Declining Competition and Investment in the U.S.*

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Abstract

The US business sector has under-invested relative to Tobin's Q since the early 2000s. 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 use Chinese imports as a natural experiment to test the main prediction of competition-based models of investment and innovation, namely that competition forces industry leaders to invest (innovate) more. We establish external validity beyond the manufacturing sector by showing that excess entry in the 1990s, 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 and, to a lesser extent, stronger winner-takes-all effects in some industries.

Gutiérrez and Philippon (2016) show that investment is weak relative to measures of profitability and valuation, and that this weakness starts in the early 2000s. 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, from low expected growth – be it supply or demand-driven – to high discount factors. They also find that financial frictions, measurement errors (due to the rise of intangibles, etc.), or globalization do not explain the lack of investment. On the other hand, they show that the investment residuals – at the firm level and at the industry level – are well explained by measures of competition.[1] Controlling for current market conditions, industries with less competition and more concentration (traditional or due to common ownership) invest less.

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[1] Governance is the other variable that explains investment residuals. 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 investment. 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).

The welfare consequences of an investment gap driven by decreasing competition are large. For instance, Jones and Philippon (2016) calibrate a standard macro-economic model to fit the evidence in Gutiérrez and Philippon (2016). 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. That macroeconomic analysis takes for granted that low competition is responsible for low investment.

The challenge for the competition hypothesis, however, is to establish a causal connection between competition and investment, as opposed to a simple correlation. The main identification issue is as follows. Consider an industry i where a set of firms operate competitively under decreasing returns to scale. Suppose industry i 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 a similar explanations could arise from anticipated productivity shocks. Of course, controlling for Q mitigates the issue because Q capitalizes the value of future shocks, but in realistic cases Q is unlikely to be a sufficient statistic for investment, even under the null hypothesis of perfect competition.[2] The existing evidence therefore cannot rule out a anticipation-driven explanation.

The goal of our paper is to demonstrate the causal impact of competition on investment. Before diving into the data, however, it is important to clarify some theoretical predictions. Any model of investment and competition has to struggle with (at least) two deep issues: (i) the exact definition of investment, including R&D or not; and (ii), the model of imperfect competition, monopolistic or oligopolistic, with or without free entry. If we consider a neoclassical production function, 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 use the simple dynamic model in Aghion et al. (2009) as a starting point. This model features an "escape competition effect" whereby neck-and-neck competitors invest more to escape competition from their peers. There is also a Schumpeterian rents effect that may lower incentives to invest for the laggards.

We argue that a fairly robust prediction in this 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

[2] There are two reasons for this. In theory, Q_t is not a sufficient statistic for investment when there are decreasing returns and endogenous entry. An in practice, there are significant measurement errors and uncertainties about the correct functional form for the adjustment cost function.

between leaders and laggards. Consider an industry where leaders are significantly more productive than laggards and potential entrants. 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, are forced to invest and innovate more, as in neck-and-neck competition. Global investment is likely to go up, but some of it happens abroad. The impact on domestic investment is therefore ambiguous.

We then test these implications in US data. We use a mixture of firm- and industry-level data and is sourced (primarily) from Compustat and the Bureau of Economic Analysis (BEA). One important feature of these data is that aggregating firm data gives results that are consistent with BEA industry data, and that aggregating industry data gives results that are consistent with NIPA data, although there are many issues along the way, as discussed in Gutiérrez and Philippon (2016). We argue that competition causes investment using a combination of natural experiments (that provide clean identification but have limited scope) and instrumental variables (that have weaker identification but apply across all firms/industries).

Our natural experiment for an exogenous increase in competition uses import exposure to China. The results align well with the prediction of the models. First, Chinese competition leads to a decrease in the number of US firms. Second, among the surviving firms we observe *more* investment, more employment, and some capital deepening. Overall, these two contradictory forces produce an ambiguous effect of foreign competition on total domestic investment. We derive our baseline results using actual Chinese imports in the US. We show that the same results hold if we instrument using Chinese imports to other rich countries as a measure of comparative advantage that does not depend on US specific demand or technology shocks. The Chinese natural experiment offers clean identification, but it is limited to manufacturing and a small set of firms. It is unclear if the result generalize to the rest of the economy.

To deal with this external validity issue, we construct an instrument for industry concentration that is orthogonal to future demand and productivity shocks. To do so, we use excess entry in the 1990s (relative to entry predicted using Q, sales, profitability, etc.) as an instrumental variable. We discuss why the peculiar features of that period – especially during the second half of the 1990s with extreme equity valuation and venture capital funding – are likely to have created more than the usual amount of randomness in entry rates (e.g., Gordon (2005); Anderson et al. (2010); Hogendorn (2011); Doms (2004)). As a matter of fact, we observe extreme cross-sectional differences in entry rates and we show that our measure of excess entry is orthogonal to shocks that occur in the 2000s. We use excess entry as an instrument for differences in concentration across industries, and we find that firms in industries with more competition invest more in the 2000s (after controlling for firm fundamentals, including Q).

Finally, we shed some light on the issue of why broad measures of concentration have increased over the past 20 years. We find strong support for the regulation hypothesis; some support for the superstar hypothesis; and limited support for the demographics hypothesis.

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.

First and foremost, our paper aims to contribute to the growing literature studying the recent under-investment in the US 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), 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)). Lee et al. (2016) find that industries that receive more funds have a higher industry Q until the mid-1990s, 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-1990s. Relatedly, Alexander and Eberly (2016) study the implications of the rise of intangibles on investment. Last, 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. They show that the trend decrease in competition can explain the joint evolution of investment, Q, and the nominal interest rate. Absent the decrease in competition, they find that the U.S. economy would have escaped the ZLB by the end of 2010 and that the nominal rate today would be close to 2%. Kose et al. (2017) study weak investment growth in emerging markets.

Second, 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. Asturias et al. (2017) studies firm entry and exit patterns in periods of slow and high productivity growth.

Third, our paper is related to a growing literature studying recent trends on competition, concentration, and entry. The downward trend in business dynamism has been highlighted by numerous papers (e.g., Decker et al. (2014)) but the trend has been particularly severe in recent years. In fact, Decker et al. (2015) argue that, whereas in the 1980s and 1990s declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000s, including the traditionally high-growth information technology sector. CEA (2016) discusses a perceived decrease in competition in the goods market. 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 conclude that "U.S. product markets [have] undergone a structural shift that has weakened competition." 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.

Fourth, our paper is related to the effect of Chinese import exposure on employment and innovation. Autor et al. (2016) study how rising import competition from China affected U.S. innovation. They control for secular trends in innovative activities, and argue 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) study the effects of Chinese import exposure on US manufacturing employment. They show that a large portion of the reduction of US manufacturing employment can be explained by Chinese import competition. They 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. However, none of these papers differentiate between the dynamics of leaders and laggards – which are critical for understanding the effect of competition on investment. This is a key contribution of our paper.

The remainder of this paper is organized as follows. Section 1 presents the relevant facts about competition and private fixed investment in recent years. Section 2 presents the model and its implications. Section 3 discusses our dataset. Section 4 presents the test results used to establish causality between competition and investment. Section 5 discusses some simple analyses aimed at explaining the rise in Concentration; and Section 6 concludes.

1 Empirical Facts

For evidence that investment is low relative to measures of profitability and valuation, and that this weakness starts in the early 2000's, please refer to Gutiérrez and Philippon (2016). 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. 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.

In this section, we highlight recent trends in concentration. In particular, the fact that entry has decreased and concentration has increased across virtually all industries. This is discussed at length in CEA (2016); Autor et al. (2017) and Grullon et al. (2016), among others, so we only highlight the key facts. For trends in ownership, please refer to Gutiérrez and Philippon (2017b).

The top chart in Figure 1 shows the establishment entry and exit rates as reported by the U.S. Census Bureau's Business Dynamics Statistics (BDS). As shown, there has been a strong decline in the establishment entry rate, while the exit rate has remained roughly stable. This downward trend in business dynamism also appears considering only Compustat firms. This trend has been highlighted by numerous papers (e.g., Decker et al. (2014)), but it has been particularly severe in recent years. In fact, Decker et al. (2015) argue that, whereas in the 1980s and 1990s declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000s, including the traditionally high-growth information technology sector.

