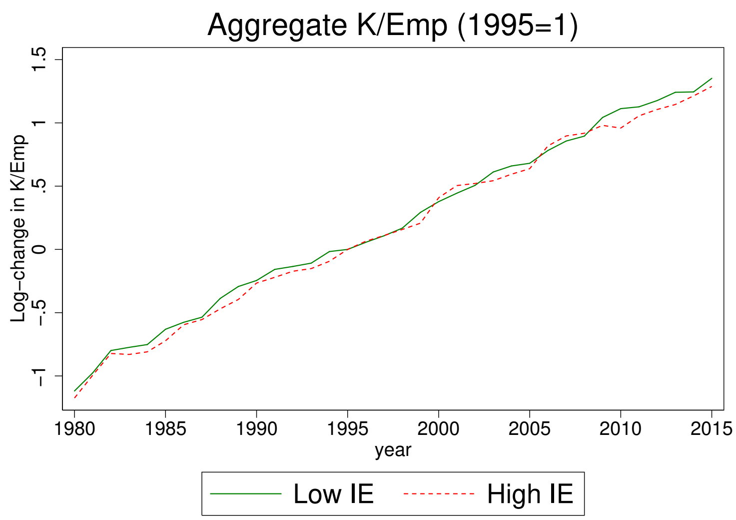
Notes: Annual data. Firm data from Compustat; import data from UN Comtrade. Manufacturing industries only, split into 'high' (above-median) and 'low' (below-median) exposure based on import penetration from 1991 to 2011. The plot includes only remaining firms for each year.

Employment. The effect of Chinese competition on employment has been widely studied – most recently in Pierce and Schott (2016); Acemoglu et al. (2016). They both show that total employment decreased in industries most affected by Chinese competition. But, again, the effects differ between leaders and laggards. As shown in Figure 15, the mean employment per surviving firm (at each year) increased drastically at high exposure firms; while it remained flat at low exposure firms. Leaders appear to have invested and grown with Chinese competition; while smaller firms exited.[29] Comparing the ratio of K/Emp across high and low exposure firms, we find largely similar patterns (see bottom chart). Note that K in this chart is defined as the sum of PP&E and balance sheet intangibles for the corresponding firms. It is critical to include intangibles, as surviving firms in high exposure industries appear to have over-invested in intangibles (see next sub-section for additional discussion).

[29]As noted above, a common path of exit appears to have been M&A – which supports the observed patterns.

Figure 15: Change in Employment and K/Emp, by Chinese Exposure





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.

4.1.3 Regression Results

We now discuss regression results, which confirm the qualitative observations from the prior section. Table 4 shows our baseline results, following Equation 12. All regressions include year and firm fixed effects; as well as industry and firm age controls. We consider three different measures of capital: PP&E, Intangible assets and total capital (equal to the sum of PP&E and Intangibles). It is well known that measuring intangible capital is challenging. Rather than developing a new definition, we use the estimates of Peters and Taylor (2016). These estimates are available in WRDS and rely on detailed investment and depreciation assumptions by intangible asset type. For robustness, we also confirm that our results are stable when using balance sheet intangibles and intangibles excluding goodwill.

As shown in columns 1 to 3, higher import penetration has a negative (unconditional) effect on capital. This is consistent with results in Pierce and Schott (2016). Separating leaders and laggards, however, we see very different results. Leaders increased capital with import exposure while laggards decreased it (specifically, the coefficient on the leading firm interaction is positive and larger than the negative coefficient for all firms). This aligns with model predictions in Proposition 3, where leaders invest more to compete with entrants; while laggards reduce investment and/or exit. The increase in investment is particularly pronounced for intangible assets. Columns 9 to 12 focus on continuing firms; and show that leaders invested more than laggards, even when compared only to firms that survived the China shock (i.e., firms that were in the sample before 1995 and after 2009).

Table 5 shows the results using $NTRGap_j$ as our measure of Chinese competition, instead of ΔIP^{US}_{jt}. Again, all regressions include year and firm fixed effects; as well as industry and firm age controls. Although the coefficient for leaders are not always larger than the coefficient for laggards, the leading firm interaction always exhibits a positive and significant coefficient. Thus, leaders appear to have reacted to increased Chinese competition by increasing their capital stock relative to laggards. This is particularly true for intangible capital.

The above results highlight that leaders increased investment relative to laggards when affected by Chinese Competition. Table 6 studies the effects on employment and K/Emp. Columns 1-3 show that (unconditionally) employment and capital decreased with import exposure. Separating leaders and laggards, again, shows different dynamics. Leaders increased both employment and capital at a similar rate. The coefficient on employment is not significant in column 2, and the leaders' coefficient on column 6 is slightly smaller than the coefficient for all firms. This likely due to a large amount of noise on the measure of employment. In fact, as shown in the appendix, both coefficients exhibit the expected signs, significance and magnitudes when using either the $NTRGap$ or ΔIP^{US}_{jt} as our measure of competition rather than instrumenting ΔIP^{US}_{jt} with $\Delta IP^{OC}_{j,91,11}$.

To summarize, we find that leaders reacted to increased Chinese competition by increasing investment relative to laggards. Exiters and/or new entrants exhibit a decrease in investment, in line with predictions of competition models with asymmetric firms. Our conclusions, however, come with two important caveats: first, they consider only manufacturing industries, which raises issues of external validity; and, second, the implications for total domestic investment are ambiguous given the use of foreign competition. The next section leverages excess entry in the 1990's as an IV for competition, in order to fill these gaps.

4.2 Instrumental Variables: Excess Entry

As noted in Section 2, a good instrument in our model is a shock that randomly changes the opportunity cost of entry across industries. In particular, variation in entry costs κ^e_j that are uncorrelated with future demand $D_{j,t}$ and productivity $A_{j,t}$ would be valid instruments to assess the impact of concentration on investment. In this section, we argue that the peculiar dynamics of

Table 4: Chinese Competition: $\log(k_t)$ results based on $\Delta IP^{US}_{j,t}$ instrumented by $\Delta IP^{OC}_{j,t}$

Table shows the results of firm-level panel regressions of measures of capital on US-based import penetration, instrumented by import penetration at 8 other advanced economies. Regression from 1991 - 2015, following equation 12. We consider three measures of capital: log-PP&E, log-intangibles and log-capital. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include lagged measures of industry-level production structure (e.g.,PPE/Emp). As shown, leaders increased their capital with Chinese competition, both in levels and relative to laggards. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(5)	(6)	(7)	(9)	(10)	(11)
	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$
$\widehat{\Delta IP^{US}_{j,t}}$	-0.278*	-0.278*	-0.218+	-0.621**	-0.655**	-0.592**	-0.858**	-0.805**	-0.787**
	[-2.41]	[-2.53]	[-1.87]	[-3.92]	[-3.41]	[-3.21]	[-3.73]	[-3.07]	[-2.99]
$\widehat{\Delta IP^{US}_{j,t} \times Lead_{99}}$				**0.813****	**0.891****	**0.885****	**1.099****	**1.168****	**1.185****
				[3.86]	**[3.00]**	**[3.43]**	**[2.96]**	**[2.72]**	**[2.95]**
$\log(Age_{t-1})$	0.391**	0.684**	0.623**	0.391**	0.684**	0.624**	0.678**	0.813**	0.761**
	[7.92]	[18.91]	[16.12]	[7.95]	[18.79]	[16.08]	[10.47]	[12.88]	[12.58]
Observations	30902	30936	30959	30902	30936	30959	11816	11805	11819
Within R^2	0.162	0.588	0.545	0.165	0.589	0.547	0.268	0.638	0.602
Industry controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sample	All firms			All firms			Continuing firms		

