The Rise of Star Firms: Intangible Capital and Competition

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Abstract

There is a divergence in the returns of top-performing (star) firms and the rest of the economy, especially in industries that rely on a skilled labor force, raising concerns of their market power. We show that the divergence is explained by the mis-measurement of intangible capital. While star status is associated with greater market power, this association is decreasing over time and especially in industries with high intangible capital investment. Moreover, star firms have higher output and investment per dollar of invested capital at every level of pricing power and are not differentially affected by exogenous competitive shocks than other firms. Our findings suggest that concerns about star firms using their market power in inefficient and welfare reducing ways may be overstated. Some exceptional firms may pose concerns due to their potential to foreclose competition in the future. *JEL Classification*: E22, L1

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Introduction

A great deal of attention has been paid to two trends in the US economy: (1) the emergence of star firms whose high returns on capital have enabled them to pull away from the rest of the economy (Furman and Orszag [2015], Koller, Goedhart, and Wessels [2017]) and (2) the introduction of new technologies with a fundamental structural change towards a more intangible intensive economy (Corrado and Hulten [2010]) with corresponding implications for corporate investment and the overall economy.[1] However, the two trends are typically analyzed separately, and the rise of star firms has been linked to a decline in market competition. In fact, we have little systematic evidence on the characteristics of these star firms. Is the rise of star firms the result of increasing market power and increasing concentration in the U.S.? What is the role of intangible capital? Is there evidence that star firms generate their high profits by exploiting market power more effectively than other firms?

In this paper, we use a dataset of publicly listed firms from the Compustat database to identify star firms[2] and their industries. We examine the role of market power, intangible capital and technological change at the industry level (dependence on routine manual tasks vs high cognitive skills) in influencing star firm status.[3] We aim to test the dominant concern that star firms are gaining their distinction through market power by restricting competition which enables them to charge high prices without investing much. In particular we test whether star firms differ in their investment and output per unit of capital compared to other firms in the economy and if they are differentially affected by shocks to their market power.

[1]Several papers have explored the implications of the rise in intangible assets and knowledge capital on corporate investment (e.g. Peters and Taylor [2017], Falato et al. [2013]) and other macroeconomic impacts (e.g. Atkeson and Kehoe [2005], McGrattan and Prescott [2010], Eisfeldt and Papanikolaou [2014] and Caggese and Perez-Orive [2017]).

[2]Following Furman and Orszag [2015], we define star firms as firms in the top 10% of Return on Invested Capital (ROIC), calculated pre-tax, in the US in a particular year. ROIC is an important profitability metric in corporate finance measuring how efficiently a company can allocate its capital to profitable investment and has been widely used in the literature (e.g. Ben-David, Graham, and Harvey [2013]) and by practitioners (e.g. Koller [1994], Koller et al. [2017]). For instance, David Benoit writing for the Wall Street Journal argued that General Motors placated activist investors with the help of higher return on invested capital (ROIC). See *The Hottest Metric in Finance: ROIC*, Wall Street Journal (2016). However, in a parallel treatment we obtain similar results when we use Tobin's Q to define star firms.

[3]While we use three measures of market power - a firm-level measure of operating markups, firm-level market share, and a raw measure of firm size, we focus our analysis on markups given the issues with interpreting market share as a measure of market power (see Syverson [2019]). Our implementation of operating markups, which follows the work of Foster et al. [2008], De Loecker et al. [2018], and Traina [2018] is discussed below.

We have the following main findings: First, we show that the large dispersion of return on invested capital (ROIC), especially the run-up in the top decile of ROIC among US publicly traded firms shown by previous studies (e.g. Council of Economic Advisors [2016], Furman and Orszag [2015], and Koller et al. [2017]) is largely due to measurement error in accounting for intangible capital consistently. Specifically, conventional return metrics do not capitalize research and development, brand capital, or other forms of organizational capital with far-reaching consequences for earnings and estimates of pricing power.[4] This measurement error is greatest in industries that rely heavily on complex cognitive skills and those that are likely to have higher amounts of intellectual and organizational capital, which is not measured by ROIC prepared according to generally accepted accounting principles. Once we re-compute the ROIC calculations to factor in estimates of intangible capital from the finance literature (see Peters and Taylor [2017] and the references therein), we find that both the run-up by top decile of firms and the much higher mean returns in the cognitively skilled industries disappear. We find similar results using Tobin's Q adjusted for intangible capital in place of ROIC.

Second, we show that markups are affected by similar measurement issues. Once we adjust the markups based on operating expenses for intangible capital, there is only a modest rise in markups over time, and most of this increase is in the top 10% of firms in high skilled industries.

Third, when we investigate the link between markups and star firm status, we do see that markups are positively related to high profits and greater probability of being a star. This is a potential concern, as high markups are commonly interpreted as evidence of welfare reducing market power. However, the concern is moderated by our finding that the relation between markups and star status is declining over time. Moreover, the relation between markups and star status is weaker in industries with high levels of intangible capital, suggesting that a general increase in markups over time may be of lower concern with the economy-wide shift to more intangible-intensive investments. More broadly, the joint existence of high profits and markups is not sufficient evidence of inefficiency or harm to consumers. As we discuss below, an increase in a firm's efficiency can both increase the

[4]The measurement error in intangible capital affects measures of firms' earnings, identification of variable costs, capital investment and estimates of pricing power, outcomes which are subject to controversy. For instance, while De Loecker and Eeckhout [2017] show that there is a dramatic rise in firm pricing power in the U.S. using Cost of Goods Sold (COGS) as a measure of variable cost, Traina [2018] argues that once we include Selling, General, and Administrative Expenses (SGA) which are an increasingly vital share of variable costs for firms and accounts for intangible organization/management capital, there is no rise in markups.

firm's markups and move the industry to an equilibrium where output prices decrease. Thus, even in the absence of increased restrictions on output that reduce customer welfare, star firms could have higher markups because of the efficiency gains.[5] This pattern is consistent with the following stylized facts in the data:

First, a large fraction of star firms have relatively low markups so there is not a one to one association between star status and high market power. Second, at every level of markup, the star firms have higher Output (sales/invested capital), Capex, and R&D investment compared to other firms. Third, when we look at industries with high intangible capital, star firms have higher investment than other firms. This is suggestive of greater heterogeneity between winners and laggards (see Haskel and Westlake [2018]) in industries with intangible capital investment. In those industries in particular, star firms are not gaining their profits by the reduction of output and under-investment.

These relations are observational, and not necessarily causal. Hence we next examine whether star firms are differentially affected compared to other firms by exogenous shocks to their market power. We measure increased competition in U.S. manufacturing by penetration of Chinese imports into the US instrumented by Chinese imports into eight other developed economies following Autor et al. [2013]. While we find that an exogenous shock to competition (increase in Chinese imports to the US) affects ROIC, output, and markups of all firms negatively, we find no evidence that star firms are differentially affected by import competition compared to other firms in the economy.

Overall, once intangible capital is taken into account, there is not a growing polarization in the economy between firms with high returns and other firms. While there is positive relation between star firm status and pricing power, star firms produce more and invest more at every level of pricing power. Taken together, these results suggest that while star firms and non-star firms with the same level of markups face similar incentives to increase prices and reduce output and investment, the efficiency and cost structures in star firms result in lower prices and higher output than for non-star firms. Thus, the conventional focus on market power that does not take into account intangible

[5]As highlighted by Syverson [2019], there are several alternate explanations for the high correlation between markups and performance other than the welfare reducing use of monopoly power. Relatedly, Crouzet and Eberly [2018] also show that greater efficiency gains due to investments in intangibles may explain increases in industry concentration.

capital has the potential of penalizing highly skilled and productive firms, with adverse effects on the economy.

Our results are robust to a number of checks and alternate specifications. We find all our conclusions above to hold even when we tighten the requirement for star status down to the top 100 or 150 firms (when ranked by ROIC) each year. There is no run-up over time of the top 100 or 150 firms once we correct for intangible capital. We do find that the effects of star status are persistent. Five years later, star firms have higher ROIC, sales growth, and Tobin's Q suggesting that our results are not driven by firms that have randomly realized high returns in specific years. We also find similar results when we use an alternative definition of star status which categorizes star firms as those in the top decile of market value (Tobin's Q), taking into account the adjustment for the value of intangible capital.

To account for the fact that cash holdings at some of the technology companies are substantial, we use yet another definition of star status where we consider only non-cash working capital in our definition of ROIC.[6] In addition, in sensitivity tests we also find that our results are robust to varying the fraction of intangible capital that is used to correct the ROIC measures.[7] All our results hold with these alternative definitions.

Determining whether the performance gap between star firms and other firms is the result of luck, market imperfections, measurement of intangible capital, or a reflection of successful idiosyncratic firm growth strategies[8] is a public policy priority that will shape policies that promote or regulate high-value firms. A policy implication of our analysis is that there is little evidence that extraordinary returns are being realized as a result of welfare reducing monopolistic behavior. To look at possible disruptive and system wide effects of star firms, we need to focus our search on a very small number of firms. The analysis of these firms is not straightforward, both because of their small numbers and their adoption of pricing policies that reduce current returns in expectation of

[6]It is not clear how we should treat firms' holdings of cash and near-cash securities. At one extreme, they are required precautionary balances, part of the firm's invested capital. At the other extreme, they mostly consist of excess cash retained by the firm's managers and should not be used in evaluating the economic value of the firm's business.

[7]We follow Peters and Taylor [2017] in constructing our measure of intangible capital to include knowledge capital (R&D expenses) and organization capital (SG&A expenses). We obtain similar results when we include only knowledge capital instead of organization capital in our definition of intangible capital.

[8]Successful idiosyncratic growth strategies may also be due to successful innovation or superior management practices (e.g. Bloom and Van Reenen [2007])

higher subsequent returns.

A very small number of firms are often cited in the press as disrupting conventional business models, Amazon, Facebook, Google, Apple, and Microsoft (AFGAM), and we do see that these firms (especially Apple) have supernormal returns to capital. However, some of their markups, such as that of Apple and Amazon are not necessarily much larger than those of the 90^{th} percentile firm over the sample period. As discussed in section 4.2 below, these firms may have more market power than is even evidenced by their markups. In particular, they may be following strategies that emphasize holding markups and profits below their short run optimal values and growing quickly as a means of dominating their industries in the long run. Such strategies pose complex public policy challenges.

Our paper is related to the growing literature exploring the rise in concentration (see Grullon et al. [2019], Baker and Salop [2015] and Kurz [2017]), decline in labor share (see Barkai [2016], Autor et al. [2017]), and hollowing out of investment in physical capital (Gutiérrez and Philippon [2017] and Alexander and Eberly [2018]). One interpretation of these related literatures is that it reflects increased market power and reduced competitiveness and economic efficiency (De Loecker and Eeckhout [2017], Gutiérrez and Philippon [2017]). An alternate interpretation is that it reflects productivity differences between firms leading to a reallocation of demand towards the most productive firms (Autor et al. [2017]. Crouzet and Eberly [2019] relate the overall decline in investment in physical capital to sectoral differences in intangible capital investment. They compare sectoral-level trends in labor productivity levels and markups to show that the joint increases in concentration and intangible investment in some sectors like manufacturing and wholesale and retail trade is due to efficiency enhancing mechanisms. In contrast to these papers, the focus in our paper is not on concentration but on understanding the characteristics of star firms and providing a link to the rise of intangible capital and increases in market power. When corrected for intangible capital, we find little evidence for the hypothesis that star firms are exercising market power in traditional ways by restricting output and under-investing compared to non-star firms. Instead we argue that conventionally measured high returns of star firms are largely due to measurement error in accounting for intangible capital investment. More generally, our paper points to the importance of adjusting for intangible capital in corporate finance research. Differences in intangible capital across firms and over time not only affect ROIC and our evaluation of investment and market power, but most likely will effect optimal capital structures, governance, and firms' cash policies.