The bottom chart in Figure 1 shows the mean Herfindahl and Modified-Herfindahl across all BEA industries in Compustat (where the Modified-Herfindahl includes an adjustment to account for anti-competitive effects of common ownership). The mean Herfindahl starts relatively high in the 1980s; decreases in the early 1990s as more firms go public and enter Compustat; and increases rapidly thereafter. As highlighted in CEA (2016); Autor et al. (2017), such increases in industry-specific concentration also appear considering all US firms. Driven by a rapid rise in the common ownership adjustment, the modified Herfindahl rises even faster than the traditional Herfindahl. [3]

2 Some Models of Competition and Investment

2.1 Basic Model

As a starting point, we can use the standard framework used in modern macro models. There are two levels of aggregation, across goods industries (cars vs legal services), and across firms within a particular industry (Ford vs GM). The simplest model uses CES aggregators. Final consumption C is an index of goods produced by different industries

$$\mathbf{C}_t \equiv \left(\int_0^1 C_{j,t}^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

where ϵ is the elasticity of substitution between industries. Typically, this elasticity is small (around 1). Utility maximization implies that the relative demand of any two goods satisfies $\frac{C_{l,t}}{C_{j,t}} = \left(\frac{P_{l,t}}{P_{j,t}}\right)^{-\epsilon}$. This then implies the existence of a price index, defined by $\mathbf{P}_t \equiv \left(\int_0^1 P_{j,t}^{1-\epsilon} dj\right)^{\frac{1}{1-\epsilon}}$, such that consumption expenditures are $\mathbf{P}_t \mathbf{C}_t = \int_0^1 P_{j,t} C_{j,t} dj$, and the demand curves are simply $C_{j,t} = \left(\frac{P_{j,t}}{\mathbf{P}_t}\right)^{-\epsilon} \mathbf{C}_t$.

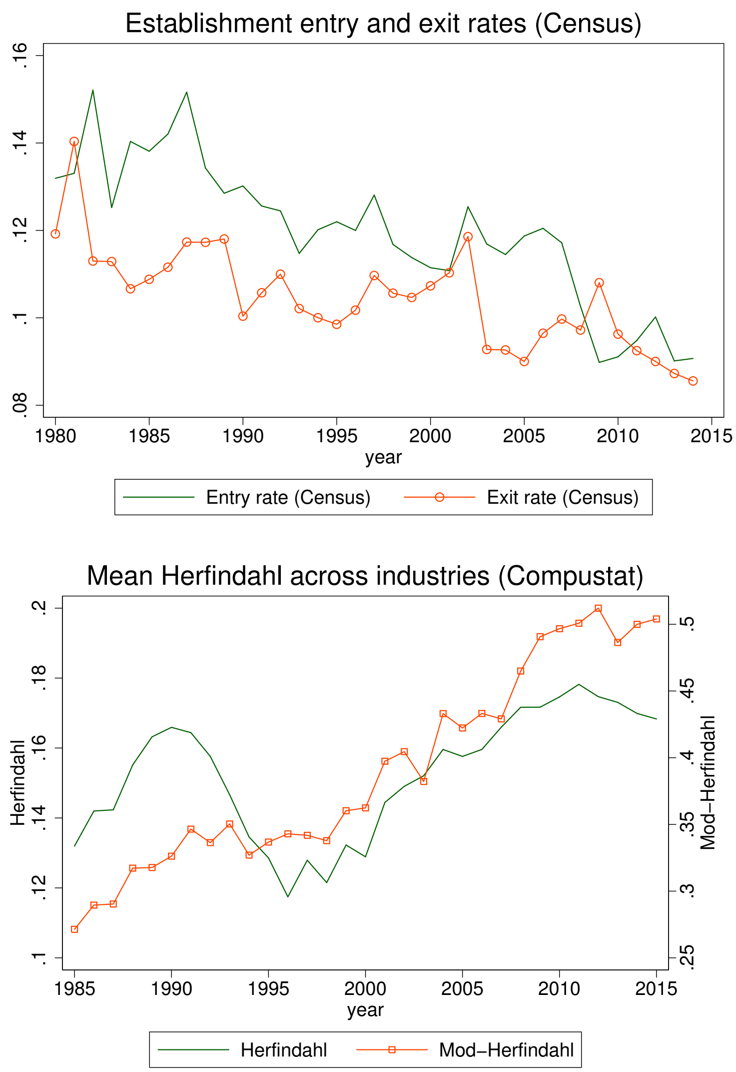
The lower level of aggregation is across firms inside industry $j \in [0,1]$. Each industry is populated by firms $i \in [0,1]$ (so technically a firm is point $(i,j) \in [0,1]^2$):

$$C_{j,t} = \left(\int_0^1 C_{i,j,t}^{\frac{\epsilon_{j,t}-1}{\epsilon_{j,t}}} di \right)^{\frac{\epsilon_{j,t}}{\epsilon_{j,t}-1}}$$

Firm i in industry j takes industry output $Y_{j,t} = C_{j,t}$ as given and sets its price to maximize its

[3] Common ownership increased with the rapid increase in institutional ownership, and the increased concentration in the asset management industry. That said, we focus on traditional measures of concentration in this paper; and discuss anti-competitive effects of common ownership in Gutiérrez and Philippon (2017b).

Figure 1: Firm entry, exit and concentration



Note: Annual data.

profits

$$\max \Pi_{i,j,t} \equiv P_{i,j,t} Y_{i,j,t} - W_t L_{i,j,t} - R^k_{t+k} K_{i,j,t},$$
$$\text{s.t. } Y_{i,j,t} = \left(\frac{P_{i,j,t}}{P_{j,t}}\right)^{-\epsilon_{j,t}} Y_{j,t},$$
$$\text{and } Y_{i,j,t} = A_{i,j,t} K^{\alpha}_{i,j,t} L^{1-\alpha}_{i,j,t}$$

where W and R^k are the rental costs of labor and capita, and the maximization is subject to the demand curve across firms. The optimal pricing implies a fixed markup over marginal cost

$$\frac{P_{i,j,t}}{P_{j,t}} = \mu_{j,t} \mathtt{MC}_{i,j,t}$$

where$\mu_j \equiv \frac{\epsilon_{j,t}}{\epsilon_{j,t}-1}$.

To keep things simple at first, we can consider an equilibrium where $A_{i,j,t} = A_t$ for all i, j, t. Since all the firms face the same factor prices, they have the same marginal cost: $\mathtt{MC}_t = \frac{1}{A_t}\left(\frac{R_{k,t}}{\alpha}\right)^{\alpha}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}$. Heterogeneity across industries is then driven by differences in average markups. We have $C_{j,t} = \left(\mu_j \mathtt{MC}_t\right)^{-\epsilon} \mathbf{C_t}$ so in relative terms

$$\log Y_{j,t} = \delta_t - \epsilon \log \mu_{j,t},$$

where δ_t is a time fixed effect that captures variations in wages, rental rate, aggregate productivity, etc. The log deviation of output depends on the industry specific markup μ_j and the inter-industry elasticity ϵ. In equilibrium all firms use the same capital labor ratio, so output and capital are proportional $Y_{j,t} = A_t K_{j,t}\left(\frac{L_t}{K_t}\right)^{1-\alpha}$. In what follows we omit the time indexes for simplicity, given the straightforward log decomposition above.

Lemma 1. *In the standard model, if the average markup in industry j goes up by 1%, relative capital demand goes down by ϵ%.*

The simplest way to think about decreases in competition is an increase in the markup.

Free Entry. In the standard model, the number of firms is fixed (normalized to 1), and markup changes come from a decrease in the intra-industry elasticity ϵ_j. An equivalent way to obtain this is to introduce free entry and endogenies the number of firms. The free entry condition says that the marginal entrant must earn the entry cost. Considering again a symmetric equilibrium we have

$$\Pi_j = \kappa^e_j,$$

where κ^e_j is the entry cost in industry j. The second condition is that profits are a decreasing function of the number of firms. This can come from equilibrium effect on the industry price level, or from changes in the elasticity, which is immediate in models of product differentiation, à la Hotelling or Salop (see Bilbiie et al. (2006) for a discussion). In that later case the average markup decreases with the number of firms, $\frac{\partial \mu_j}{\partial N_j} \leq 0$. In either case, we have the following simple result.

Lemma 2. *With endogenous differentiation, an increase in the entry cost leads to few firms, higher markups, and lower capital demand.*

It is straightforward to generalize these results to the case where there is a distribution of productivity $A_{i,j,t}$ across firms and industries.

International Trade. One critical assumption we have maintained so far is that all producers are domestic firms. As a result, there is not difference between average investment and domestic investment. Consider now the case where some producers are foreign firms. At the same time, we introduce heterogeneity across firms. There is a pool of domestic firms facing the same entry cost κ_j^e. We rank firm by their productivity $A_{i,j}$ from low $i = 0$, to high $i = 1$. We normalize the total number of potential entrants to 1, so that if all firms beyond some i enter, the number of firms is simply 1-i. As more firms enter

Lemma 3. *An domestic equilibrium is defined by a cutoff $i_j^d \in [0,1]$ such that $N_j = 1 - i_j^d$ and $\Pi_j \left(i_j^d \right) = \kappa_j^e$.*

As more firms enter, profits decrease. Entry takes place until the marginal firm's i_j^d breaks even. Now the impact of foreign entry. Assume that there are many foreign entrants with some productivity $A_f \in (A_0, A_1)$ and facing the same fixed cost κ_j^e.