Table 5: Chinese Competition: $\log(k_t)$ results based on $NTR\,Gap_j$

Table shows the results of firm-level panel regressions of measures of capital on NTR gap, following 13. We consider three measures of capital: log-PP&E, log-intangibles and log-capital. Regression over 1980 - 2015 period. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include measures of industry-level production structure (e.g.,PPE/Emp) as of 1991 interacted with the Post-2001 dummy. As shown, leaders in industries with a higher NTR gap increased their capital relative to laggards after 2001. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$	$log(PPE_t)^a$	$log(Intan_t)^b$	$log(k_t)^{a+b}$
$Post01 \times NTR\,Gap$	-0.940**	-0.28	-0.548*	-1.510**	-0.729*	-1.032**	-1.781**	-0.853*	-1.237**
	[-2.99]	[-0.96]	[-2.38]	[-4.69]	[-2.40]	[-4.32]	[-4.52]	[-2.32]	[-4.08]
$Post01 \times NTR\,Gap \times Lead_{99}$				**1.161****	**0.916****	**0.984****	**1.297****	**1.025****	**1.120****
				[7.31]	**[6.71]**	**[7.38]**	**[6.03]**	**[5.61]**	**[6.34]**
$\log(Age_{t-1})$	0.345**	0.640**	0.567**	0.346**	0.641**	0.568**	0.569**	0.753**	0.687**
	[9.81]	[19.80]	[16.75]	[10.31]	[19.44]	[16.45]	[9.36]	[12.64]	[12.48]
Observations	49831	49783	49833	49831	49783	49833	17402	17332	17360
R^2	0.223	0.635	0.591	0.233	0.64	0.599	0.347	0.688	0.661
Industry controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sample	All firms			All firms			Continuing firms		

Table 6: Chinese Competition: $\log(\frac{k_t}{Emp_t})$ results based on $\Delta IP^{US}_{j,t}$ instrumented by $\Delta IP^{OC}_{j,t}$

Table shows the results of firm-level panel regressions of measures of capital, employment and capital-deepening on US-based import penetration, instrumented by import penetration at 8 other advanced economies. Regression from 1991 - 2015, following equation 12. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include lagged measures of industry-level production structure (e.g.,PPE/Emp). As shown, leaders increased capital, employment and k/Emp with Chinese competition. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(K_t)$	$\log(Emp_t)$	$\log(\frac{k_t}{Emp_t})$	$\log(K_t)$	$\log(Emp_t)$	$\log(\frac{k_t}{Emp_t})$
$\widehat{IP^{US}_{j,t}}$	-0.218+	-0.047	-0.167	-0.592**	-0.315**	-0.263
	[-1.87]	[-0.36]	[-0.97]	[-3.21]	[-2.59]	[-1.30]
$\widehat{IP^{US}_{j,t} \times Lead_{99}}$				**0.885****	**0.635****	**0.228***
				[3.43]	**[3.38]**	**[2.06]**
$\log(Age_{t-1})$	0.623**	0.448**	0.176**	0.624**	0.447**	0.176**
	[16.12]	[11.24]	[4.36]	[16.08]	[11.24]	[4.35]
Observations	30959	30547	30536	30959	30547	30536
Within R^2	0.545	0.117	0.435	0.547	0.118	0.435
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			All firms	

entry in the late 1990's offer such an instrument.

In particular, we begin by estimating 'excess entry' as the level of entry above and beyond entry predicted by observables. We then show that our measure of excess entry does not predict future demand or productivity; but it does predict a decrease in the number of firms. It led to 'excess firms', and therefore excess competition in some industries after 2000. This makes it a valid instrument for industry-level concentration. We use it, and find that industries with more competition invest more after controlling for fundamentals.

4.2.1 Empirical strategy

We predict 'expected' entry during the 1990's based on measures of profitability, sales growth, cash flow and Q, among others[30]

$$\begin{aligned}\Delta logN_{j,90-99} = {} & \beta_0 + \beta_1 Med\,Q_{j,90-99} + \beta_2 Med\,\Delta log\,Sales_{j,90-99} \\ & + \beta_3 OS/K_{j,90-99} + \beta_4 CF/Assets_{j,90-99} + \beta_5 Med\,EPS\,Fcst_j \\ & + \beta_7 Mean\,firm\,assets_{89} + \beta_8 Mean\,firm\,age_{89} + \varepsilon_j\end{aligned}$$

where the sub-index 90-99 denotes the average value from 1990 to 1999.[31] $Med\,EPS\,Fcst_j$ denotes the median forecasted long term growth in Earnings-Per-Share by Analysts.[32] Then, we compute excess entry as the difference between actual and predicted entry

$$Excess\,Entry_{j,90-99} = \Delta logN_{j,90-99} - \Delta \widehat{logN_{j,90}}_{-99}$$

The following sub-section discusses our estimates of excess entry empirically. We find large cross-sectional variation in entry rates across industries. Industries that experienced higher excess entry in the 1990's had a lower concentration in 2000; which was offset over the 2000's as the 'excess' firms exited.

A potential concern with our identification strategy is that optimistic valuations may have led to excess investment among existing firms. In that case, investment in the 2000's would decrease independently of competition. To control for this, we estimate industry-level excess investment and excess capital in the 1990's (by regressing net investment on industry Q, age and size) and adding the cumulative residual as a control in our regression.

We therefore run the following industry-level panel regression over the post-2000 period:

$$HHI_{j,t-1} = \theta_0 + \theta_1 Excess\,Entry_{j,90-99} + \theta_2 Mean\,Q_{j,t-1} + \theta_3 Excess\,Inv_{j,90-99} + \boldsymbol{\theta X_{jt-1}} + \varepsilon_{1,jt}$$

[30] We also considered absolute changes in the number of firms during the 1990's and found largely consistent results.

[31] All variables in our Excess Entry regression are based on Compustat, except for OS/K which is based on BEA figures. This regression yields an $R^2$of 71% .

[32] Long term growth forecasts are often interpreted as 5-year growth forecasts.

$$\frac{NI_{jt}}{K_{jt-1}} = \beta_0 + \beta_1 \widehat{HHI_{j,t-1}} + \beta_2 Mean\,Q_{j,t-1} + \beta_3 Excess\,Inv_{j,90-99} + \boldsymbol{\gamma X_{j,t-1}} + \varepsilon_{2,jt} \tag{14}$$

where we use Excess Entry during the 1990's as an instrument for industry-level Herfindahl.[33] In some cases, we instrument for the 2000 Herfindahl instead of the time-varying Herfindahl. X_{jt-1} denotes industry-level controls for age. Namely, we include the mean age as of 1999 as an independent variable; and the lagged mean age as an instrument. Note that we instrument only for the 'traditional' Herfindahl, not the modified Herfindahl, because excess entry does not affect anti-competitive effects due to common ownership. If higher competition indeed causes more investment, θ_1 and β_1 should be negative. $\theta_1$because more entry leads to a lower Herfindahl; and β_1 because more competition (i.e., lower Herfindahl) leads to more investment. Recalling the definition of tests in Section 2.4, this test assesses whether $\frac{\partial K_j}{\partial C_j} > 0$ in the cross-section, where $dC_j > 0$ for those industries experiencing Excess Entry.

It is worth noting that, because excess entry is constant over time, we cannot add industry fixed effects in the above test. But we can use the time-series variation in exit rates and concentration to test another implication of our results. Industries with higher excess entry in the 1990's exhibit higher exit rates in the 2000's. As a result, the impact of excess entry on investment should decrease over time – i.e., the 'excess' competition will decrease over time ($dC_j < 0$). We test this by analyzing the coefficients on excess entry and Herfindahls over time; and by interacting the median Herfindahl across all industries with industry-level excess entry. Industries that experienced more excess entry should be more sensitive to aggregate concentration trends (i.e., the associated coefficient should be positive), which in turn leads to a larger reduction in investment over time. We include industry and year fixed effects in this second specification.

Last, note that our model predictions relate to changes in total capital, not net investment. Obviously the former is the result of cumulating the latter – but for completeness we also report results using $log\left(\frac{K_{j,t}}{K_{j,99}}\right)$ as our dependent variable. For these regressions, we include the average value of mean industry Q from 2000 to time t (denoted as $\overline{Mean\,Q_{j,00,t}}$) instead of just lagged mean Q ($Mean\,Q_{j,t-1}$). This is because investment from 2000 to time t depends on the path of Q, not just its most recent level. We find that industries with higher excess entry exhibit higher levels of capital.

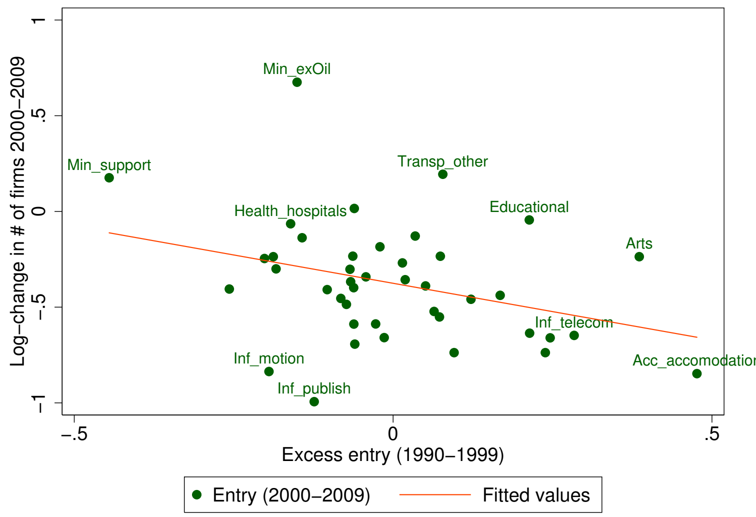
4.2.2 Exploratory data analysis.