1 Identifying Star Firms

We use data from Compustat that provides detailed financial information on publicly traded firms in the US over an extended period of time. We drop cross listed ADRs and restrict the sample to firms incorporated in the US. We also drop firms in Utilities (SIC 49), Finance, Insurance and Real estate (SIC 60-69) and Public Administration (SIC 90-99), observations with missing SIC codes, negative values for employees, sales, total assets, current assets and current liabilities, fixed assets, cash, and goodwill and missing total assets or sales.

The advantage of using Compustat is that we have detailed balance sheet information that allows us to compute intangible capital. The caveat however, is that there are firm selection issues. First, it may be that listed firms, as a class, might not consistently represent star firms. Doidge, Kahle, Karolyi, and Stulz [2018] and Kahle and Stulz [2017] show that there are fewer US listed corporations today than 40 years ago. However, Grullon et al. [2019] argue that the void left by listed firms has not been filled by an increase in the number of private unlisted businesses. Using US Census data that includes both private and public firms, they show that even though more private firms have entered the economy, their marginal contribution to the aggregate product market activity has been relatively small. Public firms also account for one third of total US employment (Davis, Haltiwanger, Jarmin, Miranda, Foote, and Nagypal [2006]) and about 41% sales (Asker, Farre-Mensa, and Ljungqvist [2014]). Also using U.S. Census data, Maksimovic, Phillips, and Yang [2017] show that high initial firm quality at birth predicts subsequent listing decision. These findings suggest that while our sample will not be picking up small and young potential star firms in their private stages, we are targeting the sample of firms among which economically significant stars are highly likely to arise.

The second, and potentially more important issue, as pointed out by Doidge et al. [2018], is that small, young, high-technology firms may benefit from private status where specific financial institutions, such as venture capital partnerships and private equity firms better meet their financing needs than public capital markets. Thus, such firms may be underrepresented in our sample of star firms. To the extent that this listing gap has emerged only since 1999 (see Doidge, Karolyi, and Stulz [2017]), the early part of our sample period is immune to this.

We define star firms as firms that realize high returns for their investors. We begin by using a standard definition of Return on Invested Capital (ROIC) as our measure of returns, where ROIC for firm i in year t is defined as:

$$ROIC_{it}^{unadj} = \frac{EBIT_{it} + AM_{it}}{Invested\,Capital_{it-1}^{unadj}} \tag{1}$$

where $EBIT$ is Earnings before Interest and Taxes (Compustat item EBIT) and AM is Amortization of Intangible Assets (Compustat item AM). ROIC, as used in the Council of Economic Advisors [2016] report and Ben-David et al. [2013], among many others, computes the earnings that a corporation realizes over a period, as a fraction of capital that investors have invested into the corporation. The advantage of ROIC is that it measures investment capital as more than physical capital (fixed asset investment) which Doidge et al. [2018] show to be a declining portion of total assets over time in the US.

We adopt a relatively conservative definition for Invested Capital as the amount of net assets a company needs to run its business:

$$\begin{aligned} Invested\,Capital_{it}^{unadj} = {} & PPENT_{it} + ACT_{it} + INTAN_{it} - LCT_{it} - GDWL_{it} \\ & - max(CHE_{it} - 0.02 \times SALE_{it}, 0) \end{aligned} \tag{2}$$

where $PPENT$ is Net Property, Plant, and Equipment, ACT is Current Assets, $INTAN$ is Total Intangible Assets, LCT is Current Liabilities, $GDWL$ is Goodwill that represents the excess cost over equity of an acquired company, CHE is Cash and Short-term Investments, and $SALE$ is net sales. All these variable labels are the corresponding items in Compustat.[9]

The intangible assets as registered in Compustat, $INTAN$, include externally purchased assets like blueprints, copyrights, patents, licenses etc. and goodwill but do not include internal intangible

[9] We replace missing values of AM and GDWL with 0.

assets like R&D and SG&A. We exclude Goodwill, which are the intangible assets arising out of M&A transactions when one company acquires another for a premium over fair market value, in the computation of invested capital in equation 2. Thus, our measure is not distorted by price premiums paid for in acquisitions, allowing for an even comparison of operating performance across companies. As a result, ROIC measures the return that an investment generates for the providers of capital and reflects management's ability to turn capital into profits.[10]

In calculating ROIC, we also subtract cash stocks in excess of those estimated required for transactions purposes. Following Koller et al. [2017], we treat cash above 2% of sales as excess cash and subtract it from the firm's invested capital. In section 4.1 we undertake robustness tests allowing for varying percentages. Our estimates are not affected by firms' decisions on whether to stockpile cash in low-tax jurisdictions in order to manage their tax liabilities, as is the case of many large U.S. multinationals.

We define $ROIC^{unadj}$ *Star* as a dummy variable that takes the value 1 if the firm's ROIC is above the 90^{th} percentile of ROIC across all firms in the US economy in a particular year and 0 otherwise. To replicate the figure in previous studies such as Furman and Orszag [2015] and Koller et al. [2017], we restrict our sample to large firms (defined as firms with assets more than $200 Million in 2009 dollars, adjusted for inflation) and drop firms with negative invested capital. Figure 1 shows that there is a large rise in capital returns over the past three decades where the ratio of the 90^{th} percentile ROIC firm to the median ROIC firm has increased by over 69%.[11] We also see that the divergence of the top decile of firms from the rest of the economy really takes off in the 1990s. These results are qualitatively consistent with Furman and Orszag [2015], Koller et al. [2017] and the Council of Economic Advisors [2016], all of which were produced using a proprietary dataset of US firms from McKinsey & Co.

[10] In particular, if we do not subtract $GDWL$ from $INTAN$ we would run the risk of capitalizing future monopoly rents reflected in high acquisition premiums, thereby incorrectly attenuating the relation between ROIC and pricing power when one firms buys another.

[11] The evidence in Council of Economic Advisors [2016], Furman and Orszag [2015], and Koller et al. [2017] is based on a proprietary dataset of US firms from McKinsey & Co. whereas Figure 1 is based on publicly available Compustat data. If we were to use the full sample of Compustat firms without restricting to large firms, we get much higher increases in ROIC for the top decile of firms.

1.1 Role of Human Capital

Firms differ in the complexity of tasks that they perform and the product market may reward certain capabilities more than others. To address this issue, we construct industry-level indices of the composition of tasks firms perform and assess how they affect the likelihood of a firm from that industry becoming a star firm. In creating these indices, we draw on a large labor market literature in economics. Autor et al. [2003], Costinot et al. [2011] and Acemoglu and Autor [2011], have argued that globalization and advances in technology and computerization have increased the comparative advantage of individuals who perform non-routine tasks requiring problem solving, intuition, persuasion, and creativity.

To obtain measures of human capital, following Ayyagari and Maksimovic [2017] we use O*NET, a database maintained by the U.S. Department of Labor that provides data on occupation-specific descriptors that define the key features of an occupation such as worker abilities, technical skills, job output, work activities, etc. We focus on the following three measures of human capital: *CPS* (Complex Problem Solving) which is identifying complex problems and reviewing related information to develop and evaluate options and implement solutions; *NRCOG* (Non-routine Cognitive Analytical skills) from Keller and Utar [2016] which is the sum of Mathematical Reasoning, Inductive Reasoning, Developing Objectives and Strategies, and Making Decisions and Solving Problems; and *RMAN* (Routine Manual) from Keller and Utar [2016] which is the sum of Spend time making repetitive motions, Pace Determined by Speed of Equipment, Manual Dexterity, and Finger Dexterity. We merge the occupation-level scores with the Occupational Employment Statistics (OES), a US establishment level dataset from the Bureau of Labor Statistics, where workers are classified into occupations on the basis of the work they perform and skills required in each occupation. We compute a weighted average across occupations in each firm weighting by the number of employees in each occupation to obtain a score for each establishment. We then take weighted averages across all establishments in an industry to compute industry-level skill scores. These skill scores are available for just manufacturing industries.

We separate our sample into high and low skill manufacturing industries based on the *CPS*, *NRCOG*, and *RMAN* scores where high skill is defined as greater than or equal to the median value for each of the skill measures and low skill is defined as less than the median value for each of the skill measures. In Figure 2, we identify star firms in each of these sub-samples as firms in the top 10% of ROIC in that sample in a particular year. We again focus on large firms to be consistent with the sample in Figure 1. Figure 2 shows that the ROIC and the run-up for star firms is higher in industries with high skill as measured by low RMAN. We find similar increases in high skill industries as measured by high CPS and high NRCOG as seen in Figure A1 of the Internet Appendix. If this finding is correct, it would imply that firms employing a high skill labor force are also more likely to earn higher returns and that there is a growing divergence between the most profitable of those firms and the other high-skill firms. We also see a large divergence between the ROIC in high skilled versus low skilled industries when we split industries by RMAN, CPS, or NRCOG. However, a concern with these estimates is that in high skilled industries, intangible capital is being mis-measured so as to reduce total invested capital, thereby inflating ROIC numbers. Indeed when we split industries by their Intangible Capital/Assets ratio into Low ICAP industries (Intangible capital/Assets ratio less than median) and High ICAP industries (Intangible capital/Assets ratio greater than or equal to median), we see the divergence to exist mainly in High ICAP industries. A detailed definition of ICAP is provided in the following section.

1.2 Mis-measurement of Intangible Capital

One of the concerns with the above definition of star firms is that financial statements do not measure intangible assets accurately and the consequent underestimation of intangible capital is likely to be more important in high skilled industries. This would lead to overestimation of ROIC and biased regression estimates. The concern that conventional measures of invested capital do not properly capitalize the value of intangibles is a long standing one. Earlier attempts to address it include Peles [1971], Hirschey [1982], and Falato et al. [2013]. More recently, Peters and Taylor [2017] have produced firm-level estimates of intangible capital and shown that including intangible capital in the definition of Tobin's q produces a superior proxy for investment opportunities. They also show that their adjustments are not sensitive to specific assumptions on the depreciation of intellectual capital. Thus, while these measures are, by construction, approximations, they are arguably the best available.

Hence, as an alternate definition of invested capital, we replace the $INTAN_{it}$ in equation (2), with the new definition of intangible capital from Peters and Taylor [2017], $ICAP_{it}$.

$$Invested\,Capital_{it} = PPENT_{it} + ACT_{it} + ICAP_{it} - LCT_{it} - GDWL_{it} \\ - max(CHE_{it} - 0.02 \times SALE_{it}, 0) \quad (3)$$

where $ICAP_{it}$, is defined as the sum of externally purchased intangible capital (Compustat item $INTAN$) and internally purchased intangible capital, both measured at replacement cost. Internally purchased intangible capital is in turn measured as the sum of knowledge capital *K_int_know* and organization capital *K_int_org*. The perpetual-inventory method is applied to a firm's past research and development expenses (Compustat item *XRD*) to measure the replacement cost of its knowledge capital. Similarly, a fraction (0.3) of past selling, general, and administrative (*SGA*) spending is used as an investment in organization capital, which includes human capital, brand, customer relationships, and distribution systems.[12] The estimates of *ICAP*, *K_int_know*, and *K_int_org* have been made publicly available by Peters and Taylor [2017].