Proposition 1. *Foreign entry leads to exit of domestic firms located in $\left[i_j^d; f \right]$. Domestic firms with $i > f$ survive, set lower markups and higher capital demand. The impact on domestic investment is ambiguous.*

We test this proposition using the surge in Chinese import competition into the US as a natural experiment.

2.2 Innovation

The analysis is more complicated if we extend investment to include R&D, and more generally, factors that increase productivity in the long run. 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. Namely, a trade-off between the profits a firm would earn if it invests, compared to what it would earn if it did not invest. The concept 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 [investment]"*. In this section, we develop a Dynamic Oligopoly model with Leaders/Followers/Entrants in the tradition of Aghion et al. (2009). We discuss the implications of the model, which guide our empirical analyses.

In line with the literature, we have in mind a model featuring an escape competition and a Schumpeterian effect. The former increases investment when industries face more neck-and-neck

Table 1: 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

competition; while 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.[4]

3 Data

We start from the same dataset as Gutiérrez and Philippon (2016) and we append data on China import exposure sourced from the UN Comtrade website. The dataset includes a wide range of aggregate-, industry- and firm-level data. The data fields and data sources are summarized in Table 1. Sections 3.1 and 3.2 discuss the aggregate and industry datasets, respectively. Section 3.3 discusses the firm-level dataset, including key definitions. Last, Section 3.4 discusses the Chinese Import Exposure 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 US Economy and the non financial sector is gathered from the US Flow of Funds accounts through FRED. These data are used in the aggregate analyses discussed in Section 1; and to reconcile and ensure the accuracy of more granular data.

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

[4] We note that these models make several other predictions (e.g., that the effect of competition on investment should be stronger for industries closer to the technological frontier), but delay discussion of them to a companion paper focused on how US firms coped with China(Gutiérrez and Philippon, 2017a).

(gross operating surplus, compensation and taxes) – are gathered from the Bureau of Economic Analysis (BEA). Note that BEA I and K now 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 'Current-Cost Net Stock of Private Fixed Assets'; depreciation rates as the ratio of 'Current-Cost Depreciation of Private Fixed Assets' to lagged 'Current-Cost Net Stock of Private Fixed Assets'; and net investment rates as the gross investment rate minus the depreciation rate. Investment rates are computed across all asset types, as well as separating intellectual property from structures and equipment.

3.3 Firm-level data

3.3.1 Dataset

Firm-level data is primarily sourced from Compustat, which includes all public firms in the US. Data is available from 1950 through 2016, but coverage is fairly thin until the 1970s. 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.[5] 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 US incorporated firms. We also gather CEO age from Execucomp, which is used to test theories of concentration (see Section 5).

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.

[5] 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

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 average), the mean and the median for all quantities, and use the specification that exhibits the highest statistical significance. 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 Definitions

Investment. We consider two main definitions of investment. First, the 'traditional' gross investment rate is defined as in **?** – specifically, as capital expenditures (Compustat item CAPX) at time t scaled by net Property, Plant and Equipment (item PPENT) at time $t-1$. Net investment rate is calculated by imputing the industry-level depreciation rate from BEA figures. In particular, note that the depreciation figures available in Compustat include only the portion of depreciation that affects the income statement, and therefore exclude depreciation included in Cost of Goods Sold. For consistency, and because we are interested in aggregate quantities, we assume all firms in a given industry have the same depreciation rate, and compute the net investment rate as the gross investment rate minus the BEA-implied depreciation rate. We use the industry-level depreciation rate for structures and equipment only since it is applied to CAPX. Second, we proxy investment in intangibles with the ratio of R&D expenses to assets (Compustat XRD / AT)[6]. We consider only the gross investment rate (i.e., do not subtract depreciation) since a good proxy for R&D depreciation is not available.

Q. Firm-level Q is defined as the book value of total assets (AT) plus the market value of equity (ME) minus the book value of equity scaled by the book value of total assets (AT). 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). Book value of equity is computed as AT - LT - PSTK. 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 consider versions of all such measures. Namely, 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, as well as (iii) sales and market value Herfindahls as measures of concentration; and (iii) the price-cost ratio (also known as the Lerner index) as a measure of market power. The Lerner index differs from the Herfindahl and Concentration ratios because it does not rely on precise definitions of geographic

[6] XRD set to zero if missing

and product markets; rather it aims to measure a firm's ability to extract rents from the market. 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. To compute the Lerner index, we follow Datta et al. (2013) and calculate the ratio of operating profit (Compustat SALE - COGS - XSGA) to sales.

The above measures are based on Compustat and therefore cover only a portion of each industry. We also gather industry measures of sales and market value concentration from the Economic Census which cover the entire US economy. These include the share of sales held by the top 4, 8, 20 and 50 firms in each industry; and 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 across industries.

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).

3.4 China import-competition data

Data on international trade for select years in the 1991 to 2011 period are sourced from the UN Comtrade Database.[7] This database includes bilateral imports for six-digit Harmonized Commodity Description and Coding System (HS) products. We map these data to six-digit NAICS codes by applying the crosswalk in Pierce and Schott (2012), which assigns 10-digit HS products to seven-digit NAICS industries. We supplement the import competition data with the NBER-CES Manufacturing Industry Database, which includes output data by 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; and to test alternate theories of concentration.[8] These datasets are discussed extensively in other papers so we refer the reader to Autor et al. (2016) and Pierce and Schott (2016) for additional details.

3.5 Other data

Regulation. 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.[9] Results are consistent, using NAICS level 3 segments – but mapping to BEA segments allows to test the impact of regulation on investment

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

[8] We also use import exposure data from Peter Schott's website in some Figures, since it is more accessible over a longer period.

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

through concentration.

Second, as a proxy for barriers to entry, we gather the share of workers requiring Occupational Licensing in each NAICS Level 3 industry from the 2008 PDII.[10]

4 Empirical tests and results

To establish causality between competition and investment, we perform two analyses. First, we use import exposure to China as a natural experiment for increased competition; and find that leader firms in manufacturing industries more exposed to the rise of China increased investment after 1995. This analysis provides clean identification but it applies only to a manufacturing industries. To improve external validity, we use excess entry in the 1990s (relative to entry predicted using Q, sales, profitability, etc.) as an instrumental variable for concentration. We find that firms in industries less concentration/more competition invested more in the 2000s. 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.

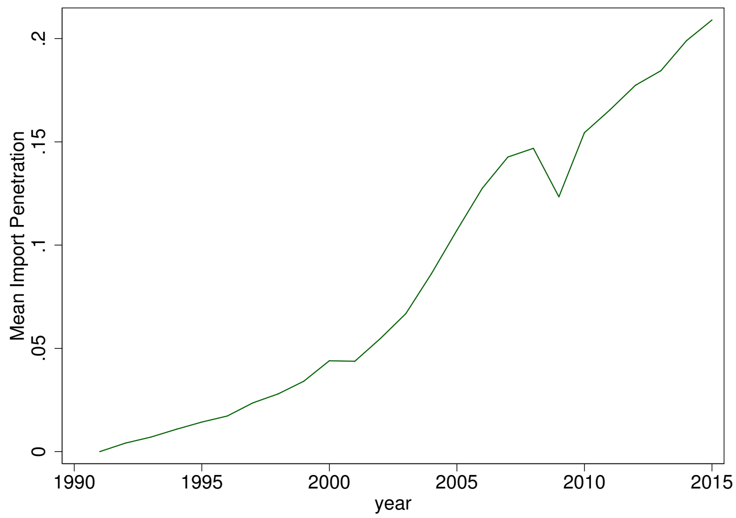
4.1 Natural Experiment: China Import Competition

4.1.1 Empirical Strategy.

We use the growth of China and associated import exposure as a natural experiment for competition in US manufacturing industries. As shown in Figure 2, imports from China started to increase in the early 1990s, and experienced a very rapid rise since about 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.

[10]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.

Figure 2: Import exposure and investment for Manufacturing Industries



Notes: Annual data for Manufacturing industries only. Mean import exposure across NAICS level 3 codes, based on data from Peter Schott's website. Import penetration computed as described in the text.

We follow Autor et al. (2016) and compute our baseline measure of trade exposure as the change in the import penetration ratio for industry j:

$$\Delta IP_{j\tau} = \frac{\Delta M_{j\tau}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}} \tag{2}$$

$\Delta M_{j\tau}^{UC}$ is the change in imports from China over a given period τ. $Y_{j,91} + M_{j,91} - E_{j,91}$ 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 US imports and exports with the rest of the world). Similar to Acemoglu et al. (2016), we consider three periods τ: 1991 to 2011, 1991 to 1999 and 1999 to 2011.