The regression results are provided in the following sub-section. This section discusses our estimates of excess entry, and the corresponding concentration dynamics to further support our identification strategy.

Figure 16 plots the log-change in firms from 2000 to 2009 against our estimated excess entry from 1990 to 1999. As shown, we find large differences in excess entry across industries during the 1990's

[33] We also considered instrumenting for Concentration ratios and obtained consistent results

Figure 16: Change in # of firms post-2000 vs. Excess entry pre-2000



Notes: Annual data from Compustat. See text for details on Excess Entry measure.

– even after controlling for industry fundamentals. Some industries, like 'Information - Telecom' and 'Accommodation', experienced a substantial amount of excess entry, while others (e.g., Mining - Support) exhibit too little entry. As noted previously, it does not matter for us 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 1999) that turn out to be orthogonal to future demand (say in 2005). Nonetheless, the literature offers three potential explanations for variations in entry rates.

The first 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 overly 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)). Per 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.

The second is the presence of sizable stock market bubbles across most industries, as documented by Anderson et al. (2010). In particular, Anderson et al. (2010) report that "well over half of the

Table 7: Post-2000 Entry and Exit vs. Pre-2000 Excess entry: Regression Results

Table shows the results of industry-level OLS regressions of entry and exit measures on excess entry. Entry and Exit based on the number of firms in Compustat. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)
	$\Delta log N_{00-09}$	$\overline{Entry}_{00-09}$	$\overline{Exit}_{00-09}$	$\overline{M\&A\,Exit}_{00-09}$
$Excess\,Entry_{i,90-99}$	**-0.569***	0.007	**0.034+**	**0.029+**
	[-2.14]	[0.45]	**[1.73]**	**[1.83]**
$\overline{MedQ_{j,00,09}}$	0.123	0.047**	0.024+	0.033**
	[0.72]	[4.73]	[1.91]	[3.27]
Observations	42	42	42	42
R-squared	0.124	0.364	0.133	0.248

S&P 500 index by market capitalization and seven of its ten sector component indices exhibited at least some bubble-like behavior over [the late 1990's]." Such bubbles likely translated into excess 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)). The presence of excess entry is documented for specific industries in several papers. For instance, Doms (2004) studies excess 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.

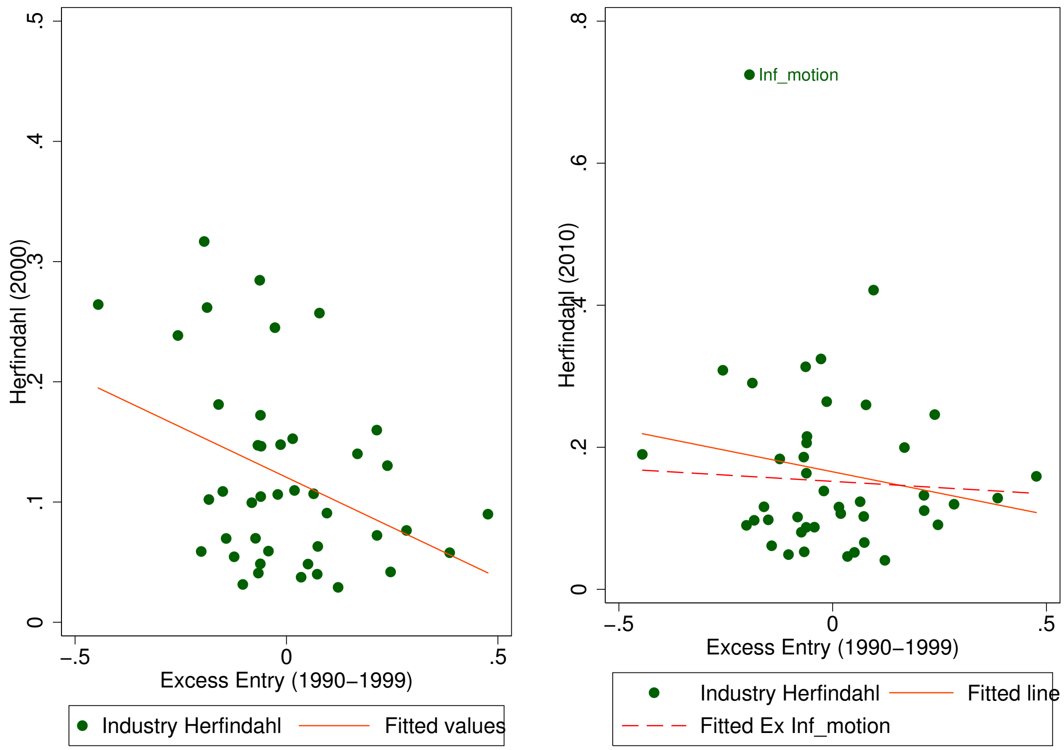
Last, differences in excess entry are likely linked to persistent technological, competitive and/or regulatory characteristics that make entry and exit easier in some industries than others. Such characteristics introduce variations in the realized entry rates even for common valuation shocks. For instance, Dunne et al. (1988) study manufacturing industries and find that *"relative differences in entry and exit patterns across industries persist over time, [which] suggests that industry-specific factors…affect both entry and exit levels."*

Interestingly, the excess entry was largely offset following the 1990's: industries that experienced higher excess entry, also experienced larger decreases in the number of firms in the 2000's. In fact, as shown in Figure 16, the number of firms decreased across most industries by much more than the excess entry. [34] Table 7 formalizes these observations. It shows the results of regressing post-2000 changes in the number of firms, as well as average entry and exit rates, on pre-2000 excess entry, controlling for Q. Higher excess entry predicts a reduction in the number of firms; primarily due to higher exit.

Industries that experienced higher excess entry in the 1990's had a lower concentration in 2000;

[34] This suggests the presence of an aggregate trend towards concentration (which is highlighted in CEA (2016), among others). We discuss this further in Section 5.

Figure 17: Excess entry (1990-1999) vs. Herfindahl (2000 and 2010)



Notes: Annual data. Herfindahl based on all U.S. incorporated firms in Compustat.

which was offset over the 2000's as the 'excess' firms exited. Figure 17 shows this graphically. The left (right) chart shows the Herfindahl as of 2000 (2010) against excess entry in the 1990's. This is essentially the first stage of our regression, excluding the additional controls. As shown, industries with higher excess entry in the 1990's had a lower Herfindahl in 2000; which was offset by 2010. Indeed by 2010, we see a very weak relationship between excess entry in the 1990's and the Herfindahl – especially once excluding Inf_motion which is a clear outlier.

Last, Table 8 shows the results of regressing post-1999 changes in industry sales and value added on excess entry. As shown, actual entry predicts changes in value added but excess entry does not. In fact, the coefficient shows the wrong sign.

To summarize, the above results suggest the existence of substantial cross-sectional variations in excess entry during the 1990's, which does not predict future demand or productivity. Excess entry does, however, predict lower concentration in 2000; which makes it a valid instrument for industry-level investment.