Correspondingly, we also adjust the profits in the numerator to account for the use of intangible capital in computing invested capital. Thus, the new ROIC is given by:

$$ROIC_{it} = \frac{ADJPR_{it}}{Invested\,Capital_{it-1}} \quad (4)$$

where

$$ADJPR_{it} = EBIT_{it} + AM_{it} + XRD_{it} + 0.3 \times SGA_{it} \\ - \delta_{RD} \times K\_int\_know_{it} - \delta_{SGA} \times K\_int\_org_{it} \quad (5)$$

where δ_{RD} is the depreciation rate associated with knowledge capital and is set to 15% following Peters and Taylor [2017] and δ_{SGA} is the depreciation rate associated with organization capital and is set to 20% following Falato et al. [2013].

[12] Since Compustat item *XSGA* is the sum of SG&A and R&D, we follow the procedure in Peters and Taylor [2017] to isolate SGA as XSGA-XRD-RDIP where RDIP is In-Process R&D. We replace missing values of XSGA, XRD, and RDIP with 0.

Note that using an adjustment for intangible capital affects ROIC in two ways. First, it increases the denominator by the amount of the adjustment for intangible capital. Second, R&D and a portion of SGA expenditure, which would previously have been expensed are now treated as additions to capital stock. Thus, it is not subtracted from the firm's conventionally calculated earnings (EBIT) to obtain the adjusted earnings. However, since the stock of intangible capital is now treated as an asset, an additional depreciation expense is now deducted from EBIT. This second adjustment either increases or decreases the numerator of ROIC, depending on the level of current R&D and SG&A expenditures compared to the stock of intangible capital.

After dropping firms with negative invested capital, missing or negative book value of assets or sales, and firms with less than $5 million in physical capital (Compustat variable $PPEGT$)[13] and top and bottom 1% outliers in $ROIC$, we define $ROIC\ Star$ as a dummy variable that takes the value 1 if the firm's $ROIC$ is above the 90^{th} percentile of $ROIC$ across all firms in the US economy in a particular year and 0 otherwise. We also focus on the years 1990-2015 for all the figures and tables henceforth since the high run-up in ROIC in Figures 1 and 2 starts around 1990.

When we correct invested capital to include intangible capital, we see no run-up in $ROIC$ for the top 10% of firms in Figure 3. These results are robust to a number of checks: As shown in Figure A2 of the Internet Appendix, we obtain a similar picture when we restrict the sample to large firms, and extend the time period to 1975 to be consistent with the sample in Figure 1. In Figure A3 of the Internet Appendix, we obtain a similar picture if we were to NOT subtract goodwill from our estimates of invested capital. Finally, in Figure A4 of the Internet Appendix, we narrow our definition of star firms and plot the mean ROIC for the Top 100 and Top 150 firms each year. Once again we find no run-up in ROIC over time for even the top 100 or 150 firms.

In Figure 4, we present estimates for high skilled versus low skilled industries. The run-up we saw in Figure 2 in high skilled (Low RMAN) industries and high ICAP industries disappears once we adjust for intangible capital. Figure A5 of the Internet Appendix shows that we obtain a similar picture if we were to define skill in terms of complex problem solving skills (CPS) or non-routine cognitive analytical skills (NRCOG). In section 4 of the paper, we discuss various robustness

[13] We apply the PPEGT filter since Peters and Taylor [2017] recommend that the intangible capital adjustment is not appropriate for firms with less than $5 million in physical capital.

tests and alternate definitions of intangible capital to address concerns with the definition of cash holdings.

2 Estimating Concentration and Market Power

As a measure of competition, we define the Herfindahl Index (HHI) of market share in each 3-digit NAICS industry in each year. Specifically, in each year t for each 3-digit NAICS industry j, industry concentration is measured as:

$$HHI = \sum_{i=1}^{N} s_i^2 \tag{6}$$

where s_i is market share of firm i given by $\frac{SALE}{\sum_j SALE}$ and N is total number of firms in industry j in year t. A higher HHI implies weaker competition.

While HHI measures industry concentration, it treats all firms in an industry identically. Thus, HHI ignores potential firm-specific indicators of market power such as firm size and market share. We use *Log(Assets)* as a measure of firm size where assets are the Compustat item AT. *Market Share* is the ratio of firm i's sales to total industry j's sales in a particular year, to allow for the possibility that large market share firms in a concentrated industry realize different returns compared to low market share firms.

We also use firms' markup of price over marginal cost, *Markups*, as a firm-level measure of the firm's pricing power. De Loecker and Eeckhout [2017] show that average markups have increased from 18% above marginal costs (where variable costs are measured by Cost of Goods Sold) in 1980 to 67% above marginal cost by 2014. Recent work by Traina [2018] however argues that $COGS$ grossly underestimate firms' variable costs. Other expenses, such as SGA are increasingly a lion's share of variable costs for US firms. Traina shows that once we include SGA in the calculation of marginal costs, there is no increase in public firm markups.

Consistent with Traina [2018], we base our measure of variable inputs on Operating expenses (Compustat item $OPEX$) rather than Cost of Goods Sold (Compustat $COGS$) as in De Loecker and Eeckhout [2017]. $OPEX$ includes SGA expenses whereas $COGS$ only includes costs of production such as material, labor, and overhead and does not include SGA expenses. COGS has been a declining share of variable costs for US firms as shown in Figure A6 of the Internet Appendix. We differ from Traina [2018] in our adjustment of operating expenses to include the correction for intangible capital. Specifically, following Peters and Taylor [2017], we treat research expenditures as an intangible investment and a portion of the SGA as an organizational investment. Thus, intangible investments such as R&D and a portion of SGA are subtracted from *OPEX* in order to obtain our measure of variable costs, *OPEX**:

$$OPEX^* = OPEX - XRD - RDIP - 0.3 \times SGA \tag{7}$$

The standard definitions of markups rely on the cost shares framework by Foster et al. [2008] or the production framework by De Loecker and Warzynski [2012] and De Loecker and Eeckhout [2017]. To estimate markups, we primarily rely on the cost shares approach where markups can be computed directly from the data (Markups is simply Sales/Variable Cost, that is *Sales/OPEX**), as discussed in Foster et al. [2008]. While requiring constant returns to scale, the derivation is transparent and is not subject to econometric and optimization challenges faced by alternative methods that rely on explicit estimates of productivity using the control function approach Rovigatti and Mollisi [2018]. Furthermore, this is close to the Lerner Index (measured by the difference between the output price of a firm and the marginal cost divided by the output price) that is widely used in the literature as a measure of market power (see e.g. Grullon et al. [2019], Gutiérrez and Philippon [2017]). However, for consistency with the preceding literature we also detail our estimation of markups using the production function approach in the Internet Appendix. The latter is based on the cost minimization of a variable input of production, without additional assumptions on firm demand or competition. Heuristically, this measure takes the firm's capital stock as given, and estimates the markup that the firm can charge customers over its variable costs.

Table A1 of the Appendix presents summary statistics of the main variables in our analysis. We drop top and bottom 1% outliers in constructing all our firm-level variables. In addition to the variables discussed above we also use a proxy for firm age which is defined as the number of years since the firm first appears in Compustat following Giroud and Mueller [2010].

The mean *ROIC* in our sample once we adjust for intangible capital is 13%. By definition, 10% of our sample is classified as star firms. Once we take into account intangible capital, the average markup is 1.31 using the cost shares approach ($Markups$) and 1.221 using the production function approach ($Markups\_prodfn$). The latter has fewer observations because they are first estimated within each industry necessitating a minimum number of firms in that industry. The average Herfindahl industry concentration is 0.09 and the average firm market share is 0.015.

Using marginal costs measured by COGS, De Loecker and Eeckhout [2017] document a stunning rise in markups in the US over the past three decades. Traina [2018] however argues that COGS are a declining share of firm costs and once we use operating expenses that includes COGS and SGA, there has been no rise in firm markups. This is an important policy question as it also speaks to the discussion on the rise in industrial concentration and decline in labor share (see Grullon et al. [2019], Autor et al. [2017], Hartman-Glaser et al. [2017], and Kehrig and Vincent [2018]). Once we do take into account intangible capital, how have markups evolved over this period?

In Figure 5, we estimate the evolution of markups using capital adjustments, $Markups$, in the US economy over our sample period. We see an upward trend only for the 90^{th} percentile firms. To see if there is dispersion in markups by industry skill, we look at industries that rely heavily on routine manual tasks versus those that do not rely heavily on routine manual tasks and industries that have high vs low ratio of intangible capital/assets in Figure 6. We find that markups are higher in high skilled industries (low RMAN) than low skilled industries and in high ICAP industries than low ICAP industries for the top 10% of firms.

Overall, we see that there has indeed been a rise in markups once we adjust operating expenses for investment in intangible capital. While there is just a modest divergence between the top 10% of firms with the highest markups and the rest of the economy, we see these differences amplified in high skilled industries which use more intangible capital.

3 Empirical Findings

In this section we examine which firm characteristics are associated with star firms and in particular, if star firm status is associated with high markups. To begin, we first examine if there is persistence in star firm status which would imply that there are some long term consequences associated with being a star firm.

3.1 Future Performance of Stars

We define a firm as a star firm in a given year if its return on invested capital is in the top 10% of firms in that year. It could be the case that there is a lot of churning in this top 10% of firms each year with different sets of firms randomly realizing high returns each year. In this sub-section we explore if these high returns are persistent and if being a superstar is associated with superior performance. To this end, we construct five non-overlapping panels: 1990-1995, 1995-2000, 2000-2005, 2005-2010, and 2010-2015 and examine if being a star is associated with higher average performance in the subsequent five year period. Specifically, for firm i in industry j in year t, the regression we estimate is as follows:

$$\begin{aligned} Performance_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{it-5} + \beta_2 \times Log(Age)_{it-5} + \beta_3 \times Star_{it-5} \\ (or ROIC_{it-5}) + \phi_j + \gamma_t + \epsilon_{ijt} \end{aligned} \quad (8)$$

We look at the following four performance measures: 5-year average $ROIC$, *Sales growth* computed as the five year log difference in sales divided by 5, *Employment growth* computed as the five year log difference in employment divided by 5, and 5-year average *Labor Productivity*. Using stacked panel regressions, we examine the association between each of these measures and star firms identified at the beginning of each panel. We also control for size and age at the beginning of each panel. All regressions also include industry and year fixed effects.

Columns 1 and 2 of Table 1 shows that both star status and high $ROIC$ are on average positively associated with higher average $ROIC$ in the subsequent five year period. The predicted value of average 5-year $ROIC$ for firms that were superstars five years ago is 44.01 compared to 7.48 for firms that were not superstars five years ago. Columns 3-8 show that prior star status is also associated with higher sales growth, employment growth, and labor productivity. Replacing $ROIC$ Star by $ROIC$ yields very similar results except for sales growth where it is not significant.