Note that we use 2 as an indirect proxy for competition in industry j, not as a measure of bilateral trade flows as it is used in the trade literature (e.g., in Acemoglu et al. (2016)). This substantially mitigates endogeneity concerns related to US industry import demand shocks. A US firm in industry j faces increased competition from China if imports of relevant products have increased – irrespective of whether this is due to a domestic supply shock or a foreign supply shock. Nonetheless, a concern with 2 may be that changes in the US import penetration ratio reflect domestic shocks to US industries; not competition shocks from the rise of China. To address this concern, we repeat all regressions using import exposure from China to eight other high-income countries as an instrument for US trade exposure. Namely, we compute

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j\tau}^{OC}}{Y_{j,91} + M_{j,91} - E_{j,91}}$$

where $\Delta M_{j\tau}^{OC}$ is the growth in imports from China in industry j during the period τ to eight other high-income countries; while the denominator is the same as above.[11] In using this instrument, we assume that high-income economies are similarly exposed to competition from China, but exhibit uncorrelated demand shocks. As noted in Acemoglu et al. (2016), the identifying assumption is that industry import demand shocks are uncorrelated across the sample countries, and that there are no strong increasing returns to scale in Chinese manufacturing which might imply that US demand shocks will increase efficiency in the affected Chinese industries, and induce them to export more to other high-income countries.

Given the above measure of trade exposure, we examine the link between increased competition and net investment using a generalized OLS difference-in-differences (DID) specification similar to that in Pierce and Schott (2016):

$$\begin{aligned} log(K_{it}) = \beta_1 Post - 1995 \times \Delta IP_{j,99-11} + \beta_2 Post - 1995 \times \Delta IP_{j,99-11} \times Leader \\ + \boldsymbol{+Post - 2000 \times X_i{}'\gamma} + \boldsymbol{X'_{it}}\lambda + \eta_t + \mu_i + \alpha + \varepsilon_{it} \end{aligned} \quad (3)$$

where the dependent variable is the net investment rate of firm i in year t. The first two terms on the right-hand side are the DID terms of interest. The first one is an interaction between import penetration and an indicator for the post-1995 period. The second term adds an indicator for leader firms[12], to capture differences in investment between leaders and laggards. The remaining terms are controls. They include interactions of the post-2000 indicator and time-invariant industry characteristics, such as initial year (1991) industry capital and skill intensity ($Post - 2000 \times \boldsymbol{X_i}'\gamma$); time-varying firm (or industry) characteristics ($\boldsymbol{X'_{it}}\lambda$), as well as a constant, year and firm fixed effects (α, η_t and μ_i , respectively). The first term on the second line allows for the possibility that the relationship between employment and industry characteristics changes in the post-2000 period, while the second term on the second line captures the impact of time-varying industry characteristics. Firm fixed effects capture the impact of any time-invariant firm characteristics; 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 1980 to 2015, but results are robust to starting and ending earlier. We include all manufacturing firms, irrespective of entry/exit dates in our baseline specification; but also report results including only continuing firms [13] 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

[11] 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 US following HS codes is available only since 1991 in UN Comtrade. Prior to 1991, data is based on SITC codes; which would require yet another mapping to NAICS codes. Moreover, our focus is on the 1995-2011 period, so 1991 already embeds a lag to reduce endogeneity concerns.

[12] Defined as firms with above-median Q as of 1995 within each NAICS Level 4 industry

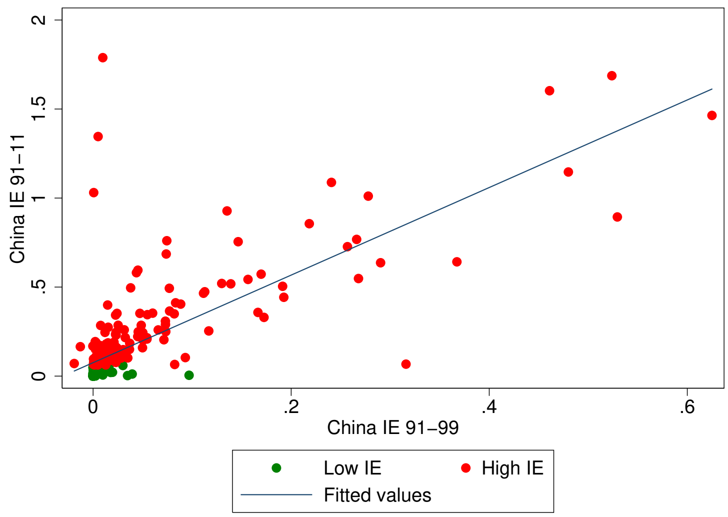
[13] Defined as firms that existed prior to 1995 and remain in the sample after 2009

volatile. They are heavily affected by movement in the depreciation rate. The level of K is far more stable. It 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 only, 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 US 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, if we consider all firms simultaneously, we find that capital decreases with import penetration. This is not surprising. As discussed above, theoretical models do not imply that a given firm's or even the aggregate 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.

Last, we use the change in import penetration from 1999 to 2011 as our base measure of import penetration and study changes in investment from before to after 1995. The 1999 to 2011 import exposure period is chosen because it corresponds to the largest increase in Chinese imports; and to the period of observed under-investment in the US economy (as discussed in Gutiérrez and Philippon (2016)). We study changes in investment from before to after 1995 for two reasons: first, import competition from 1999 to 2011 was foreseeable so that leading firms likely increased investment prior to 1999 (see Figure 3, which compares import exposure from 1991 to 1999 against 1991 to 2011). Second, 1995 allows for a sufficiently long period (1980-1995) to compare investment before and after the rise of China. Using 1990 yields a limited sample as the number of Compustat firms increases the most in the mid 1990s. That said, using alternate periods for import exposure (including 1991 to 2011, 1995 to 2011) and break-points for investment (e.g., 2000) yield broadly consistent results.

Figure 3: China import exposure: '91-'11 vs. '91-'99



4.1.2 Exploratory data analysis.

We first discuss broad trends in Chinese competition, firm entry and exit, and investment that lend support to our identification strategy and results. The following sub-section includes regressions results.

Number of firms, entry and exit rates. Figure 4 shows the change in total number of firms in industries with 'high' (above-median) and 'low' (below-median) Chinese import penetration from 1991 to 2011. 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 1980s, increased rapidly in the 1990s and decreased with the dot-com bubble. The patterns diverge, however, starting in the early 2000s. 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 4: Number of firms by Chinese exposure (1995 = 1)

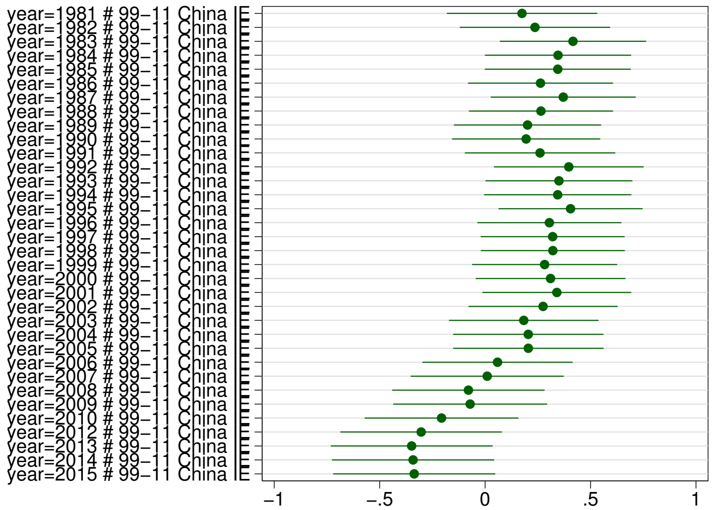
Notes: Annual data. Firm data from Compustat; import data from UN Comtrade. Manufacturing industries only, split into 'high' (above-median) and 'low' (below-median) exposure based on import penetration from 1991 to 2011.

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

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

where $log(N_{i,t})$ denotes the log-number of firms in industry i at time t; μ_i 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 5 shows the results, which support our hypothesis. Chinese competition appears to have led to a statistically significant reduction in the number of firms.