4.2.3 Regression Results

Let us begin by showing that industries with more excess entry in the 1990's exhibit more investment and more capital after 2000. Namely, we run the following regressions for each year separately

Table 8: Excess Entry vs. Sales: Regression Results

Table shows the results of industry-level OLS regressions of sales and value added on total and excess entry. Sales and value added from BEA. Entry from Compustat. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)
	$\Delta log(Sale)_{99-04}$		$\Delta log(V.Add)_{99-04}$	
$\Delta log(\#\, firms)_{94-99}$	0.102		**0.321***	
	[0.85]		**[2.64]**	
$Excess\, Entry_{90-99}(i)$		-0.148		-0.179
		[-0.68]		[-0.75]
Observations	43	42	43	42
R^2	0.017	0.011	0.145	0.014

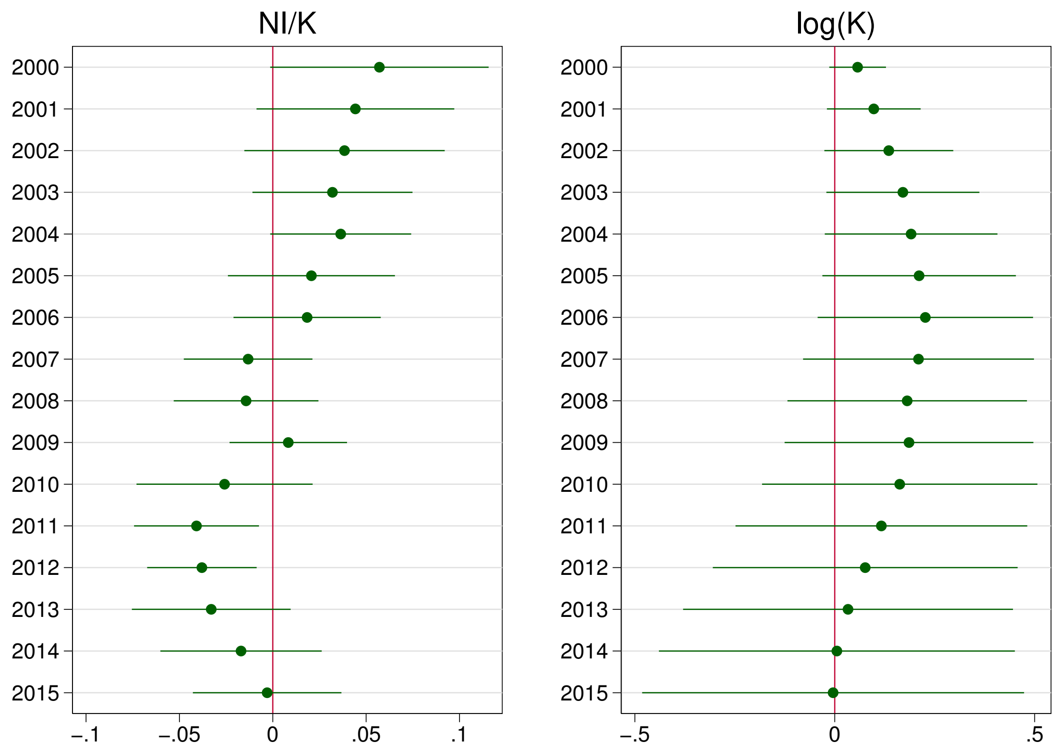
$$log\left(\frac{NI_{j,t}}{K_{j,t-1}}\right) = \beta_1 Mean\, Q_{j,t-1} + \beta_2 Excess\, Entry_{j,90-99} + \beta_3 Excess\, Inv_{j,90-99} + \varepsilon_{jt} \tag{15}$$

$$log\left(\frac{K_{j,t}}{K_{j,99}}\right) = \beta_1 \overline{Mean\, Q_{j,00,t}} + \beta_2 Excess\, Entry_{j,90-99} + \beta_3 Excess\, K_{j,99} + \varepsilon_{jt}$$

where $\overline{Mean\, Q}$ denotes the average value of the industry average Q from 2000 to time t. We use chained-quantity indices for regressions on K and current-cost values for NI/K.

Figure 18 shows the results, along with 10% confidence intervals. As shown, the coefficient on excess entry is positive for both investment and capital. In both cases, the coefficient is largest on the years immediately following 1999, and it decreases over time as 'excess firms' exit and concentration increases. The coefficient is not always significant, but this is mostly driven by time-series variation: the following section includes panel regression results. Similar, although slightly less significant patterns are obtained when instrumenting the Herfindahl with excess entry, instead of including excess entry directly in the regression.

Figure 18: Excess entry coefficient



Notes: Figure plots the coefficient of separate, annual regressions of net investment and chained-quantity of capital on our measure of excess entry, following equation 15. As shown, industries with higher excess entry experience a temporary increase in investment and capital. 10% confidence intervals are shown.

Next, Table 9 contains the results of our IV panel regressions following equation 14, which instruments the sales Herfindahl with excess entry. Columns 1 and 2 show the basic regression. As expected, the coefficient on excess entry is negative as more entry leads to a lower Herfindahl; and the coefficient on the Herfindahl is negative as lower competition (i.e., higher Herfindahl) leads to less investment. Columns 3 and 4 interact the median Herfindahl across all industries with industry-level excess entry. This allows us to include industry and year fixed effects. As expected, industries that experienced more excess entry appear to be more sensitive to aggregate concentration trends, which in turn leads to a larger reduction of investment over time. Columns 5 and 6 replace the U.S. Herfindahl with an import-adjusted Herfindahl defined as described in Section 3.3.2. It shows results are robust to controlling for foreign competition.

Table 10 shows similar results based on $log(K_{j,t})$ instead of net investment. Columns 1 and 2 include excess entry directly, and focus on the 2001 to 2004 period – the period over which excess entry has the largest impact on investment. As shown, higher excess entry predicts higher capital. Columns 3-4 and 5-6 instrument the U.S. and import-adjusted Herfindahl, respectively,

Table 9: Excess Entry: NI/K Regression Results

Table shows the results of industry-level 2SLS regressions of net investment on Herfindahls, instrumented by excess entry. Columns (1) and (2) focus on cross-sectional variation, and instrument the Herfindahl with excess entry. Industries with higher excess entry exhibit lower Herfindahl's and higher investment. Columns (3) to (6) study time series variations and include time- and industry- fixed effects. They interact excess entry with aggregate series of concentration and investment, and use the interactions to predict industry concentration and investment. Columns (3) and (4) consider the US-based Herfindahl HHI^{US},while columns (5) and (6) consider the import-adjusted Herfindahl, HHI^{IA}. T-stats in brackets. Columns (1) and (2) based on random effects panel model; columns (3) to (6) based on FE panel regression with standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	1st St.	2nd St.	1st St.	2nd St.	1st St.	2nd St.
	$HHI^{US}_{j,t}$	Net I/K	$HHI^{US}_{j,t}$	Net I/K	$HHI^{IA}_{j,t}$	Net I/K
	≥2000	≥2000	≥2000	≥2000	≥2000	≥2000
Mean Q (t-1)	0.002	**0.022****	0.002	0.026**	-0.002	0.023**
	[0.32]	**[6.30]**	[0.33]	[3.50]	[-0.31]	[3.20]
$Excess\,Inv_{90-99}$	-1.29*	-1.035**				
	[-2.34]	[-3.22]				
$Excess\,Inv_{90-99}(i) \times NIK^{US}_t$			-0.07	46.543**	6.13	50.793**
			[-0.00]	[3.44]	[0.40]	[4.82]
$Excess\,Entry_{90-99}(i)$	**-0.14****					
	[-3.40]					
$Excess\,Entry_{90-99}(i) \times Med\,HHI_t$			**3.89***			
			[2.05]			
$Excess\,Entry_{90-99}(i) \times Med\,HHI^{IA}_t$					**3.19***	
					[2.23]	
$HHI^{US}_{i,t}$		**-0.355****		**-0.715***		
		[-3.51]		**[-2.23]**		
$HHI^{IA}_{i,t}$						**-0.755****
						[-2.67]
Mean log(age) ('99)	0.00	-0.01				
	[0.10]	[-0.70]				
Mean log(age) (t-1)	0.07**					
	[4.17]					
Year FE	No		Yes		Yes	
Industry FE	No		Yes		Yes	
Observations	672	672	672	672	672	672
R^2(RMSE)		0.113		(0.036)		(0.032)

with excess entry. Industries with higher excess entry exhibit a lower Herfindahl and higher capital. Columns 7-10 extend the period to 2010 and show results remain robust (or nearly so) over the longer period. Ultimately, these conclusions suggest that the U.S. is still in the increasing part of the competition-investment curve – i.e., more competition leads to more investment.

5 What explains the increase in concentration?

We have argued that the rise in concentration is responsible for a significant part of the gap in corporate investment. But what has driven the increase in concentration? Several explanations have been put forth in the literature. Grullon et al. (2016) consider five such hypotheses: (i) antitrust enforcement; (ii) competitive barriers to entry and incumbent innovation; (iii) omission of private firms in Compustat-based measures; (iv) the presence of foreign firms, and (v) consolidation in unprofitable industries. They find some support for the first two hypotheses; and argue against the latter three.