While the above results rely on defining star firms based on returns to invested capital, as an alternate definition, we define stars in terms of Tobin's Q. Again following Peters and Taylor [2017], we define Q as the ratio of Firm value to $TOTCAP$ which is the sum of physical ($PPENT$) and intangible capital ($ICAP$):

$$Q_{it} = \frac{V_{it}}{TOTCAP_{it}} \tag{9}$$

where V is the market value of the firm defined as the market value of equity (=total number of common shares outstanding (Compustat item $CSHO$) times closing stock price at the end of the fiscal year (Compustat item $PRCC$) plus the book value of debt (sum of Compustat items $DLTT$ and DLC) minus the firm s current assets (Compustat item ACT) which includes cash, inventory, and marketable securities. After dropping top and bottom 1% outliers in Q, we define Q *star* as a dummy variable that takes the value 1 if the firm's Q is above the 90^{th} percentile of Q across all firms in the US economy in a particular year and 0 otherwise.

While Q has the advantage of using a market valuation of the firm's prospects, the measure is prospective in that it captures the value of the firm's investment opportunities given the market's view of its investment plans (e.g. Tobin [1956], Lindenberg and Ross [1981], Hayashi [1982], Erickson and Whited [2000])). In Internet Appendix Table A1, we find that Q stars are also associated with higher Tobin's Q, sales growth, employment growth, and labor productivity in the subsequent five year period. We find similar results replacing Q Star by Q.

Overall these results suggest that star status is associated with higher future performance and there is a fair degree of persistence in star status as firms that were stars five years ago have higher average returns, valuation, growth, and productivity over the subsequent five-year period than firms that were not stars.

3.2 What are the characteristics of star firms?

In this subsection we explore the firm characteristics that are associated with being a star firm. For firm i in industry j in year t, we estimate the following regression:

$$Star_{ijt} = a + \beta_1 \times Log(Assets)_{it-1} + \beta_2 \times Log(Age)_{it-1} + \beta_3 \times MarketShare_{it-1} + \beta_4 \times Markups_{it-1} \\ + \beta_5 \times HHI_{jt} + \phi_j + \gamma_t + \epsilon_{ijt} \quad (10)$$

where *Star* is a dummy variable that takes the value 1 if the firm is a star firm and 0 otherwise. We estimate the equation using *ROIC Star* as the definition of a star firm and using $Markups$ that incorporate intangible capital. *Log(Assets)* and *Log(Age)* are measures of firm size and size, *HHI* is Herfindahl Index measure of industry concentration, and *Market Share* is firm level market share. All the regressions are estimated using ordinary least squares (linear probability models) but we get similar results using Logit estimation. We cluster the standard errors at the firm level to capture the lack of independence among the residuals for a given firm across years (Petersen [2009]).

The main coefficient of interest in the above specification is β_4 which shows the sensitivity of star status to firm markups. A high markup is consistent with market power, as competition would erode the firm's ability to charge above variable costs. Importantly, since markups do not take into account the cost of tangible and intangible capital, high markups are consistent with both high and low rates of return to invested capital. Intuitively, it is natural to think of high markups as resulting from a firm's exercise of market power by reducing sales and thereby realizing high returns on invested capital. However, it is possible for a firm to have a low markup, high sales per unit of invested capital and to be a star firm. Thus, the extent to which star status is related to high markups is an empirical question.

In Table 2, we estimate specification 10 to examine firm and industry characteristics that are associated with star status. We first estimate the equation with industry and year fixed effects in panel A so we can examine the association between star status and HHI and in panel B we use industry x year fixed effects. In panel A, in columns 1-4 we focus on the full sample of firms, in column 5 we look at only manufacturing firms for which we have data on skills, in column 6 we look at large firms (defined as firms with more than $200 million in assets in real terms obtained by deflating Compustat item AT by GDP deflator) and in column 7 we focus on young firms (defined as firms that are less than five years of age). In column 8 we repeat the full sample specification in column 4 using an alternate measure of star status based on Tobin's Q rather than ROIC. We drop firms with negative invested capital in all regressions.

The results in columns 1-4 of panel A of Table 2 show that after correcting for intangible capital, we find evidence that high markups predict $ROIC$. The effects are also economically significant. There is a 5 percentage point increase in the probability of being a star firm when markups go up by one standard deviation. We also see that high $ROIC$ firms are on average large and young. These results on size, age, and markups hold in the different sub-samples in columns 5-7 for manufacturing, large firms, and young firms respectively. Column 8 shows that markups are also associated with star status when we define star firms on the basis of Tobin's Q. We find limited evidence that firm level market share or industry concentration at the 3-digit NAICS level (HHI) predicts star status. Following the discussion on measurement of market power in Syverson [2019], going forward we only focus on markups as our measure of market power. We find similar results if we use industry x year fixed effects in panel B.

Our results are robust to a number of checks as seen in Tables A2 and A3 of the Internet Appendix. In Table A2 we find our results robust to using firm fixed effects. We do not use firm fixed effects in our main specification because we are interested in understanding time invariant human capital or skill characteristics that explain variation in ROIC. In Table A3 in columns 1 and 2 we explore alternate dependent variables - continuous measures of ROIC and Tobin's Q. We find high markups to be associated with high ROIC and Tobin's Q in columns 1 and 2 respectively. In columns 3 and 4 we use the production function approach to estimate Markups, $Markups\_prodfn$ and find similar association between these markups and star status. It is likely that the effect of market power indicators may vary across levels of $ROIC$. In unreported tests, we re-estimate the full model (column 4 of Table 2) using quantile regressions. This approach also has the advantage of being directly suggested by the original star firm hypothesis, which is formulated focusing on the differences between the top 10% of firms and the rest. We use the generalized quantile regression estimator developed in Powell [2016] that allows us to estimate unconditional quantile effects in the presence of additional covariates. The results show that the profitability of firms at the top of the distribution of *ROIC* appears more sensitive to markups than that at the bottom.

3.3 Are star firms' profits associated with lower output and investment?

An important policy concern is that firms in the economy are extracting value by restricting output and investment. There are two ways in which that may occur. First, star firms may have more market power than other firms and they utilize this market power to restrict output, thereby generating high profits. In this scenario, star firms are just like any other firm, except that they happen to have more market power which they use in the same way other firms use it. In this case star status would be associated with loss of welfare to consumers. Second, it might be the case that at each level of market power star firms may be better at generating profits, without cutting, and perhaps even increasing, output and investment. In this scenario, star firms are more efficient than other firms and they do not reduce consumer welfare.[14]

To fix ideas and show that star status, high markups and high output can all occur without loss to consumer welfare, we start with a simple model of a Cournot duopoly with imperfect competition. In terms of notation, subscript i signifies firm 1 or 2 and subscript j signifies the other firm. If firm 1 produces the output x_1 and firm 2 produces the output x_2, then the price at which each unit of output is sold is $\mathrm{P}(x_1 + x_2)$, where P is the linear inverse demand function given by:

$$p = a - b(x_1 + x_2) \tag{11}$$

If firm 1's total cost function is c_1x_1 and firm 2's cost function is c_2x_2, the profits respectively are:

$$\pi_i = p_ix_i - c_ix_i = (a - b(x_1 + x_2))x_i - c_ix_i \tag{12}$$

Consider a simple symmetric equilibrium scenario where the firms face constant marginal cost,

[14] It is of course possible to consider a scenario whereby these firms are constrained by regulation to increase output even further. That raises the question whether such regulations can be implemented without reducing the firms' incentives to innovate. This is subject to further research.

$c_1 = c_2 = c$, the two first-order conditions are:

$$\begin{aligned}
\frac{\partial \pi_1}{\partial x_1} &= a - 2bx_1 - bx_2 - c = 0 \\
\frac{\partial \pi_2}{\partial x_2} &= a - bx_1 - 2bx_2 - c = 0
\end{aligned} \tag{13}$$

Solving the first order conditions simultaneously for x_1 and x_2 produces:

$$x_1 = x_2 = \frac{a - c}{3b} \tag{14}$$

Given the market demand and profit functions, the equilibrium price and profits are given by:

$$p = \frac{a + 2c}{3} \tag{15}$$

$$\pi_1 = \pi_2 = \frac{(a - c)^2}{9b} \tag{16}$$

Defining markup as price to cost ratio, $m = \frac{p}{c}$

$$m_1 = m_1 = m = \frac{a + 2c}{3c} \tag{17}$$

In an alternate scenario, assume that firm 1 is more efficient with lower marginal costs. The lower marginal costs may be the results of prior fixed costs in intangible capital or investment, F. Specifically, let $c_1 = \theta c$, where $\theta < 1$. The two first-order conditions are now:

$$\begin{aligned}
\frac{\partial \pi_1}{\partial x_1} &= a - 2bx_1 - bx_2 - \theta c = 0 \\
\frac{\partial \pi_2}{\partial x_2} &= a - bx_1 - 2bx_2 - c = 0
\end{aligned} \tag{18}$$

Solving the first order conditions now produces different equilibrium outputs for firms 1 and 2:

$$x_1^* = \frac{a + (1 - 2\theta)c}{3b} \tag{19}$$

$$x_2^* = \frac{a + (\theta - 2)c}{3b} \tag{20}$$

The market price and individual firm markups are given by:

$$p^* = \frac{a + (1+\theta)c}{3} \tag{21}$$

$$m_1^* = \frac{a + (1+\theta)c}{3\theta c} \tag{22}$$

$$m_2^* = \frac{a + (1+\theta)c}{3c} \tag{23}$$

Since $\theta < 1$,

$$x_1^* > x_1 = x_2 > x_2^* \tag{24}$$

$$m_1^* > m_1 = m_2 > m_2^* \tag{25}$$

$$p^* < p \tag{26}$$

Thus, under this alternate scenario, firm 1's markup increases, the firm increases output, and since $p^* < p$, consumers are also better off. Firm 1's operating profit increases and becomes higher than that of firm 2. Thus, firm 1 may become a star firm. Whether it becomes a star firm or not depends in part on whether the increase in its profits is larger or smaller than the additional investment F which the firm needs undertake in order to cut marginal costs. Under plausible assumptions, the firm will only invest F if doing so leads to higher overall profits. Moreover, the opportunity to invest F in order to gain advantage may differ systematically across industries. While we have modeled the additional investment F as simple cost cutting, firms may also invest in features that make their products more valuable to customers.