Figure 5: Import exposure interaction coefficients



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

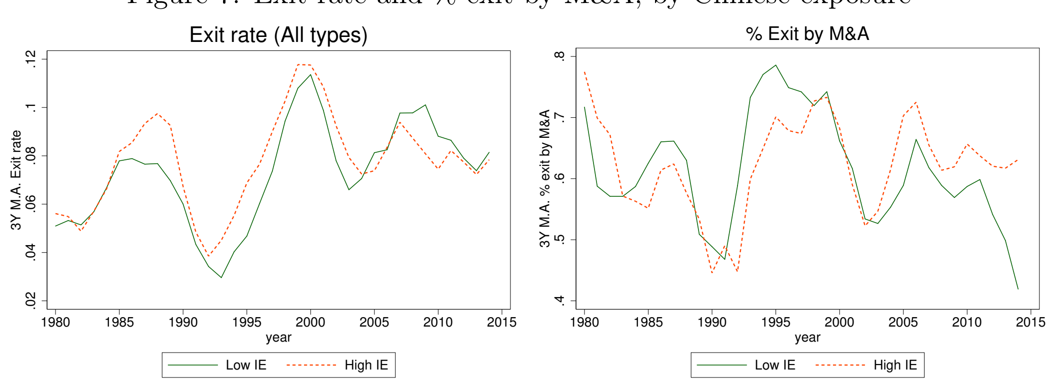
Is the decline in the number of firms due to lower entry or higher exit? As shown in Figures 6 and 7, primarily lower entry. In particular, Figure 6 shows the 3-year moving average aggregate entry rate across high and low exposure industries. High exposure industries had traditionally higher entry rates than low exposure industries. But this pattern flipped in the late 1990s/early 2000s. 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 6: Firm entry and exit 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 7 shows the 3-year moving average aggregate exit rates, and the percent exit rate through M&A, by level of import exposure. The exit rates appear roughly similar across segments; but exit through M&A exhibits different behavior. In particular, the share of firms that exited through M&A was lower at high-exposure industries in the 1980s and 1990s, yet increased drastically since the early 2000s. By contrast, exit through M&A decreased at low exposure industries. 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.

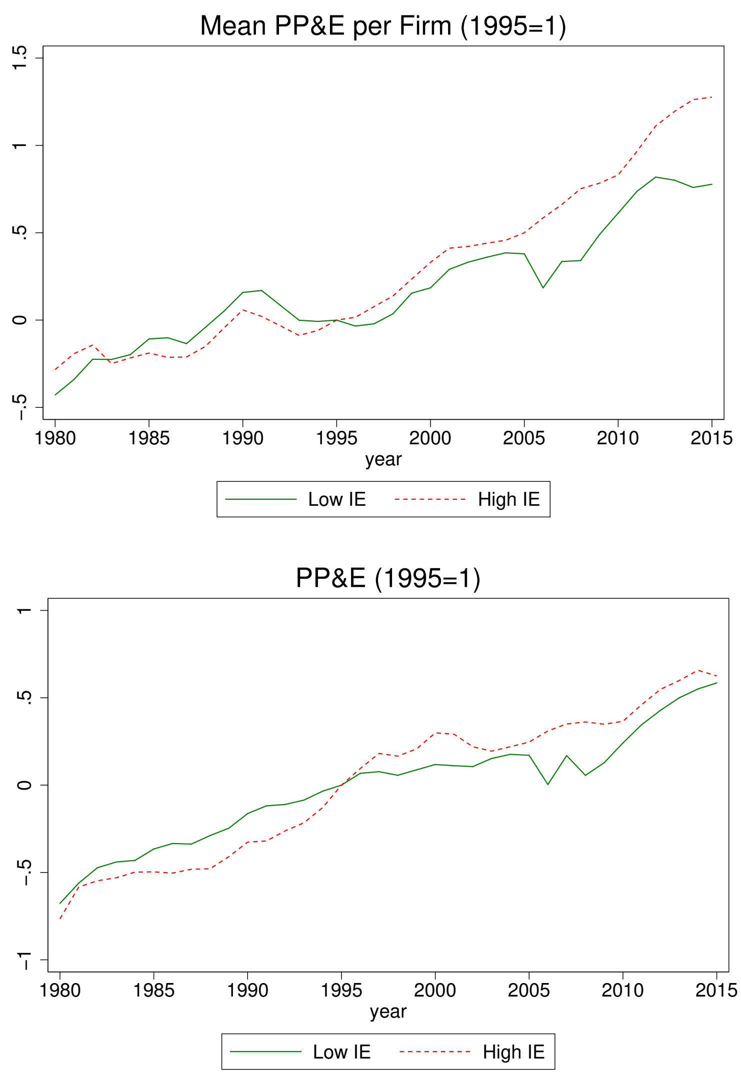
Figure 7: Exit rate and % exit by M&A, by Chinese exposure



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 8 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. In fact, as shown in the bottom chart, even the total amount of capital increased more in high exposure industries than in low exposure industries (among firms in our sample). This is a striking pattern, particularly since the number of firms decreased drastically.

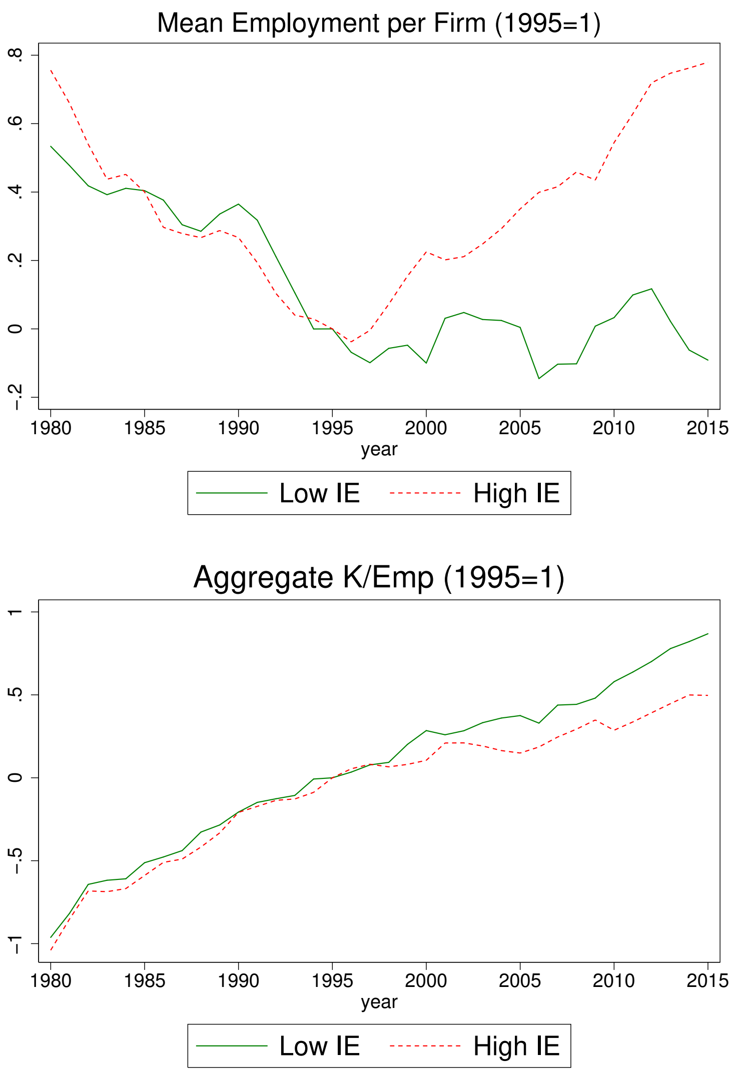
Figure 8: Change in PP&E by Chinese Exposure (surviving firms only)



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. Includes surviving firms only.

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 9, the mean employment per firm 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.[14] Comparing the ratio of K/Emp across high and low exposure firms, we find largely similar patterns (see bottom chart). High exposure firms show slightly lower K/Emp ratios, but the patterns are extremely similar.

Figure 9: Change in Employment and K/Emp, by Chinese Exposure



[14] A common path of exit appears to have been M&A. That said, we do not find statistically significant results using Compustat data.

4.1.3 Regression Results

We now discuss regression results.

Table 2 shows the results of our base tests. All regressions include year and firm fixed effects; as well as industry and firm age controls. We consider three different measures of capital (total assets, PP&E and Intangible assets excluding goodwill). As shown in columns 1 to 3, import exposure leads to a negative effect on capital (which is consistent with results in Pierce and Schott (2016)). But the effect varies across firms. Columns 4 to 6 separate leaders and laggards, which highlights the differences. Leaders increased capital and investment substantially with the Chinese import shock, while laggards decreased it (specifically, the coefficient on the leading firm interaction is positive and much larger than the negative coefficient for all firms). This aligns with model predictions, where firms increase investment if they can compete with entrants; but decrease it if they are unable to remain competitive. Columns 7 to 9 focus on continuing firms; and show that investment increased at leaders firms even when compared only to firms that survived the China shock (i.e., firms that were in the sample before 1995 and after 2009).