We discuss and provide some analyses for the following three hypotheses:

- **Enforcement and Regulation:** changes in the enforcement of antitrust laws may have allowed firms to significantly increase their market shares over time. And rising regulation/lobbying may have allowed dominant firms to erect barriers to entry and increase market power (see, for example, CEA (2016); Bessen (2016); Grullon et al. (2016)). Faccio and Zingales (2017) provide a case study for the mobile telecommunication sector. They find that pro-competition regulation reduces prices, but does not hurt quality of services or investments. They conclude that competition in the U.S. is well-below levels of competition in Europe. U.S. consumers would gain \$65bn a year if U.S. mobile service prices were in line with German ones and \$44bn if they were in line with Danish ones.

- **IT and the rise of superstar firms:** technological change may have made markets increasingly "winner take most" such that superstar firms with higher productivity capture a larger slice of the market (see, for example, Autor et al. (2017))[35]

- **Demographics**: the decrease in business dynamism may be driven by a decline in the growth rate of the labor force beginning in the late 1970's. Such a decline may reduce the start-up rate while leaving incumbent dynamics largely unaffected (e.g., Pugsley et al. (2015))

To differentiate across these hypotheses, we gather/compute the following measures and explore their relationship with concentration

[35] This could be complemented by a rise in the likelihood of incumbent innovation, which could increase the gap between leaders and laggards. This is analyzed in Grullon et al. (2016), who show that post-2000, firms in concentrated markets possess not only a larger number of patents, but also the most valuable ones.

Table 10: Excess Entry: Log(K) Regression Results

Table shows the results of industry-level 2SLS regressions of changes in chained industry-level capital on Herfindahls, instrumented based on excess entry. We report results over the 2000-2004 period – the one most affected by excess entry – as well as the 2000-2009 period. Columns (1) and (2) regress changes in capital on excess entry directly. The remaining columns instrument the U.S. Herfindahl HHI^{US}, (columns 3-4, 7-8) and the import-adjusted Herfindahl HHI^{IA} (columns 5-6, 9-10). We include our estimated excess capital as of 1999 as a control in all regressions. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			1st St.	2nd St.	1st St.	2nd St.	1st St.	2nd St.	1st St.	2nd St.
	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$	$HHI^{US}_{j,00}$	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$	$HHI^{IA}_{j,00}$	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$	$HHI^{US}_{j,00}$	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$	$HHI^{IA}_{j,00}$	$log\left(\frac{K_{j,t}}{K_{j,99}}\right)$
	2000-2004	2000-2009	2000-2004		2000-2004		2000-2009		2000-2009	
$\overline{mean\,Q_{j,00,t}}$	0.112*	0.182**	-0.04	0.093*	-0.02	0.101*	-0.03	0.158*	-0.02	0.168*
	[2.68]	[2.76]	[-1.57]	[1.99]	[-0.74]	[2.06]	[-1.34]	[2.14]	[-0.64]	[2.21]
$Ex.\,K_{j,90-99}$	0.76	-0.473	-1.48+	-0.056	-1.14	-0.012	-1.51+	-1.543	-1.15	-1.474
	[0.90]	[-0.37]	[-1.77]	[-0.05]	[-1.28]	[-0.01]	[-1.83]	[-0.93]	[-1.32]	[-0.82]
$Ex.\,Entry_{90-99}(i)$	**0.134***	**0.170***	**-0.24****		**-0.20***		**-0.24****		**-0.20***	
	[2.37]	**[2.23]**	**[-3.21]**		**[-2.37]**		**[-3.27]**		**[-2.42]**	
$HHI^{US}_{i,00}$				**-0.549+**				**-0.707+**		
				[-1.89]				**[-1.81]**		
$HHI^{IA}_{i,00}$						**-0.678+**				**-0.87**
						[-1.72]				**[-1.62]**
Year FE	Yes		Yes		Yes		Yes		Yes	
Observations	210	420	210	210	210	210	420	420	420	420
R^2 (RMSE)	0.216	0.261		(0.121)		(0.129)		(0.171)		(0.183)

- **Enforcement and Regulation**: we rely on the Regulation index published by the Mercatus Center at George Mason University as a measure of industry-level regulation.[36]

- **Superstar firms:** For superstar firms, we follow Autor et al. (2017) and explore the relationship between changes in concentration and changes in industry productivity. We use census-based measures of concentration at the NAICS Level 6; along with manufacturing industry characteristics from the NBER-CES Manufacturing Industry Database. In particular, we compute the change in industry 4- and 5-factor TFP, as well as the ratio of output and value-added to capital and labor.

- **Demographics:** we compute the median age of CEOs in each industry based on data from ExecuComp. Industries with older CEOs are likely to be more affected by demographics, hence should exhibit rising concentration.

We find strong support for the regulation and enforcement hypothesis; some support for the superstar hypothesis; and limited support for the demographics hypothesis.

5.1 Regulation and enforcement

There is some evidence that enforcement of antitrust laws by the Department of Justice and the Federal Trade Commission declined during the administrations of George W. Bush and Barack Obama, as argued in Grullon et al. (2016). They show that the number of investigations by the Department of Justice filed under Section 2 of the Sherman Act – which allows antitrust agencies to prevent an increase in market power of existing firms – has declined from an average of 12 cases per year during 1980–1999 to fewer than 3 during 2000–2015. This is true despite the rise in concentration shown in Figure 1. Grullon et al. (2016) also show that completion rates for M&A transactions have been increasing over time; and the number of merger enforcement actions filed by the Federal Trade Commission have remained roughly stable since 1996 despite a rise in M&A activity. Combined, these facts support the idea that anti-trust regulators are now less likely to block proposed mergers.

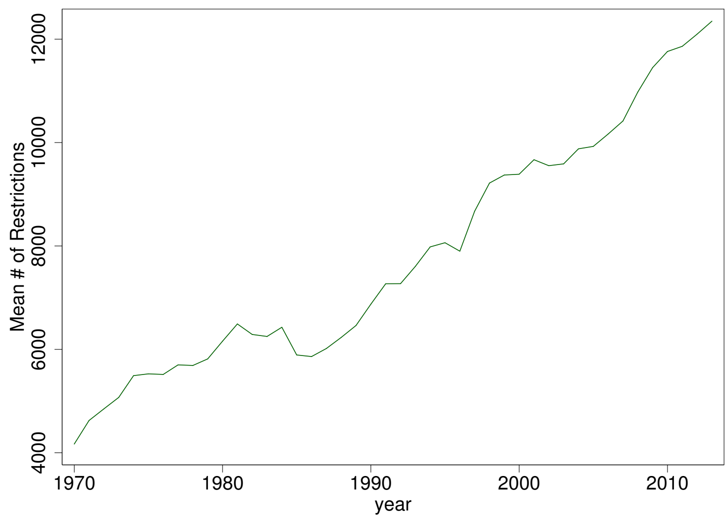
These observations support the argument that declines in enforcement contribute to rising concentration. However, we must be careful not to draw causal inferences from this analysis – and realize that these are only a limited set of data points. In fact, other measures of anti-trust enforcement exhibit opposite trends. For instance, CEA (2016) provides evidence of increased enforcement in the form of fines/penalties and prison sentences.

To make progress on this issue, we need a measure of regulation that varies across industries. Figure 19 shows the average number of applicable regulatory restrictions by industry, from 1970 to 2015. As shown, the number of restrictions was relatively stable in the 1970's and early 1980's but

[36]We also compute the share of workers requiring Occupational Licensing in each NAICS Level 3 industry from the 2008 PDII as a proxy for barriers to entry. The 2008 PDII was conducted by Westat, and analyzed in Kleiner and Krueger (2013). It is based on a survey of individual workers from across the nation. However, we find no no statistically significant effect.

increased rapidly thereafter. This is critical, as regulation can lead to increased concentration in three ways: (i) regulations often require a large fixed cost component which benefits larger firms; (ii) regulation may introduce barriers to entry; and (iii) increased rent seeking may allow larger firms to affect regulation through lobbying, thereby strengthening their position as leaders.[37]

Figure 19: Mean # of relevant restrictions, by industry

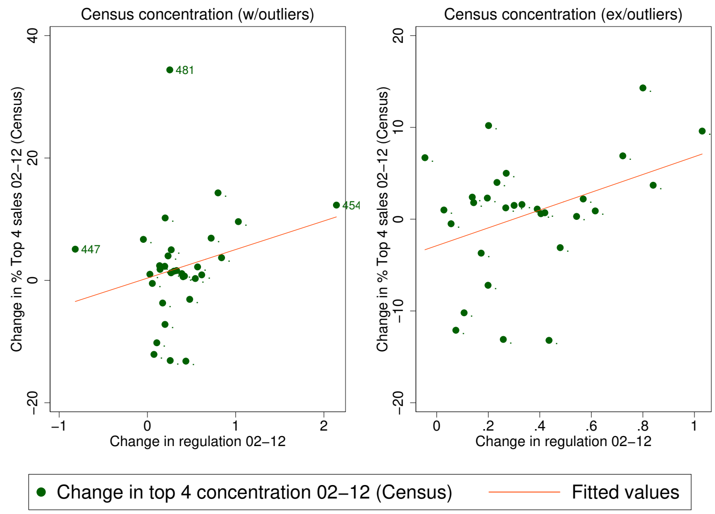


Notes: Annual data. Mean number of relevant restrictions across BEA industries in our sample. Based on Mercatus Regulation index.