Overall, in this alternative scenario, an increase in markups by the more profitable firms is not associated with any loss of consumer welfare, and is beneficial to the economy relative to the prior state.[15]

To explore this empirically, we first examine how the association between markups and star status varies with human capital, both the industry indices of high skilled versus low skilled industries

[15] Note that this is not the only possible outcome. For a sufficiently high c, firm 2 will shut down (since output cannot be negative) leaving firm 1 in a monopoly position. Moreover, there is a dynamic question of how prior competitive structure affects the incentive to invest F in order to cut marginal costs. However, this example establishes that there is no presumption that star firm status, even when combined with increased markups, necessarily leads to reduced welfare.

and firms' reliance on intangible capital. We estimate the following equation:

$$Star_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{it} + \beta_2 \times Log(Age)_{it} + \beta_3 \times Markups_{it} \\ + \beta_4 \times Log(Assets)_{it} \times Industry\,Skill_j + \beta_5 \times Markups_{it} \times Industry\,Skill_j + \tau_{jt} + \epsilon_{ijt} \quad (27)$$

In Table 3, we examine the role of industry skill and intangible capital in predicting star status controlling for industry x year fixed effects. In columns 1-4, since the industry skill, RMAN is time invariant, we do not include the main effect by itself as it is subsumed by the industry fixed effect. Columns 1-4 show that in industries that rely heavily on routine manual skills (low skilled industries), large firms are less likely to be in the top 10% of ROIC (or Tobin's Q) firms in a year. The interactions of markups and RMAN are not significant. When we interact each of these variables with intangible capital/asset ratios, we find that large firms with high intangible capital and firms with high markups and high intangible capital are less likely to be in the top 10% of ROIC (or Tobin's Q) in a year. In unreported tests, we find similar results replacing the industry skill RMAN with CPS (complex problem solving skills) or NRCOG (non-routine cognitive analytical skills). These results suggest that the association between markups and star status is weaker in high intangible capital industries.

In Figure 7, we explore the sensitivity of ROIC to markups over time by plotting the regression coefficients from the following regression:

$$ROIC_{ijt} = a + \beta_1 \times Log(Assets)_{it-1} + \beta_2 \times Log(Age)_{it-1} + \beta_3 \times Markups_{it-1} \\ + \beta_4 \times Markups_{it-1} \times YearDummies + \phi_j + \gamma_t + \epsilon_{ijt} \quad (28)$$

The coefficient of interest is β_4 which plots the sensitivity of ROIC to markups over time. The figure shows that ROIC is less responsive to markups over time. In Figure 8 we examine splits across industries with high and low intangible capital to assets ratios and find that the declines are steeper in the industries with high intangible capital to asset ratios. This is further confirmed in Figure 9 which shows a significant positive association between markups and intangible capital/asset ratio over time.[16] Together, these figures provide suggestive evidence that pricing power increases are associated with the high investment in intangible capital.

To gain further intuition about the role of markups in the case of star firms, we explore the relation between markups, ROIC, and a measure of output - the ratio of sales to invested capital - in non-parametric regressions for star firms and for all other U.S. public firms in general. In Figure 10 we present a histogram of markups for firms that were classified as $ROIC$ stars and for all other firms and for each of those sub-samples, a non-parametric smoothed scatter plot of $ROIC$ against markups using kernel weighted local polynomial smoothing. The figure shows that while firms are distributed across the range of markups even when we look at just the star firms, the tails are thin so there are few firms with very low markups and very high markups for both star firms and all other firms. In general, we see a monotonically increasing relationship between $ROIC$ and markups suggesting that high profits are associated with pricing power. However, for star firms the plot is quite flat, indicating that there is no visible association between markups and $ROIC$ within the sample of firms that have passed the threshold to be classified as star firms. In unreported robustness tests, when we define superstars as firms that have $ROIC$ in the top decile in 5 or more years over the period, we find the scatter plot for superstars to be similar to that of the star firms.

We explore the relation between star status and output and investment more formally In Table 4 in a multivariate regression framework, controlling for *Log Assets*, *Log Age*, industry x year fixed effects. For output, we use *Sales/Invested Capital* and for investment, we use both physical investment *Capex/Invested Capital* and intangible investment (*XRD/Invested Capital*). All the independent variables are lagged by one period. The table shows that both $ROIC$ and Q star firms have higher Sales/Invested Capital and greater investment, both CAPEX, and Intangible (R&D) Investment compared to all other firms. We find these results to be robust to a number of checks including scaling $CAPEX$ by $PPENT$ and XRD by intangible capital ($ICAP$). In unreported tests using firm fixed effects (within firm regressions), we find that growth in markups is positively associated with growth in sales and invested capital. When we look across industries, growth in markups is always associated with growth in invested capital but is significantly associated with growth in output in only high skilled industries.

[16]This figure is drawn over the more recent period 2000-2015 which saw a rapid increase in intangible capital investment. In unreported tests we obtain a similar figure over the entire sample period.

To further examine the association between star status and output, we present a nonparametric estimator of the regression function in Figure 11 with and without covariates. Specifically, following Cattaneo et al. [2019], we present binned scatterplots of Sales/Invested Capital against markups with robust confidence intervals and uniform confidence bands over the period 1990 to 2015 for all firms in the economy and for ROIC stars. We present the binscatter regressions first without controlling for covariates and next after controlling for firm size, age, industry and year fixed effects. The figure shows that there is a decline in Sales/Invested Capital with Markups for both ROIC Stars and other firms. However, for star firms, Sales/Invested Capital is higher at each level of markup than for all firms in general, suggesting that these firms are not restricting output more than other firms with the same markups. The difference is particularly high at lower markups, suggesting that low-margin star firms, in particular, are adopting a high volume marketing strategy.[17]

Figure 12 shows the relationship between CAPEX Investment and Markups and R&D Investment and Markups. The figure shows that while ROIC stars have higher R&D investment than non-stars at all levels of markups, they have lower CAPEX investment than non-stars at high levels of markups and higher CAPEX investment than non-stars at lower levels of markups. We investigate this further in Figure 13 where we look within high and low ICAP industries. The figure shows that in industries that require high human capital (low RMAN industries) star firms have higher output and investment at all levels of markups than non-star firms. The only cause for concern is in low skilled industries where star firms seem to have lower investment but that is not significant and even there they have higher R&D investment than all other firms.

The above tables do not control for the total factor productivity of firms. As detailed in the Internet Appendix, we have a measure of such productivity from the production function estimations used to derive markups, $Markups\_prodfn$ that measures the productivity of firms relative to other firms in its industry. In Table 5, we introduce total factor productivity (TFP) and compare how the productivities of firms predict star status of firms and contrast that to the predictive power of markups.[18] With the introduction of TFP we also present specifications with

[17]Figure A8 in the Internet Appendix shows the binscatter regression plots when we define ROIC stars three and five years back. Figure A9 in the Internet Appendix shows the binscatter regression plots when we define stars in terms of Tobin's Q.

[18]Note that a firm with high pricing power (high markups) may have high or low total factor productivity, depending on how much tangible and intangible capital it uses in production. Conversely, a firm with high productivity may or may not have pricing power, depending on whether or not it can maintain prices above marginal cost.

Tobin's Q stars as the principal measure of star status. Using Q as an alternate definition of star status alleviates concerns about a mechanical dependence between the return on invested capital and measures of productivity.

Our results show that both markups and productivity are positive and significant in predicting star status. The economic significance is similar for markups and productivity when we look at Q. A one standard deviation increase in productivity increases the probability of being a Q star by 2.31% whereas a one standard deviation in markups increases the probability of being a Q star by 3.4%.

3.4 Import Competition and Star Firms

We would expect that an increase in competitive pressure would cause a decline in ROIC, Markups, and output. However, those firms that have market power, are going be less affected than firms without such advantages.[19] Thus, if star firms rely on market power to generate profits more than other firms, then we would expect that an exogenous increase in competitive pressure in their industry would affect them less than non-star firms. We test this in Table 6.

We investigate the effect of market competition on firm star status directly by examining the effect of increased market competition on markups, ROIC, output and investment of both star and non-star firms. below. We measure increases in market competition by the penetration of Chinese imports at the 4-digit NAICS level. To address endogeneity issues we instrument Chinese imports into the U.S., $ImportsUSA$, by Chinese imports into eight other developed economies, $ImportsOTH$. Our identification strategy is derived from Autor et al. [2013] and identifies the component of US import growth that is due to Chinese productivity and trade costs. Autor et. al. identify the supply-driven component of Chinese imports by instrumenting the growth in Chinese imports to the United States using contemporaneous composition and growth of Chinese imports in eight other developed countries. The identifying assumption underlying this strategy is that the surge of Chinese exports across the world is primarily driven by China-specific events: China's transition to a market-oriented economy and its accession to the WTO and the accompanying rise in

[19] Market power can arise because firms have differentiated brands and products, unique products, control of distribution channels, network externalities, and regulatory capture among other reasons.

its comparative advantage and falling trade costs explain the common within-industry component of rising Chinese imports to the United States and other high-income countries.

In panel A of Table 6, we find that, as expected, imports reduce Markups, ROIC, and Output in general. We see very little evidence of the effect of import competition on Capex or R&D potentially because firms are investing to meet the competitive challenge. In panel B, we present some descriptive tests to see if star firms are differentially affected by import competition by interacting import competition with star status. To mitigate reverse causality, we measure star status as of two years prior. We instrument $ImportsUSA$ and $ImportsUSA$ x $ROICStarStatus_{ijt-2}$ two years prior with $ImportsOTH$ and $ImportsOTH$ x $ROICStar_{ijt-2}$.[20] All the interaction terms are insignificant. In particular, interactions in the markups and ROIC regressions are insignificant, suggesting that star firms do not have differentially smaller declines in markups or ROIC when faced with import competition in their industry compared to other firms in their industry. In panel B, the Cragg-Donald F statistic test (Stock and Yogo [2002]) which is a weak identification test for the excluded exogenous variables, is highly significant. This test is essential when the number of endogenous variables is more than one and the standard F-test may not truly reflect the relevance of instruments (for details see Baum et al. [2007]).

Overall, our results indicate that while markups strongly predict high profits, not all star firms have high mark-ups and star firms are not restricting output or investing less than other firms with the same markups. Thus, concerns about star firms exploiting their market power by cutting investment and output and hurting consumer welfare may be overstated.

4 Robustness and Additional Tests

In this section, we subject our findings to a series of robustness tests. At the outset, our results are crucially dependent on the adjustment for intangible capital in the measurement of ROIC and markups. In unreported robustness tests we investigate whether our results are affected if the adjustment is partial. We vary the intangible capital adjustment from 25% to 75% of the amount recommended by Peters and Taylor [2017] and repeat the specifications in columns 4-6 of Table 3.

[20]The results are unaffected when we measure star status in the current year or three years prior.

All our results are materially similar suggesting that our results are robust to smaller adjustments to intangible capital.

4.1 Measurement of Excess Cash

There is a great deal of controversy in how to treat a firm's cash holdings in the computation of a firm's invested capital. It is standard financial reporting practice to include a firm's cash holdings in the definition of its invested capital. However, financial analysts routinely subtract a large fraction of cash holdings, say any cash in excess of 2% of annual revenues, from the firm's calculated investment capital (e.g. Koller et al. [2017]). The rationale for that is that the excess cash is unnecessary to support operations and confounds valuations of product market opportunities. This view is also supported by a large body of academic work (e.g. Jensen [1986]; Harford et al. [2008]; Dittmar and Mahrt-Smith [2007]) which argues that large cash holdings are a reflection of agency conflicts between managers and firms shareholders, and are not relevant to the valuation of a firm's operations.