A few items are worth highlighting regarding these results. First, the results rely on the US import penetration ratio as the dependent variable, which as discussed above may be contaminated by domestic shocks to US industries. Instrumenting the US import penetration ratio with import penetration ratio of other developed countries yields consistent, and significant results. Second, all regressions include log-age and several measures of industry-level production structure as controls. In particular, we interact the 1991 value of the following measures with the post-1995 indicator to allow for changes in the relationship between employment and industry characteristics after the China shock: the percent of production workers, the ratio of capital to employment and capital to value added; and the average (total and production) wages. We tested several other controls and neither affected the results. The remaining time-invariant characteristics are captured by the firm fixed effects.

The above results highlight that investment increases with Competition – particularly at leading firms. Table 3 studies the effects on employment and K/Emp. Columns 1-3 show that both employment and capital decreased with import exposure when considering all firms. Separating leaders and laggards, however, shows different dynamics. Leaders increased both PP&E and Employment. They increased capital more than employment, leading to slight capital deepening relative to laggards.

To summarize, we find that leaders reacted to increased Chinese competition by increasing investment, which suggests that increasing competition leads to more investment. Exiters and/or new entrants exhibit a decrease in investment, in line with predictions of competition models with asymmetric firms. This analysis, however, has two limitations: it considers only manufacturing industries, and it relates to a particular natural experiment. The next section leverages excess entry in the 1990s as an IV for competition, in order to fill these gaps.

Table 2: Competition natural experiment: 'Core' regression results

Table shows the results of firm-level panel regressions of measures of capital on China import exposure, following 3. We consider three measures of capital: log-assets, log-PP&E and log-intangibles excluding goodwill . Regression over 1980 - 2015 period. As shown, leaders more exposed to the China shock increased investment after 1995. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01. Standard errors clustered at the firm-level. Results robust to clustering at industry-level or instrumenting for ΔIP with ΔIP_{oc}.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log(AT_t)$	$\log(PPE_t)$	$\log(Intan_t)$	$\log(AT_t)$	$\log(PPE_t)$	$\log(Intan_t)$	$\log(AT_t)$	$\log(PPE_t)$	$\log(Intan_t)$
$Post95 \times \Delta IP_{j,99,11}$	-0.210*	-0.228*	-0.218	-0.414**	-0.468**	-0.445+	-0.592**	-0.476**	-0.414
	[-2.42]	[-2.29]	[-1.01]	[-3.92]	[-4.00]	[-1.79]	[-2.97]	[-2.69]	[-0.88]
$Post95 \times \Delta IP_{j,99,11} \times Lead^{\S}$				**0.658****	**0.765****	**0.860***	**0.808***	**0.729+**	**0.992**
				[4.32]	**[4.67]**	**[2.06]**	**[2.18]**	**[1.89]**	**[1.01]**
$\log(Age_{t-1})$	0.240**	0.331**	0.018	0.235**	0.325**	0.017	0.548**	0.457**	0.219
	[7.70]	[9.22]	[0.24]	[7.59]	[9.12]	[0.23]	[8.37]	[7.81]	[1.60]
Observations	50376	50235	29925	50376	50235	29925	17633	17659	11847
Within R^2	0.45	0.22	0.35	0.46	0.22	0.35	0.33	0.57	0.46
Overall R^2	0.09	0.07	0.10	0.09	0.07	0.10	0.14	0.15	0.12
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	

§ Leaders defined as firms with above-median Q as of 1995 within each NAICS Level 4 industry
† Industry controls include measures of industry-level production structure (e.g.,K/Emp) as of 1991. See text for details.

Table 3: Competition natural experiment: Employment regression results

Table shows the results of firm-level panel regressions of measures of capital, employment and capital-deepening on China import exposure, following 3. Regression over 1980 - 2015 period. As shown, leaders more exposed to the China shock increased investment, employment and K/Emp after 1995. Annual data, primarily sourced from Compustat. Only US-incorporated firms in manufacturing industries included. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01. Standard errors clustered at the firm-level. Results robust to clustering at industry-level or instrumenting for ΔIP with ΔIP_{oc}.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(PPE_t)$	$\log(Emp_t)$	$\log(\frac{PPE_t}{Emp_t})$	$\log(PPE_t)$	$\log(Emp_t)$	$\log(\frac{PPE_t}{Emp_t})$
$Post95 \times \Delta IP_{j,99,11}$	-0.228*	-0.195*	-0.051	-0.468**	-0.363**	-0.128+
	[-2.29]	[-2.28]	[-0.91]	[-4.00]	[-3.72]	[-1.87]
$Post95 \times \Delta IP_{j,99,11} \times Lead^{\S}$				**0.765****	**0.548****	**0.249****
				[4.67]	**[3.81]**	**[2.99]**
$\log(Age_{t-1})$	0.331**	0.409**	-0.084**	0.325**	0.405**	-0.086**
	[9.22]	[13.45]	[-4.05]	[9.12]	[13.38]	[-4.16]
Observations	50235	49649	49543	50235	49649	49543
Within R^2	0.22	0.109	0.216	0.224	0.113	0.217
Overall R^2	0.07	0.19	0.10	0.07	0.18	0.10
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	

§ Leaders defined as firms with above-median Q as of 1995 within each NAICS Level 4 industry

† Industry controls include measures of industry-level production structure (e.g.,K/Emp) as of 1991.

4.2 Instrumental Variables: Excess Entry

4.2.1 Empirical strategy

The main problem with using measures of concentration in the OLS regressions reported in Gutiérrez and Philippon (2016) is that entry – and therefore concentration – at t depends on expected demand at $t+\tau$. As a result, entry predicts investment even under "perfect" competition

$$\frac{I}{K} = F\left(\frac{K^{\star}}{K}; \texttt{Comp}, \texttt{Gov}\right)$$

Addressing this issue requires a variable that predicts entry/concentration but is not correlated with future demand. We construct such a variable, using the variations in the entry rate during the 1990s. In particular, we predict 'expected' entry during the 1990s based on measures of profitability, sales growth, cash flow, intangibles and Q, among others[15]

$$\Delta log N_{i,90-99} = \beta_0 + \beta_1 Q_{i,MA5} + \beta_2 Med\, \Delta log\, Sales_{i,90-99} + \ldots + \beta_n Mean\, firm\, age_{90} + \varepsilon_j$$

Then, we compute excess entry as the difference between actual and 'expected' entry

$$Excess\, Entry_{i,90-99} = \Delta log N_{i,90-99} - \Delta \widehat{log N_{i,90}}_{-99}$$

The following sub-section discusses our estimates of excess entry empirically. We find substantial cross-sectional variations in excess entry during the 1990s, which support the use of this variable as an IV for Concentration. Industries that experienced higher excess entry in the 1990s had a lower concentration in 2000; which was offset over the 2000s as the 'excess' firms exited.

The exclusion restriction for using excess entry as an IV is as follows:

Exclusion restriction: *Controlling for industry fundamentals, excess entry in the 1990s is uncorrelated with industry demand post-2000* This is supported by the fact that excess entry does not predict sales growth. Once the dot-com bubble crashed, excess entry was realized and industry demand post-2000 returned to its proper trend. Industries with higher excess entry experienced higher exit rates. In other words, our results are consistent with differences in beliefs and/or idiosyncratic opportunities among industries. See the following subsection for additional discussion.

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 2000s would decrease independently of competition. To control for this, we estimate industry-level excess investment in the 1990s (by regressing net investment on industry Q, age and size) and add the cumulative residual as a control in our regression.

Thus, we run the following industry-level panel regression over the post-2000 period:

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

$$HHI_{i,t-1} = \theta_0 + \theta_1 Excess\,Entry_{i,90-99} + \theta_2 Q_{i,t-1} + \theta_3 Excess\,Inv_{i,90-99} + \theta_4 HHI^{adj}_{i,t-1} + \boldsymbol{\theta X_{it-1}} + \varepsilon_{1,it}$$

$$\frac{NI_{it}}{K_{it-1}} = \beta_0 + \beta_1 \widehat{HHI_{i,t-1}} + \beta_2 Q_{i,t-1} + \beta_3 Excess\,Inv_{i,90-99} + \beta_4 HHI^{adj}_{i,t-1} + \boldsymbol{\gamma X_{it-1}} + \varepsilon_{2,it}$$

where we use Excess Entry during the 1990s as an instrument for industry-level Herfindahl.[16]; and X_{it-1} denotes industry-level controls for age and size. We include the mean age and size as of 1999 as independent variables; and the lagged mean age and size as instrumental variables because excess entry affects both of these quantities. Note that we instrument only for the 'traditional' Herfindahl, not the common ownership adjustment. This is 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.