We therefore study the relationship between increased industry-level regulation and concentration. To begin with, Figure 20 shows a scatter plot of changes in Census-based concentration ratios (% of sales by Top 4 firms in each industry) from 2002 to 2012, by NAICS level 3 code. As shown, industries with increases in regulation experienced substantial increases in concentration – especially after removing outliers. We find similar patterns using Compustat-based measures of concentration.

[37]Bessen (2016) provides evidence that political factors are the primary drivers of increased profitability since 2000.

Figure 20: Change in regulation (2002-2012) and change in Concentration



Notes: Concentration based on the Economic Census at NAICS level 3; changes in regulation based on Mercatus index, also at NAICS Level 3.

Using Census-based measures of concentration captures all firms in the economy; but also introduces two limitations to our analysis. First, Census-based concentration measures are available only every 5-years, which limits our ability to exploit cross-sectional differences in regulation and concentration over time. Second, focusing on the post-crisis period omits the 1990-2000 period over which regulation increased drastically (see Figure 19).

We use Compustat-based concentration measures to address these limitations. In particular, Table 11 shows the results of regressing measures of competition and investment, using the regulation index. Column 1 regresses the top 4-firm concentration ratio on the regulation index, to show that industry concentration increased with regulation.[38] Columns 2 and 3 focus on the post 1995 period and regress net investment on the import-adjusted Herfindahl, instrumented by regulation. As shown, industries with rising regulation became more concentrated and invested less.[39] Columns 4 and 5 regress the log-chained quantity of capital, $log(K_{j,t})$, on the U.S. Herfindahl instrumented by the industry-level log-regulation index. It yields similar conclusions. Note that columns 4 and 5 include the 5-year lagged Herfindahl as an instrument for the Herfindahl and the 5-year lagged level of capital as a predictor. These variables are included to focus on the effect of regulation in relatively short-term industry dynamics.

Superstar firms. Let us move on to superstar firms, as discussed in Autor et al. (2017) to explain the fall in the labor share. The hypothesis is that the efficient scale of operation has increased,

[38] These results are consistent with Bailey and Thomas (2015) who show that increases in Regulation are correlated with decreases in Firm entry.

[39] We use the post-1995 period because import data is available only from 1989; and the 1989-1995 period exhibits substantial entry into Compustat due to the IPO boom (in fact, the Herfindahl reaches it's lowest level on 1995). The post 1995 provides more stable cross-sectional patterns of regulation and concentration.

Table 11: Regulation: Regression results

Table shows the results of industry-level panel regressions of Top 4 firm concentration ratio, Herfindahls, net investment and chained capital on regulation index. Concentration measures and Q from Compustat. Regulation index from Mercatus. Capital and investment from BEA. Columns 1, 4 and 5 exclude Nondurable Textiles – an industry heavily affected by foreign competition which leads to an excessively high U.S. Herfindahl. Columns 2 and 3 include all industries, since they are based on the import-adjusted Herfindahl. As noted in Section 3.3.2, we assume perfect competition among foreign firms if there are less than 15 firms in the corresponding U.S. industry. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

		1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)
	$CR4_{i,t}$	$Log\left(HHI_{j,t}^{IA}\right)$	NI/K	$HHI_{i,t}^{US}$	$\log(K_{jt})$
	≥1980	≥1995	≥1995	≥1980	≥1980
Log(Reg index)(t-4)	**0.045***	**0.18***		**0.007****	
	[2.75]	**[2.13]**		**[2.72]**	
Median $Q_{j,t-1}$	0.011	0.06	0.025*		
	[0.59]	[0.76]	[2.38]		
Median $Q_{j,t-1}$ MA5				-.035*	0.131**
				[-2.09]	[2.72]
$HHI_{j,t}^{US}$					**-0.726****
					[-2.68]
$HHI_{j,t-5}^{US}$				.477**	
				[8.71]	
$Log\left(HHI_{j,t}^{IA}\right)$			**-0.084+**		
			[-1.77]		
$log(k_{jt-5})$				-.045**	0.767**
				[-2.76]	[21.11]
Year FE	Yes	Yes		Yes	
Industry FE	Yes	Yes		Yes	
Observations	1007		622		996
WithinR^2	0.159		-		0.923

so that better firms account for a larger share of industry output. According to this hypothesis, concentration is driven by 'superstar' firms and industries that become more concentrated should also become more productive. To test this hypothesis, we estimate the relation between changes in concentration and productivity across NAICS Level 6 industries.[40] Changes in concentration are based on the five year periods when Census data is available (1997, 2002, 2007 and 2012) as well as cumulatively from 1997 and 2002 to 2012. Changes in productivity are based on the same periods, except that the last observation ends on 2009 (the last year available in the NBER CES database).

We find positive correlations between concentration and value-added per worker, which would be true under essentially any model of increasing market power. The relation between concentration and TFP, however, is inconsistent. We find a positive and significant correlation before 2002, but an insignificant and sometimes negative correlation after 2002. These results roughly match the qualitative discussion in Autor et al. (2017). They report that "industries that became more concentrated ... were also the industries in which productivity—measured by either output per worker, value-added per worker, TFP, or patents per worker—increased the most." The main differences – the time-sensitive correlation between concentration and TFP – are likely driven by different time periods, levels of granularity and approaches. In particular, Autor et al. (2017) consider NAICS Level 4 industries, over what appears to be a longer period of analysis (1982 to 2012).

Relatedly, Gutiérrez and Philippon (2017a) compare concentration trends between the U.S. and Europe. They find that concentration has increased in the U.S. yet decreased in Europe in industries that are very similar in terms of technology. Over the same period, anti-trust enforcement has arguably weakened in the U.S. and mergers approvals have increased; while the opposite has happened in Europe. This suggests that technological factors are not the main driver of concentration.

Demographics. We estimate the correlation between the level and changes in concentration and median age of CEOs in a given industry. Industries where the median age of CEOs was higher as of 2002 exhibit statistically higher concentration as of 2012; and industries where the median age of CEOs decreased from 2002 to 2012 exhibit decreasing levels of concentration. Together, these results suggest that industries able to attract young talent remain competitive; while industries with aging executives have decreasing competition. We note, however, that these results are fairly sensitive to time periods and choice of measure of concentration (e.g., Compustat vs. Census); hence are not conclusive. And the median age of CEOs is likely not the best proxy for changing demographics. Still, these results and associated literature suggest the demographics may be one of many drivers of increasing concentration.

6 Conclusion

We argue that declining competition is (partly) responsible for the low rate of investment in the U.S. Our argument relies on the idea that firms that do not face the threat of entry do not have a strong urge to invest and innovate. We use Chinese import exposure as a natural experiment to test this

[40] We measure productivity by industry-level TFP; output and value-added per worker; and output and value-added per unit of capital

idea. We find that industries most affected by Chinese competition saw a decline in the number of domestic firms, but at the same time, leaders in these industries increased investment the most. We also show that firms in industries with higher excess entry in the 1990's invested more in the 2000's, after controlling for firm fundamentals. Combined, these results suggest that the U.S. remains in the increasing part of the competition-investment curve – i.e., more competition leads to more investment. Last, we provide evidence suggesting that regulation is partly responsible for rising concentration. If we are correct, the welfare consequences are significant. The welfare losses from an investment gap driven by decreasing competition are large. For instance, Jones and Philippon (2016) calibrate a standard macro-economic model assuming that the investment gap is driven by declining competition. They find that the capital stock is 5% to 10% lower than it should be, and that the Zero Lower Bound (ZLB) on short term rates would have been lifted by early 2012 if competition had remained at its level of 2000.