A second reason to subtract excess cash from invested capital is to circumvent the policy of many large U.S. multinationals to stockpile cash in low-tax jurisdictions in order to manage their tax liabilities (e.g. Faulkender and Petersen [2012]; Faulkender et al. [2017]. Against that, there are numerous findings that high cash positions occur typically in R&D intensive firms, and that these cash holdings may be economically rational (see Boyle and Guthrie [2003]; Bates et al. [2009]; and Harford et al. [2014]). In particular, to the extent that R&D intensive firms face higher operational risks, and that intellectual capital cannot be easily used as collateral for bank loans, high cash positions are economically motivated. Moreover, from the perspective of the firms' owners, the relevant returns should be calculated as a function of all the capital committed, not just the portion which would have been committed under an alternative corporate governance regime. Moreover, as Damodaran [2005] notes, the 2% ratio has been used as a rule of thumb among analysts and does not have a deep theoretical basis. This ratio can be higher or lower depending on the working capital needs of a business. In this section, we examine whether our findings are sensitive to the treatment cash holdings.

Hence as an alternate variation, we define invested capital to only include working capital and physical and intangible capital. Thus

$$Invested\, Capital_{it}^{CASH} = PPENT_{it} + ACT_{it} + ICAP_{it} - LCTit - GDWL_{it} \tag{29}$$

Analogously we define ROIC with this new adjustment as:

$$ROIC_{it}^{CASH} = \frac{ADJPR_{it}}{Invested\, Capital_{it}^{CASH}} \tag{30}$$

In Figure A10 of the Internet Appendix, we present four $ROIC$ graphs where $ROIC$ is re-computed using cash above 1% of sales, 5% of sales, 10% of sales, and 20% of sales respectively as excess cash. Across all the figures, we see that there is no run-up in $ROIC$ for the top 10% of firms as in Figure 3.

In Table 7, we repeat the interactions with Intangible Capital/Assets in Table 3 but re-estimate $ROIC$ using different treatments of cash. In columns 1-3, we use the firm's total cash holdings in computing ROIC, $ROIC^{\mathrm{CASH}}$, in columns 4-6, we consider excess cash to be any cash over 1% of sales, $ROIC^{\mathrm{1per}}$, and in columns 7-9 we consider excess cash to be any cash over 10% of sales, $ROIC^{\mathrm{10per}}$. Across the columns, we obtain similar results wherein large firms with high intangible capital and firms with high markups and high intangible capital are less likely to be in the top 10% of ROIC in a year.

4.2 Superstar Firms

The conclusion that the exercise of market power by star firms is relatively modest contrasts with the popular public policy debate in the US that has been dominated by anecdotal evidence of a few star firms - Facebook (FB), Amazon.com (AMZN), Apple (AAPL), Microsoft(MSFT) and Alphabet (GOOGL). These firms are often accused of using monopoly power as a result of proprietary technology and increasing returns to scale. To take a close look at this, we examine the returns to capital and markups of these in relation to the rest of the economy. Figure 14 shows that these firms (especially Apple) have abnormally high returns to capital which exceed even the top 10% of *ROIC* firms. Their markups in Figure 15 show that for some of these firms like Apple and Amazon, the markups are below the 90^{th} percentile of markups in our sample for most of the sample period.[21]

Therefore, surely a small number of superstar firms are truly diverging from the rest and disrupting conventional business models in the process. For these firms, their markups may be understating their market power. Indeed, in some cases these firms might be limiting their short-run profits in the hopes of realizing future market dominance. An example of this might be Amazon. In his letter to Amazon shareholders in 1997, Jeff Bezos stated that Amazon makes decisions and weighs tradeoffs differently than most other firms:

We believe that a fundamental measure of our success will be the shareholder value we create over the long term. This value will be a direct result of our ability to extend and solidify our current market leadership position. The stronger our market leadership, the more powerful our economic model. ***Market leadership can translate directly to*** *higher revenue, higher profitability, greater capital velocity, and correspondingly* ***stronger returns on invested capital.***

Our decisions have consistently reflected this focus. We first measure ourselves in terms of the metrics most indicative of our market leadership: customer and revenue growth, the degree to which our customers continue to purchase from us on a repeat basis, and the strength of our brand. ***We have invested and will continue to invest aggressively*** *to expand and leverage our customer base, brand, and infrastructure as we move to* ***establish an enduring franchise.*** (Emphasis added)[22]

Thus, Amazon prioritized growth over profits to achieve enough scale that was central to their business model. This suggests that even for some of the most capable star firms like Amazon, metrics such as ROIC and markups may understate their potential market power. By the same token, these firms are not exercising that potential market power in ways that harm consumers in the short run. Of course, firms that follow this strategy are likely hoping that their dominant position will enable them to profit from their market dominance in the future. As seen in Figures 14

[21] Figure A11 in the Internet Appendix reproduces this figure using Markups estimated by the production function approach and finds similar results.

[22] See Damodaran (2018, April 26). Amazon: Glimpses of Shoeless Joe? [Blog post]. Retrieved from http://aswathdamodaran.blogspot.com/2018/04/amazon-glimpses-of-shoeless-joe.html

and 15, ROIC and markups of most of these elite firms seem to be reasonable initially when they are in the "franchise" building stage and then explode for a couple of firms that have built up a large enough market, which compounds the measurement issues. Khan [2016] also argues that the current anti-trust laws and their focus on short-run consumer welfare are just not equipped to recognize the anti-competitive nature of Amazon's predatory pricing and ability to use its dominance in one sector to gain market share in another.

Building a franchise in the expectation of future profits is not new, and these star firms of today may be likened to the superstars in the early part of the 20th century like US Steel, Standard Oil and Sears, and Roebuck and Company who have passed into history. This suggests that the critical concern for policy is not only to control the exercise of market power by these few firms, but to ensure that markets remain contestable and that entrants with new technologies are able to challenge the current market leaders. Policy measures could include limitations of acquisitions of new technologies through mergers. For instance, see Cunningham et al. [2018] for a discussion of mergers and the subsequent liquidation of new technologies by incumbent firms in order to maintain market dominance.

5 Conclusion

We assess the performance of publicly-listed star firms in the United States. When we use financial statement data as conventionally presented, a small percentage of firms seem to be pulling away over time from other firms in the economy in terms of their return on capital. In particular, star firms in highly skilled industries and industries with high levels of intangible capital seem to be pulling away from the others.

However, conventional financial statements do not capitalize R&D expenditures or organizational capital. Once we adjust firms' returns to capital to address these shortcomings, there is little evidence that the most profitable 10% of firms are pulling away from the rest of the economy, and the differences in firm returns in highly skilled and other industries shrink dramatically. Furthermore, once we adjust markups based on operating expenses for investment in intangible capital, we only find a modest increase in market power especially in high skilled industries. Star firms tend to be larger, younger, and have higher markups. While they may have more pricing power than other firms, at each level of markup star firms tend to produce more than other firms. We also find no evidence that star firms are differentially affected by import competition compared to other firms in the economy.

Overall, we see little evidence that these star firms are using their market power to reduce output and raise prices to achieve super normal returns more than other firms. However, there may be reason for concern regarding a smaller subset of elite publicly-listed firms. The usual suspects for membership in such an elite group are Apple, Facebook, Google, Amazon, and Microsoft. When we examine these firms individually, the ROIC and markups of most of these elite firms do not seem extraordinary initially and then explode but again only for a couple of firms that have built up a large enough market. Even for these firms, the critical policy concern may not only be the regulation of their use of market power today, but also the need to maintain contestable markets that allow the creation of independent technologies in the future.

Our work suggests that the conjecture that high performing firms are exploiting their market power needs to be reassessed once we take firms' investment in intangible capital into account. More broadly, understanding differences in intangible capital investment across firms is likely to play a first order role in research on a wide range of corporate finance and firm governance policies.

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Figure 1: **Rise in Star Firms**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital (ROIC) (unadjusted for intangible capital) in each year across all large public firms (defined as firms with assets more than $200 million in 2009 dollars, adjusted for inflation) in the US economy. Detailed variable definitions are in the Appendix.

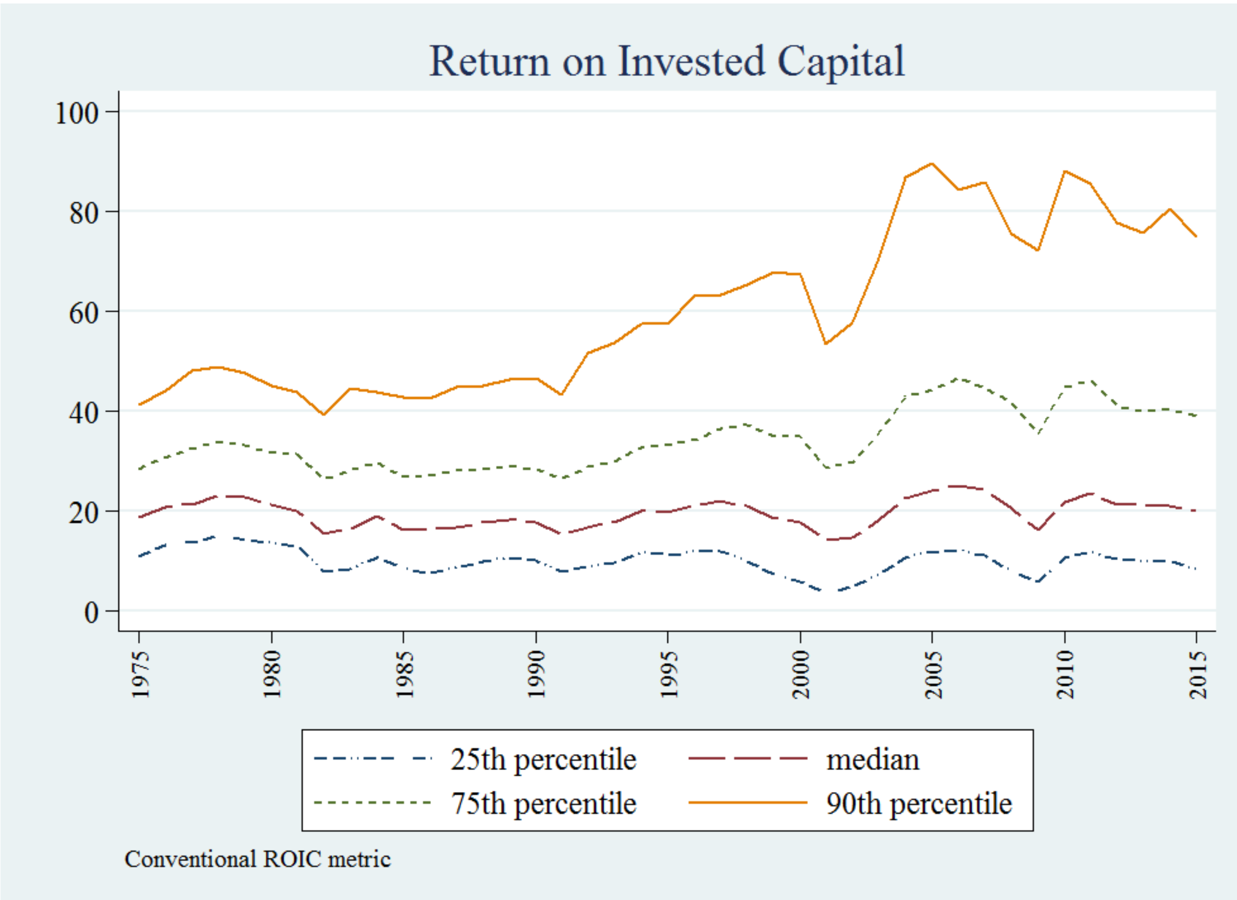
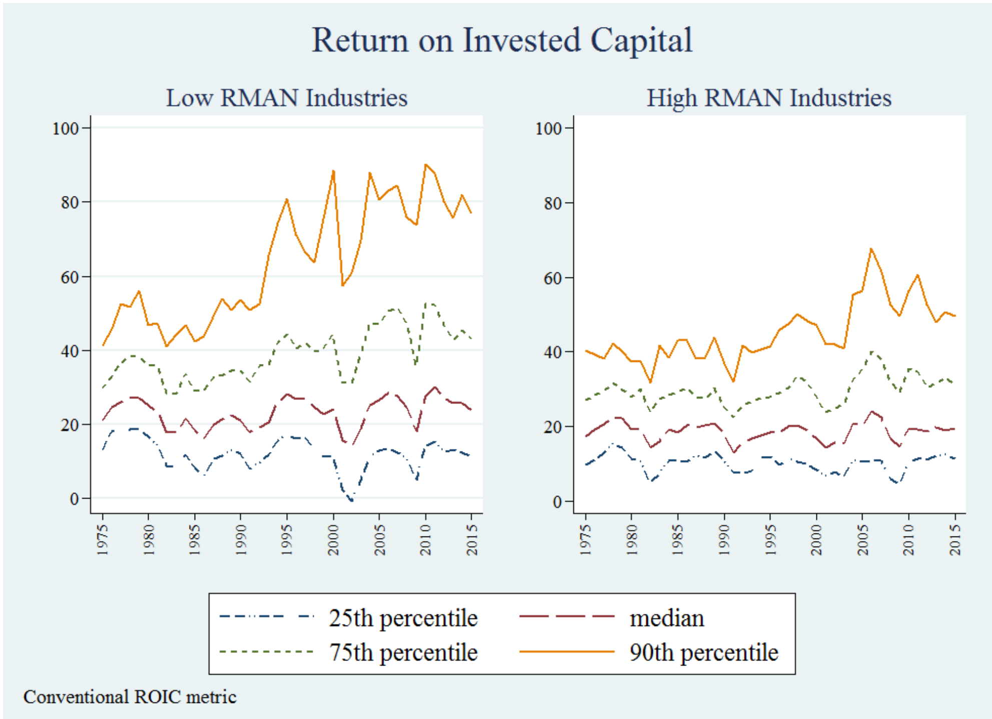