Note that, because excess entry is constant over time, we cannot add industry fixed effects in the above test. However, 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 1990s exhibit higher exit rates in the 2000s. As a result, the impact of excess entry on investment should decrease over time. We test this 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 of investment over time. This second specification allows us to include industry and year fixed effects.

4.2.2 Exploratory data analysis.

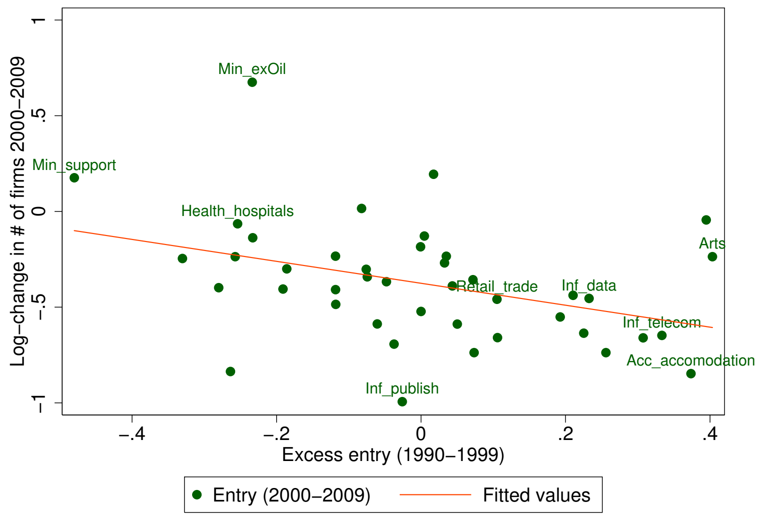
The regression results are provided in the following sub-section. However, to further support our identification strategy, we first discuss our estimates of excess entry and the associated concentration dynamics qualitatively.

As shown in Figure 10, we find large differences in excess entry across industries during the 1990s – 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. This is likely driven by three effects.

The first is the overly optimistic environment in the late 1990s, which led to extreme valuations and 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

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

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



Note: Annual data. Flow of Funds Q for Non Financial Corporate sector due to data availability. Compustat Q for selected sample.

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 S&P 500 index by market capitalization and seven of its ten sector component indices exhibited at least some bubble-like behavior over our sample period." Such bubbles likely translated into excess entry – especially because firm entry increases precisely during periods of high-growth such as the late 1990s (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 – including all 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 in response to optimistic valuations. 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."*

Table 4: Regression Results: Post-2000 Entry vs. Pre-2000 Excess entry

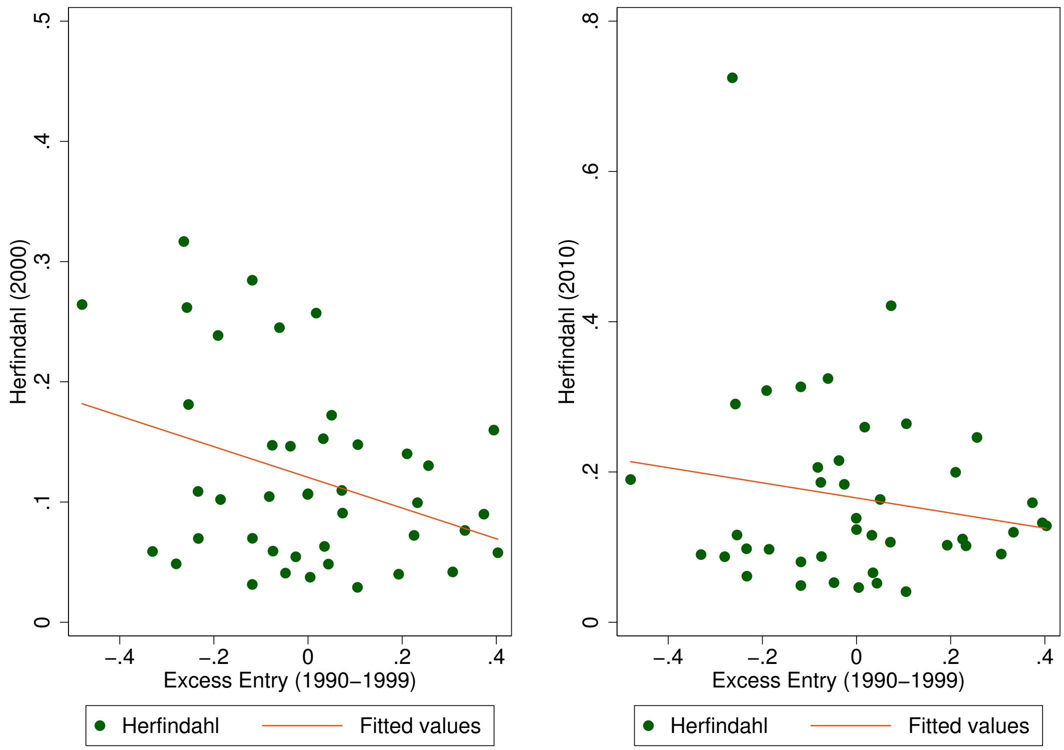
Table shows the results of industry-level OLS regressions of alternate industry-level entry and exit measures on excess entry. Entry and Exit based on the number of firms in Compustat. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01.

	(1)	(2)	(3)	(3)	(4)	(4)
	$\Delta log N_{00-09}$	$\Delta log N_{00-05}$	$\overline{Entry_{00-09}}$	$\overline{Entry_{00-05}}$	$\overline{Exit_{00-09}}$	$\overline{Exit_{00-05}}$
$Excess\, Entry_{i,90-99}$	-0.589**	-0.262+	-0.003	0.018	0.036+	0.047*
	[-2.72]	[-1.82]	[-0.16]	[1.10]	[1.88]	[2.05]
Constant	-0.375**	-0.261**	0.047**	0.045**	0.086**	0.089**
	[-8.35]	[-8.73]	[12.53]	[13.09]	[21.61]	[18.69]
Observations	42	42	42	42	42	42
R-squared	0.156	0.076	0.001	0.029	0.081	0.095

Interestingly, the excess entry was largely offset following the 1990s: industries that experienced higher excess entry, also experienced larger decreases in the number of firms in the 2000s. In fact, as shown in Figure 10, the number of firms decreased across most industries by much more than the excess entry; suggesting the presence of an aggregate trend towards concentration (which is highlighted in CEA (2016), among others). Table 4 formalizes these observations. It shows the results of regressing post-2000 changes in the number of firms, entry and exit rates, on pre-2000 excess entry. Higher excess entry predicts a reduction in the number of firms; primarily due to higher exit.

Industries that experienced higher excess entry in the 1990s had a lower concentration in 2000; which was offset over the 2000s as the 'excess' firms exited. Figure 11 shows this graphically. The left (right) chart shows the Herfindahl as of 2000 (2010) against excess entry in the 1990s. Industries with higher excess entry in the 1990s had a lower Herfindahl in 2000; which was offset by 2010. By 2010 we see a very weak relationship between excess entry in the 1990s and the Herfindahl – with the slope on the line driven entirely by the outlier industry with a Herfindahl above 0.7. This is essentially the first stage of our regression, excluding the additional controls.

Figure 11: Excess entry (1990-1999) vs. Herfindahl (2000 and 2010)



Note: Annual data. Herfindahl based on all US incorporated firms in Compustat; capped at 0.4 for illustration purposes, although higher value still yields consistent result.

To summarize, the above results suggest the existence of substantial cross-sectional variations in excess entry during the 1990s, which supports the use of excess entry as an IV for Concentration. Industries with higher excess entry in the 1990s exhibit a lower concentration in 2000; an effect that disappears by 2010 as the 'excess' firms exited. These results also pose a question: what is driving the aggregate increase in concentration across most industries since the late 1990s? We discuss potential answers to this in Section 5; following the results of our IV regressions.

4.2.3 Regression Results

Table 5 contains the results of our IV regressions, which instrument 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.

Table 5: Competition IV: Regression results

Table shows the results of industry-level 2SLS regressions of alternate industry-level 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.