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Appendix I: Estimating Mark-ups

We were able to identify four broad approaches for estimating Mark-ups in the literature that can be implemented with the available data. We implement the first and third approach, which yield consistent, and fairly conclusive results. Results under the first approach are discussed in the main body of the paper. This appendix contains a brief description and summary results for the third approach. We refer the reader to Gutiérrez (2017) for additional details. We refrain from implementing the second and fourth approach given the additional complexity.

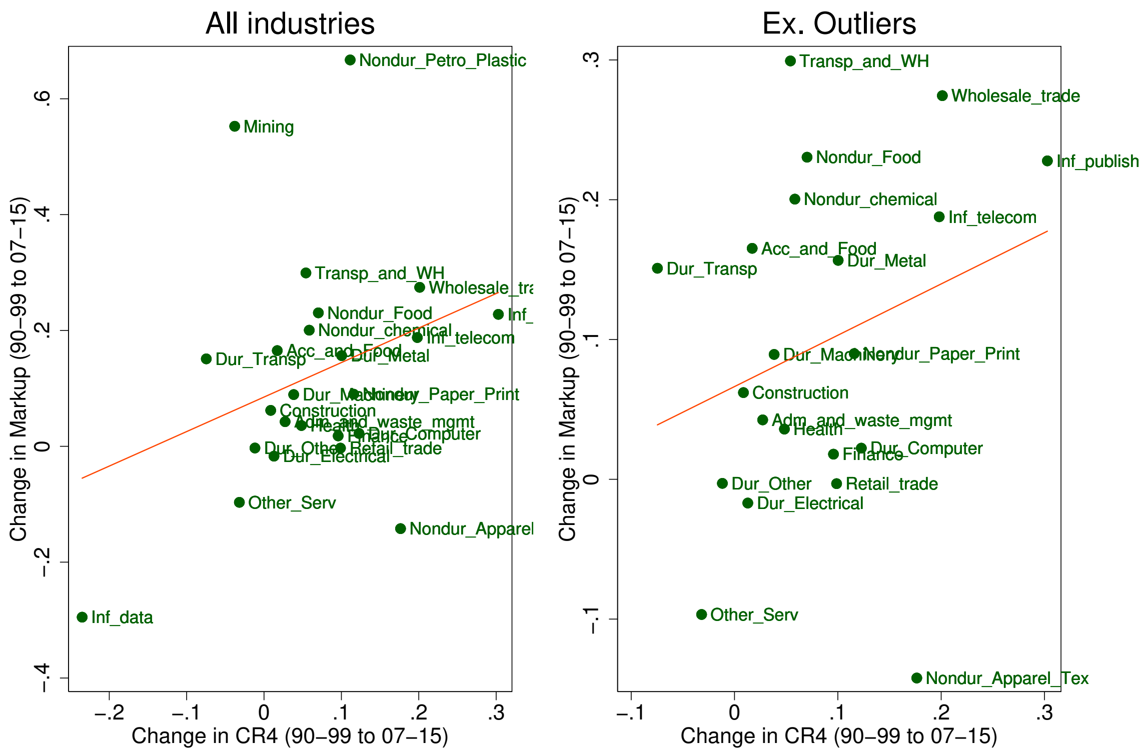
1. **Lerner Index**: A purely empirical measure of mark-ups can be computed through the Lerner Index. This measure is entirely data-driven – it is simple and easy to implement. However, as discussed in the text, the Lerner Index fails to account for a variety of issues, such as deviations between prices and marginal costs due to efficient use of scale or the need to cover fixed costs. It may also be affected by changes in the capital shares and the cost of capital, which are critical issues over the period of interest (see Caballero et al. (2017) for a discussion of recent trends and interactions between Mark-ups and Technical Change). Nonetheless, the Lerner index provides a simple empirical measure of Mark-ups. See Grullon et al. (2016) for a detailed analysis of the correlation between concentration and mark-ups in the U.S.

2. **Elasticity of outputs to inputs**: The second approach was introduced by Robert Hall, and is described in Hall (1988). It suggests a simple way to estimate (industry) **average** markups based on firm or industry level usage of inputs and total value of shipments. In its simplest form, mark-ups are estimated by regressing industry-level changes in outputs on changes in inputs.[41] However, this approach poses several short-comings. Identification of the mark-up parameter typically relies on time series regressions. Aggregate instrumental variables are often used to deal with the potential correlation between input growth and productivity growth. As a result, this method can only recover (average) mark-ups over relatively long time-periods. Mark-ups over shorter periods could be estimated from the cross-section of firms, but the identification issues become more problematic.

3. **User Cost-implied mark-ups:** Third, mark-ups can be estimated by calculating user costs of capital from required returns. Barkai (2017) implements such an approach for the U.S. Non Financial Corporate Sector. In particular, he estimates the user cost of capital from expected returns on either bond or equity capital, which combined with labor costs yield an implied mark-up. We implement a similar approach at the industry-level. In particular, we estimate industry-level equity risk premia based on firm-level analyst forecasts as described in Claus and Thomas (2001). We then combine these forecasts with output, taxes and labor costs from the BEA to estimate industry-level mark-ups over three periods: 1990-1999, 2000-2007 and 2007-2014. Figure 21 plots the estimated change in industry-level average mark-ups

[41] More advanced methods have been proposed since

Figure 21: Mark-up Estimates from User Costs



Notes: Figure plots the estimated change in industry-level average mark-ups from 1990-1999 to 2007-2015, against the change in Top 4 firm concentration ratio. As shown, Mark-ups increased the most at industries that became more concentrated. Estimates based on a broader industry segmentation than used throughout the paper to support more robust ERP estimates.

from 1990-1999 to 2007-2015, against the change in Top 4 firm concentration ratio. As shown, Mark-ups increased the most at industries that became more concentrated.

4. **Firm-level estimates from production data**: De Loecker and Warzynski (2012) propose an approach for estimating firm-level mark-ups based on production data. This approach relies on cost minimization and there being (at least) one variable input of production free from adjustment cost for which the wedge between that input's revenue share and its output elasticity is a direct measure of the firm's markup. So far, all implementations assume constant coefficients in the production function, which would fail to account for capital-biased technical change. In principle, the model can be estimated with time-varying coefficients – but this may be computationally challenging. Moreover, the approach relies on a broad set of data and is therefore more challenging to implement.

Appendix II: Proofs

It is convenient to define the function

$$\nu(\theta) \equiv \frac{1 - F(\theta)}{f(\theta)}$$

In the case of an exponential distribution, for instance, we have $F = 1 - e^{-\theta/\nu}$ and $\nu(\theta)$ is constant. To say something about the response of the leader when the follower's quality improves, we need to make the following assumption.

Assumption 1. The distribution F is such that, for all θ

$$\nu'(\theta) < 1$$

or equivalently

$$2f(\theta) + f'(\theta)\frac{1 - F(\theta)}{f(\theta)} > 0$$

We need Assumption 1 is needed to prove that vertical differentiation decreases price competition. Assumption 1 is not restrictive, however. It holds for all the distributions that we would consider using.[42]

Competitive Fringe

The profits of the leader are $\pi_2 = (p_2 - \chi_2)(1 - F(\theta_2))$ and $p_2 = p_1 + \theta_2\Delta$, where we define for convenience $\Delta \equiv z_2 - z_1$ as the quality advantage of the leader. Since $p_1 = \chi_1$ we can write profits are

$$\pi_2(\theta_2) = (a + \theta_2\Delta)(1 - F(\theta_2))$$

where we define $a \equiv \chi_1 - \chi_2$. Under Assumption 1, the first order conditions are sufficient because the profit function is concave ($\pi" < 0$) at all points where $\pi' = 0$. The first order condition is

$$\theta_2 = \nu(\theta_2) - \frac{a}{\Delta}$$

We can see that Assumption 1 to rules out multiple equilibria, and that θ_2 increases with Δ as long as a is positive. This proves the main proposition.

Finally, note that the condition $\theta_1 < \theta_2$ requires

$$\nu(\theta_2) > \frac{\chi_1}{z_1} + \frac{\chi_1 - \chi_2}{z_2 - z_1} = \frac{\chi_1}{z_1} + \frac{\chi_1 - \chi_2}{z_2 - z_1}$$

It simply says that the competitive fringe cannot be too inefficient relative to the leader, otherwise it would be priced out.