Figure 2: **Differences in Human Capital**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital (ROIC) (unadjusted for intangible capital) in each year in low and high routine manual (RMAN) manufacturing industries in the first figure and in industries with low and high intangible capital/assets ratio in the second figure. Detailed variable definitions are in the Appendix.



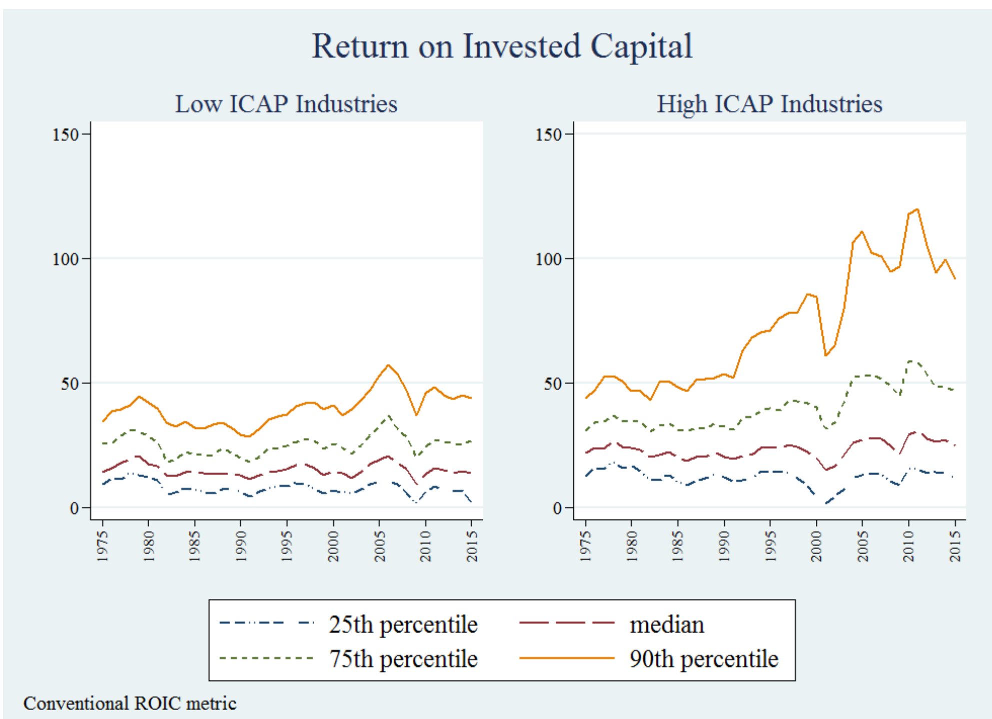


Figure 3: **Rise in Star Firms - correcting for intangible capital**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital ($ROIC$) in each year across all public firms in the US economy. $ROIC$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

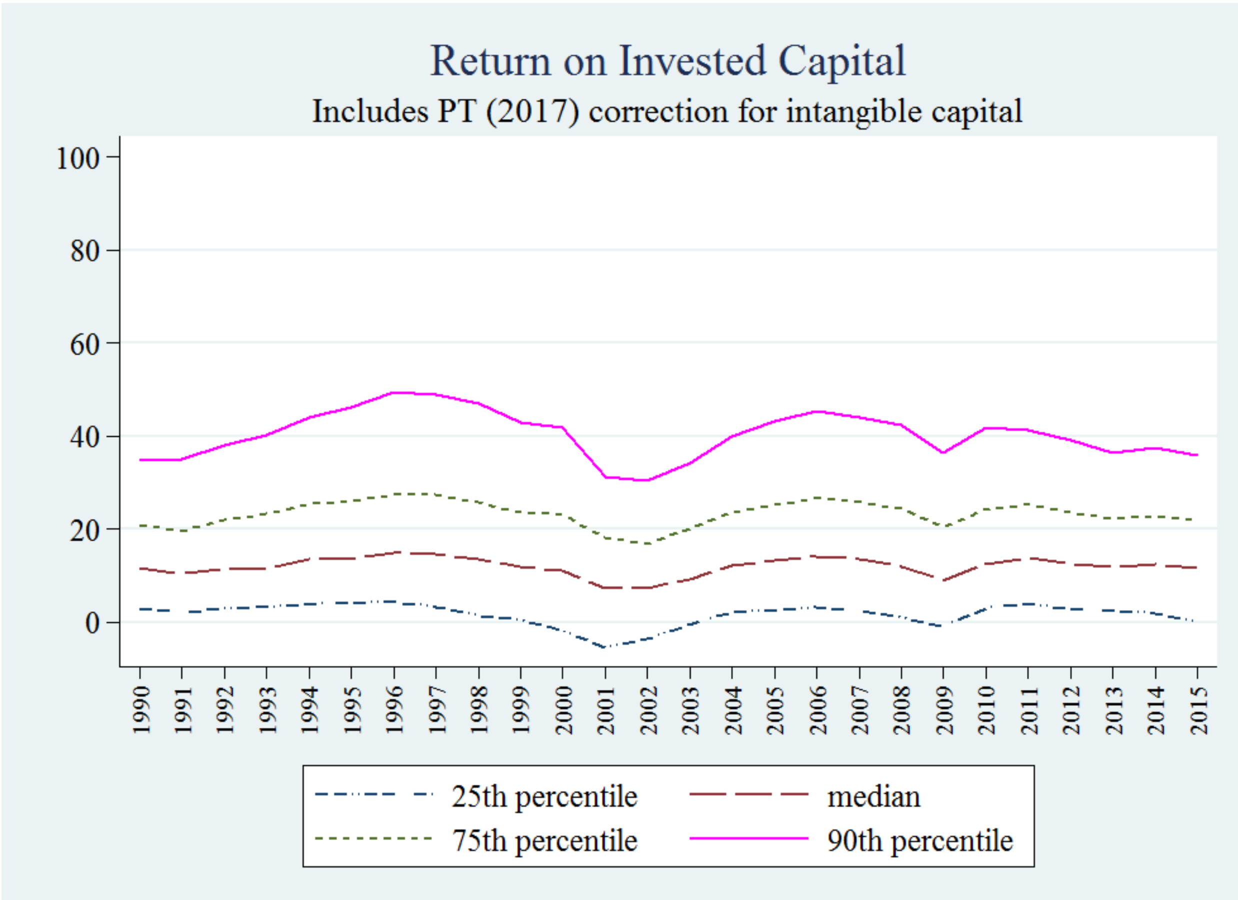
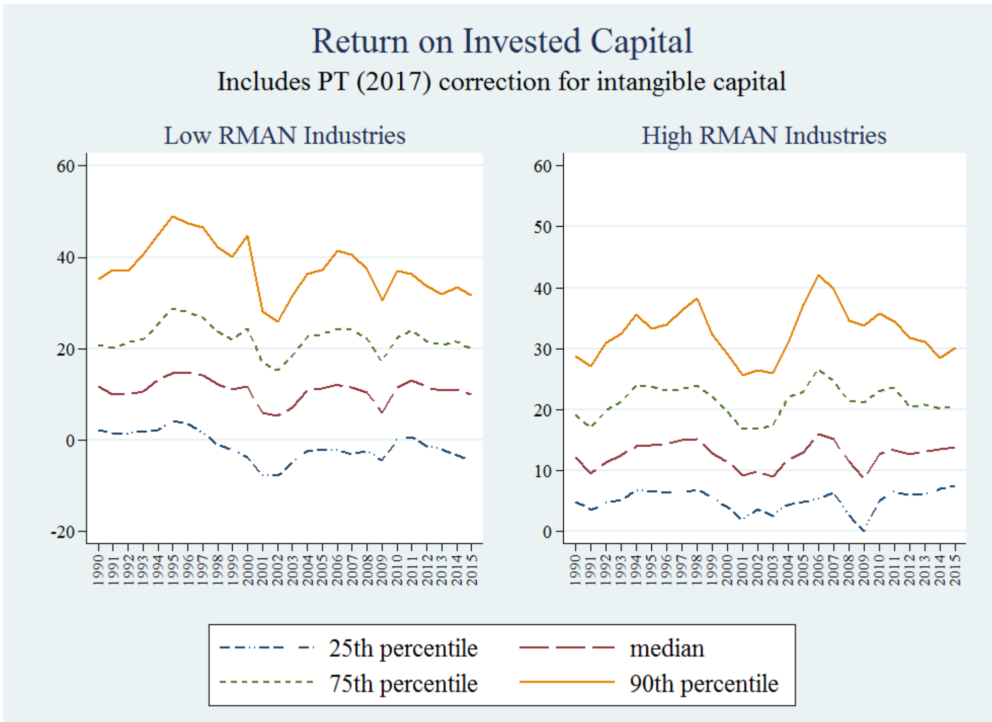


Figure 4: **Differences in Human Capital - correcting for intangible capital**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital ($ROIC$) in each year in low and high routine manual (RMAN) manufacturing industries in the first figure and in industries with low and high intangible capital($ICAP$)/assets ratio in the second figure. $ROIC$ and $ICAP$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.