	1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)
	$HHI_{i,t-1}$	Net I/K	$HHI_{i,t-1}$	Net I/K
	≥2000	≥2000	≥2000	≥2000
Mean Stock Q (t-1)	0.016**	0.029**	0.022**	0.033**
	[2.61]	[10.40]	[3.89]	[7.42]
$Excess\,Inv_{90-99}$	-0.569	-0.589*	Omitted	
	[-1.08]	[-2.41]		
$Excess\,Entry_{90-99}(i)$	**-0.153****		Omitted	
	[-4.76]			
$Excess\,Entry_{90-99}(i) \times Med\,HHI(t)$			**1.295+**	
			[1.66]	
Herfindahl (t-1)	-0.246**	**-0.249****		**-0.539****
	[-6.96]	**[-5.06]**		**[-5.41]**
Comm. Own. adj. (t-1)		**-0.063****	-0.120**	**-0.080****
		[-3.80]	[-3.34]	**[-2.71]**
Mean log(assets) ('99)	0.033*	0.019**	Omitted	
	[2.16]	[3.15]		
Mean log(age) ('99)	-0.052+	-0.033**	Omitted	
	[-1.72]	[-2.81]		
Mean log(assets) (t-1)	0.015+		-0.032**	
	[1.89]		[-3.8]	
Mean log(age) (t-1)	0.080**		0.086**	
	[5.06]		[6.02]	
Year FE	No		Yes	
Industry FE	No		Yes	
Observations	672	672	672	672
OverallR^2		0.078		0.045

5 What explains the increase in concentration?

The results reported in Section 4.2 suggest the existence of a secular trend towards concentration; which drives a lot of our results. Three main explanations have been put forward in the literature:

- **Regulation and barriers to entry:** Others argue that the increase in concentration is driven by rising regulation, lobbying and occupational licensing. Such barriers allow dominant firms to limit entry by actual and potential rivals; thereby increasing market power (see, for example, CEA (2016)).

- **IT and the rise of superstar firms:** The last set of explanations argue that technological change has made markets increasingly "winner take most" (such that superstar firms with higher productivity capture a larger slice of the market). This could be complemented by a rise in the likelihood of incumbent innovation, which may increase the gap between leaders and laggards (see, for example, Autor et al. (2017))

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

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

- **Regulation and barriers to entry**, we use the Regulation index published by the Mercatus Center at George Mason University as a measure of industry-level regulation; and the share of workers requiring Occupational Licensing in each NAICS Level 3 industry from the 2008 PDII as a proxy for barriers to entry.[17]

- **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 output, and value-added to capital and labor ratios.

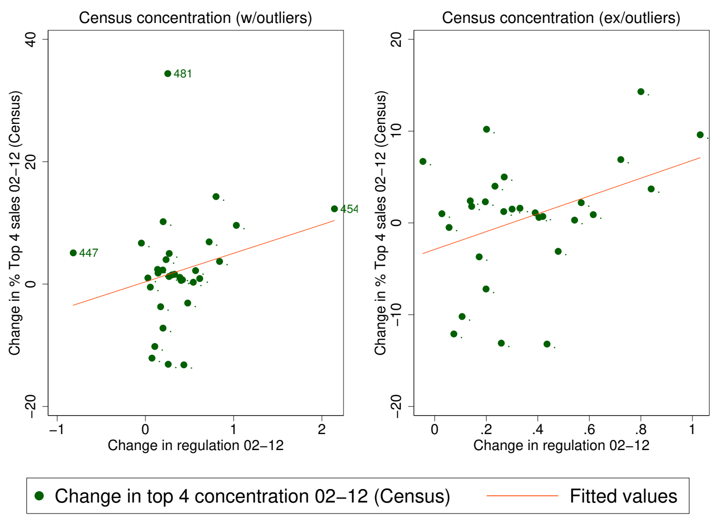
- **Demographics:** we compute the median age of CEOs in each industry. Industries with older CEOs are likely to be more affected by demographics, hence should exhibit rising concentration.

[17] 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.

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

Regulation. Let us begin with regulation. Figure 12 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.

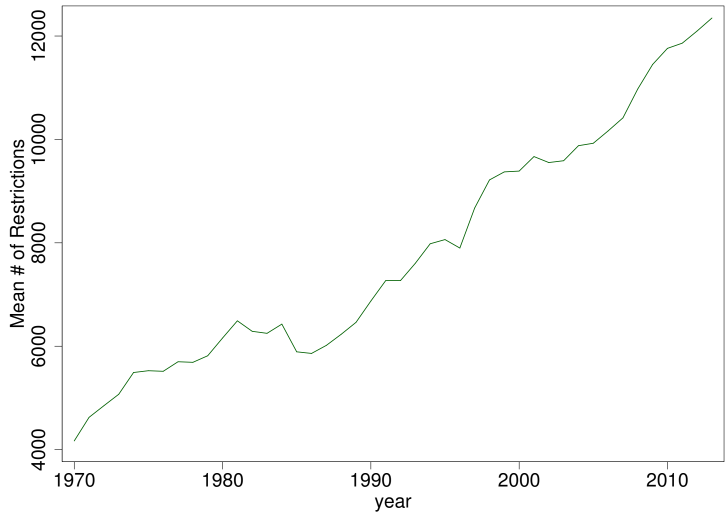
Figure 12: Change in regulation (2002-2012) and change in Concentration



Note: 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, as shown in Figure 13, regulation was relatively stable in the 1970s and 1980s but increased rapidly since the mid-1980s. By focusing on the post-crisis period, the above analysis fails to capture a large part of the increase in regulation.

Figure 13: Mean # of relevant restrictions, by industry



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

We use Compustat-based concentration measures to address these limitations. In particular, Table 6 shows the results of regressing measures of competition and investment, using the regulation index. In particular, column 1 regresses the top 4-firm concentration ratio on the regulation index, as well as measures of profitability (OS/K), cash flow over assets, market value (mean Q), age and size as controls. As shown, increases in regulation are correlated with rising industry concentration.[18] Columns 2 and 3 outline a 2SLS regression, where the top 8-firm concentration ratio is instrumented by the industry-level log-regulation index. As shown, more regulation predicts a higher concentration ratio, which in turn predicts lower investment. We note that these results – particularly the link to investment – are sensitive to the choice of concentration measure and time period. Still, they suggest a positive relationship between regulation, concentration and investment that will likely feature in any plausible explanation of rising industry concentration.

Superstar firms. Let us move on to superstar firms. If concentration is indeed driven by 'superstar' firms capturing a larger share of output, industries that became more concentrated should also become more productive. We estimate the correlation between changes in concentration and changes in industry-level productivity – measured by industry-level TFP; output and value-added per worker; and output and value-added per unit of capital. We measure changes in concentration over the five year periods when Census data is available (1997, 2002, 2007 and 2012) as well as cumulatively from 1997 and 2002 to 2012. Similarly, we measure changes in productivity over the same periods, except that the last observation ends on 2009 (the last year available in the NBER CES database). We perform this analysis using NAICS Level 6 segments.

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

Table 6: Regulation as IV: Regression results

Table shows the results of industry-level OLS and IV regressions. Column 1 regresses % of sales by Top 4 firms on log-regulation index. Columns (2) and (3) provide an IV regression of net investment, with the % sales by top 8 firms instrumented using the regulation index. Concentration measures and controls from Compustat; Regulation index from Mercatus. T-stats in brackets. Standard errors clustered at the industry-level. + p<0.10, * p<0.05, ** p<.01.

		1st Stage	2nd Stage
	(1)	(3)	(4)
	$CR4_{i,t}$	$CR8_{i,t-1}$	Net I/K
	≥1980	≥1995	≥1995
Log(Reg index)(t-4)	**0.038+**	**0.03***	
	[1.99]	**[2.03]**	
Mean Stock Q (t-1)	0.022	0.03**	0.03**
	[1.24]	[3.05]	[3.18]
Mean log(age) (t-1)	0.150**	-0.11**	0.03
	[3.19]	[-5.18]	[0.62]
Mean log(assets) (t-1)	-0.107**	0.18**	-0.02
	[-3.46]	[5.73]	[-0.52]
Mean QIX own(t-1)		-0.20+	-0.25**
		[-1.7]	[-2.98]
Comm. Own. adj. (t-1)		-0.16	-0.09
		[-0.5]	[-0.49]
CR8 (t-1)			**-0.34+**
			[-1.68]
Year FE	Yes	Yes	
Industry FE	Yes	Yes	
Observations	1062	591	
R^2	0.267	-0.014	

We find consistently positive correlations between concentration and value-added per worker; a generally positive correlation between concentration and output/value-added per unit of capital; and a time-sensitive correlation between concentration and industry-level TFP. In particular, 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).[19]

Nonetheless, like the results of Autor et al. (2017), our results suggest the presence of some correlation between concentration and productivity – especially during the late 90s/early 2000s. Superstar firms are therefore likely part of the drivers of concentration.

Demographics. We estimate the correlation between the level and changes in concentration and the corresponding values for the 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 US. Our argument is based 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 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 1990s invested more in the 2000s, after controlling for firm fundamentals. We also study potential drivers of rising concentration; and find support for two hypotheses: increasing regulation, and superstar firms.

[19] They provide limited details on the calculation approach in the referenced paper; and refer to an unpublished document for details. Absent additional details on their calculation approach, we cannot reconcile our results.

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