[42] For example, it holds for exponential, normal, log-normal, Pareto, Weibull, inverse Gaussian, gamma, and Kumaraswamy distributions.

Duopoly

We sketch the case of a differentiated duopoly. There are two firms, with quality z_1 and $z_2 > z_1$, competing à la Bertrand without price discrimination (for instance because θ is not observable). Both firms have the same marginal cost χ (we can assume that they have the same Cobb-Douglass production function described above) and the same fixed cost κ. It is straightforward to show that, in equilibrium, the high quality firm charges a higher price, so we have $p_2 > p_1$. Assume for now that both firms are active, i.e., that $\pi_1 > \kappa$, where π_1 are the profits of firm 1 under duopoly. There are two marginal types to consider. Type θ_1 is indifferent between buying from 1 and not buying at all, so $\theta_1 z_1 - p_1 = 0$. Type θ_2 is indifferent between buying from 1 and buying from 2: $\theta_2 z_1 - p_1 = \theta_2 z_2 - p_2$. Therefore

$$\theta_1 = \frac{p_1}{z_1},$$
$$\theta_2 = \frac{p_2 - p_1}{z_2 - z_1},$$

Consumers in the range $[0, \theta_1]$ are priced out, $[\theta_1, \theta_2]$ buy from firm 1, and $[\theta_2, \infty)$ buy from firm 2. Notice the key property that the price elasticity of θ_2 increases when the gap in quality decreases. The profits of firm 1 are $\pi_1 = (p_1 - \chi)(F(\theta_2) - F(\theta_1))$ and the profits of firm 2 are $\pi_2 = (p_2 - \chi)(1 - F(\theta_2))$.[43] The Nash equilibrium is characterized by $p_1 = \arg\max_p \pi_1(p; p_2)$ and $p_2 = \arg\max_p \pi_2(p_1; p)$. The first order conditions are

$$p_2 - \chi = \frac{1 - F(\theta_2)}{f(\theta_2)}(z_2 - z_1)$$

for the high quality firm, and $p_1 - \chi = \frac{F(\theta_2) - F(\theta_1)}{\frac{f(\theta_1)}{z_1} + \frac{f(\theta_2)}{z_2 - z_1}}$ for the low quality firm. We can then solve for the equilibrium prices and quantities. If $\pi_1 > \kappa$, we have found an equilibrium. If, on the other hand, $\pi_1 < \kappa$, then firm 1 cannot profitably enter, and we need to consider the monopoly outcome, denoted by m. We have $p_m = \theta_m z_2$ and the first order condition is

$$p_m - \chi = \frac{1 - F(\theta_m)}{f(\theta_m)} z_2.$$

It is clear that $\theta_2 < \theta_m$: production (and investment) by the high quality under duopoly firm alone is higher than total production under monopoly. This holds a fortiori if we add production by the low quality firm. Under Assumption 1, Pagnotta and Philippon (2011) prove (in the case where the marginal costs are both zero), that θ_1 and θ_2 decrease (so production increases) when $z_2 - z_1$ decreases.

[43] It is straightforward to generalize to N firms. In that case we have $\pi_i = (p_i - c)(F(\theta_{i+1}) - F(\theta_i))$ with the convention that $\theta_{N+1} = \infty$.

Appendix III: Additional Results on Chinese Competition

This appendix includes the following additional regression results on Chinese competition:

- Table 12: $log(K)$ results on $\Delta IP_{j,t}^{US}$
- Table 13: Employment, Capital and K/Emp results on $\Delta IP_{j,t}^{US}$
- Table 14: Employment, Capital and K/Emp results on $NTRGap_j$

Table 12: Chinese Competition: $\log(K_t)$ results based on $\Delta IP^{US}_{j,t}$

Table shows the results of firm-level panel regressions of measures of capital on US-based China import exposure. Regression from 1991 - 2015, following equation 12. We consider three measures of capital: log-PP&E, log-intangibles and log-capital. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include lagged measures of industry-level production structure (e.g.,PPE/Emp). As shown, leaders increased their capital with Chinese competition, both in levels and relative to laggards. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(5)	(6)	(7)	(9)	(10)	(11)
	$\log(PPE_t)$	$\log(Intan_t)$	$\log(K_t)$	$\log(PPE_t)$	$\log(Intan_t)$	$\log(K_t)$	$\log(PPE_t)$	$\log(Intan_t)$	$\log(K_t)$
$\Delta IP^{US}_{j,t}$	-0.293**	-0.220**	-0.167*	-0.577**	-0.457**	-0.422**	-0.822**	-0.671**	-0.644**
	[-3.04]	[-3.09]	[-2.28]	[-4.59]	[-4.42]	[-4.03]	[-4.46]	[-3.22]	[-3.14]
$\Delta IP^{US}_{j,t} \times Lead_{99}$				**0.669****	**0.559****	**0.601****	**0.854****	**0.815****	**0.851****
				[4.32]	**[3.34]**	**[3.91]**	**[2.81]**	**[2.66]**	**[2.91]**
$\log(Age_{t-1})$	0.391**	0.683**	0.623**	0.391**	0.683**	0.623**	0.680**	0.815**	0.763**
	[7.91]	[18.89]	[16.12]	[7.94]	[18.83]	[16.10]	[10.44]	[12.89]	[12.57]
Observations	31259	31296	31318	31259	31296	31318	11819	11808	11822
Within R^2	0.162	0.588	0.545	0.165	0.59	0.547	0.268	0.639	0.602
Industry controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sample	All firms			All firms			Continuing firms		

Table 13: Chinese Competition: $log\left(\frac{kt}{Emp_t}\right)$ results based on $IP^{US}_{j,t}$

Table shows the results of firm-level panel regressions of measures of capital, employment and capital-deepening on US-based import penetration. Regression from 1991 - 2015, following equation 12. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include lagged measures of industry-level production structure (e.g.,PPE/Emp). As shown, leaders increased capital, employment and k/Emp with Chinese competition. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(k_t)$	$\log(Emp_t)$	$\log(\frac{k_t}{Emp_t})$	$\log(k_t)$	$\log(Emp_t)$	$\log(\frac{k_t}{Emp_t})$
$\Delta IP^{US}_{j,t}$	-0.167*	-0.185**	0.021	-0.422**	-0.384**	-0.035
	[-2.28]	[-2.63]	[0.26]	[-4.03]	[-4.89]	[-0.38]
$\Delta IP^{US}_{j,t} \times Lead_{99}$				**0.601****	**0.471****	**0.133+**
				[3.91]	**[3.35]**	**[1.96]**
$\log(Age_{t-1})$	0.623**	0.449**	0.174**	0.623**	0.449**	0.174**
	[16.12]	[11.19]	[4.24]	[16.10]	[11.19]	[4.24]
Observations	31318	30906	30894	31318	30906	30894
Within R^2	0.545	0.117	0.436	0.547	0.119	0.436
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			All firms	

Table 14: Chinese Competition: $\log(\frac{k_t}{Emp_t})$ results based on $NTRGap_j$

Table shows the results of firm-level panel regressions of measures of capital, employment and capital-deepening on NTR gap. Regression from 1980 - 2015, following equation 13. Leaders defined as firms with above-median Q as of 1999 within each NAICS Level 4 industry. Industry controls include measures of industry-level production structure as of 1991 (e.g.,PPE/Emp) interacted with the post-2001 dummy. As shown, leaders increased capital, employment and k/Emp with the NTR Gap. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(k_t)$	$\log(Emp_t)$	$\log(\frac{kt}{Emp_t})$	$\log(k_t)$	$\log(Emp_t)$	$\log(\frac{k_t}{Emp_t})$
$Post01 \times NTRGap$	-0.548*	-0.491*	-0.061	-1.032**	-0.888**	-0.164
	[-2.38]	[-2.14]	[-0.35]	[-4.32]	[-3.69]	[-0.89]
$Post01 \times NTRGap \times Lead_{99}$				**0.984****	**0.781****	**0.203****
				[7.38]	**[6.20]**	**[2.95]**
$\log(Age_{t-1})$	0.567**	0.409**	0.160**	0.568**	0.409**	0.160**
	[16.75]	[13.99]	[5.21]	[16.45]	[14.40]	[5.16]
Observations	49833	49254	49130	49833	49254	49130
Within R^2	0.591	0.111	0.562	0.599	0.119	0.562
Overall R^2	0.21	0.207	0.374	0.226	0.224	0.373
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			All firms	