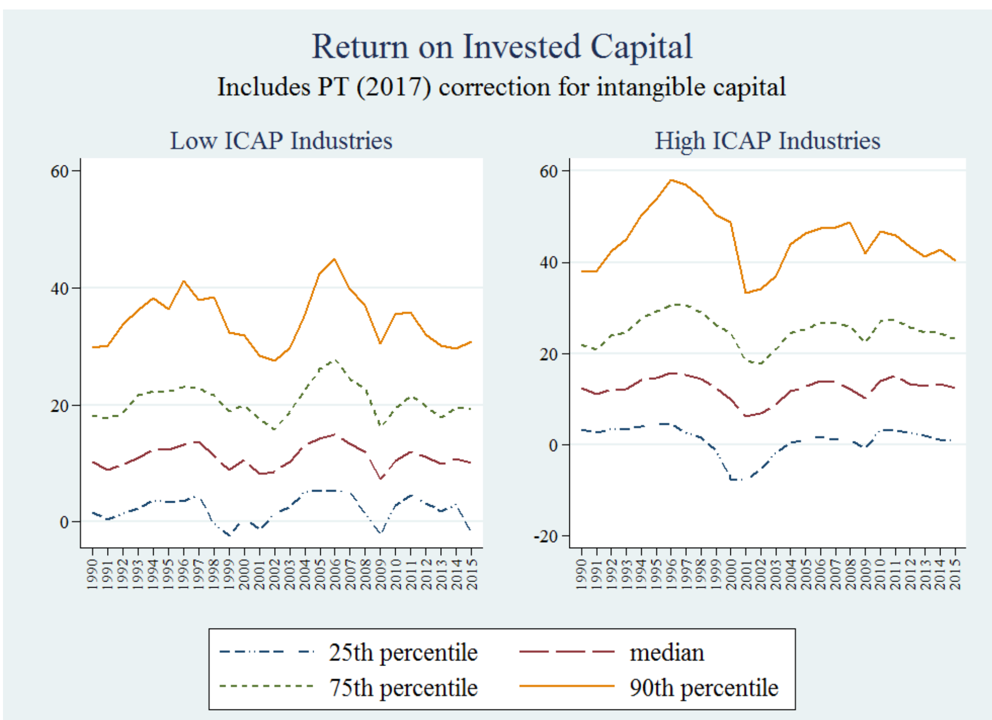


Figure 5: **Markups in the US Economy**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of $Markups$ in each year across all public firms in the US economy. $Markups$ are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost. Detailed variable definitions are in the Appendix.

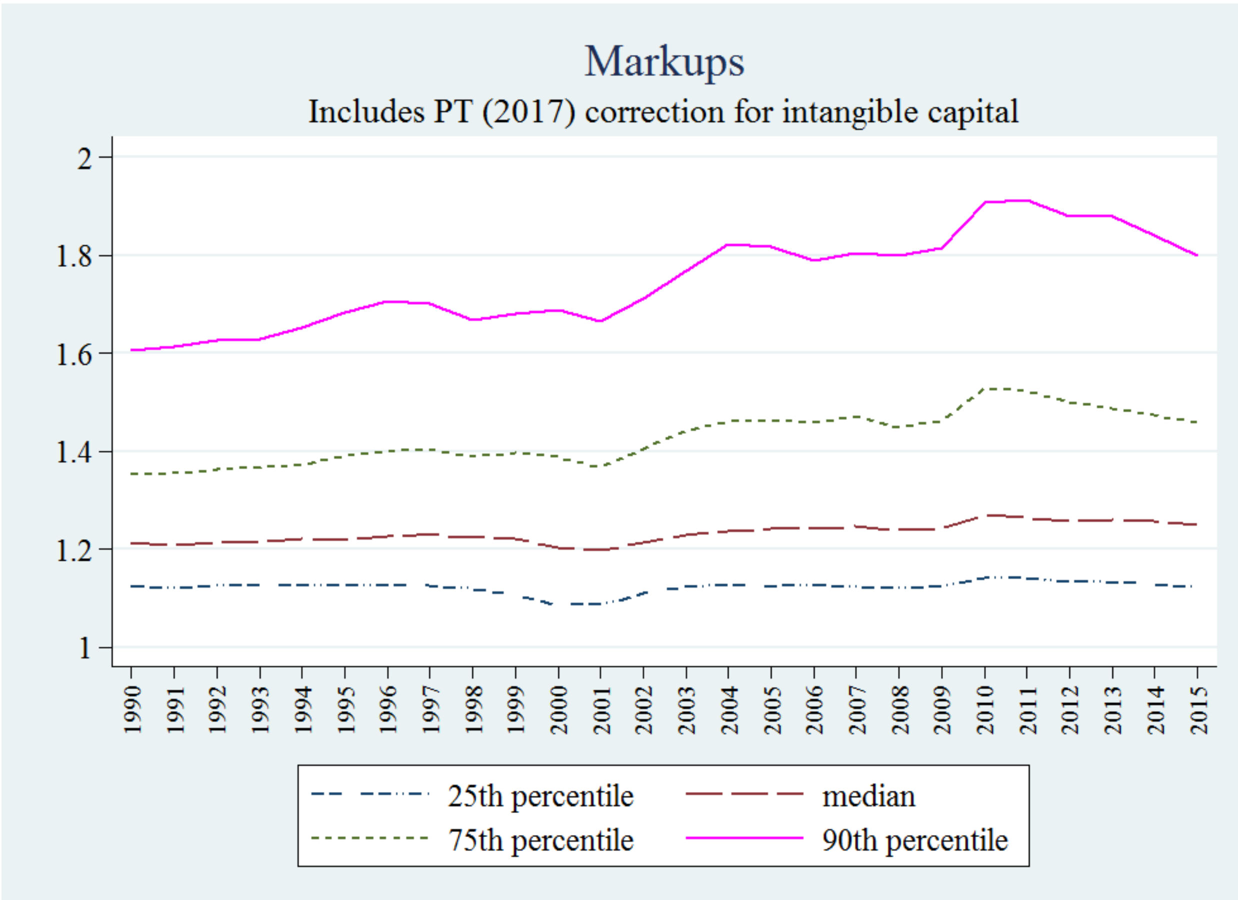
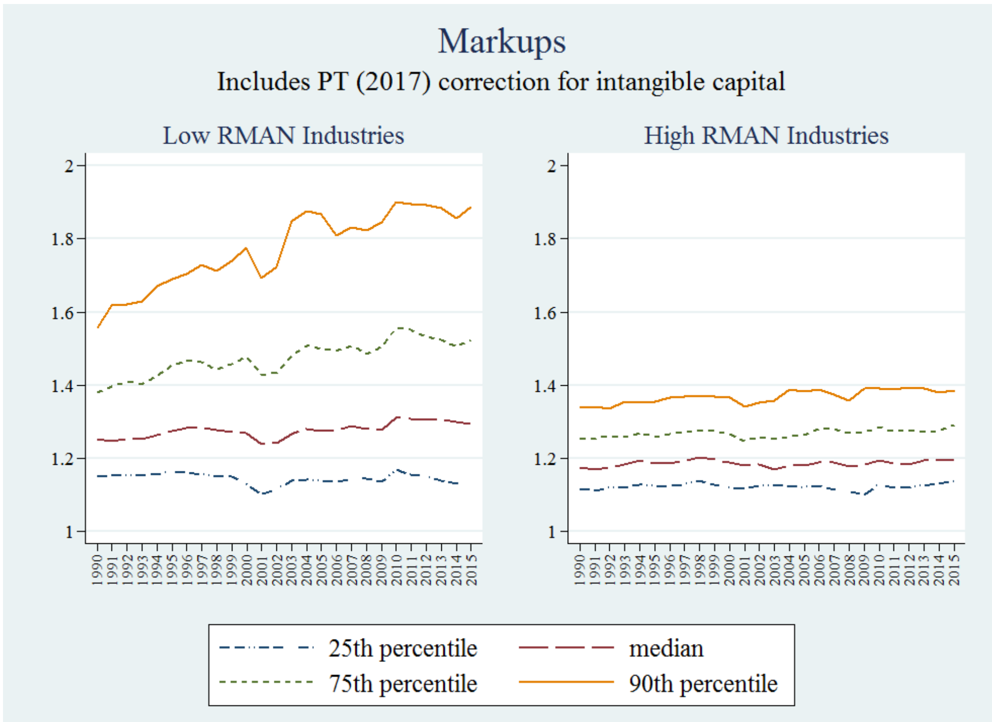


Figure 6: **Markups in the US Economy - Differences in Human Capital**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of $Markups$ in each year in low and high routine manual (RMAN) manufacturing industries and in industries with low and high intangible capital($ICAP$)/assets ratio. $Markups$ are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.



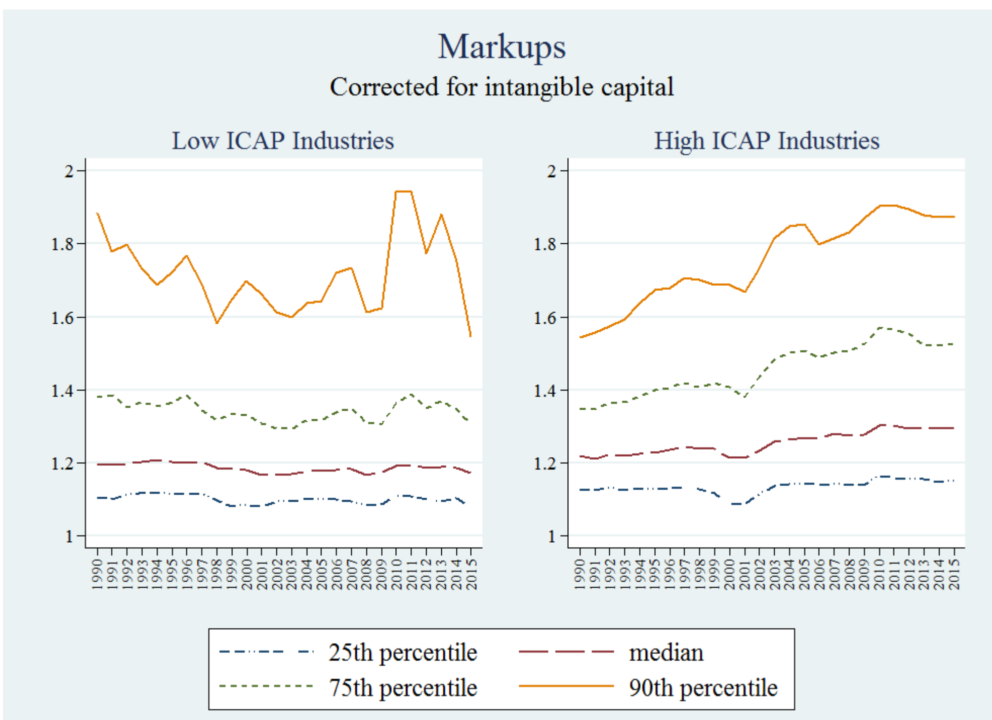


Figure 7: **ROIC and Markups over time**

This figure plots the interaction coefficient of markups and year dummies from a regression of ROIC on Markups, Log(Assets), Log(Age), Markups x Year, industry and year fixed effects. *ROIC* includes the Peters and Taylor [2017] adjustment for intangible capital. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

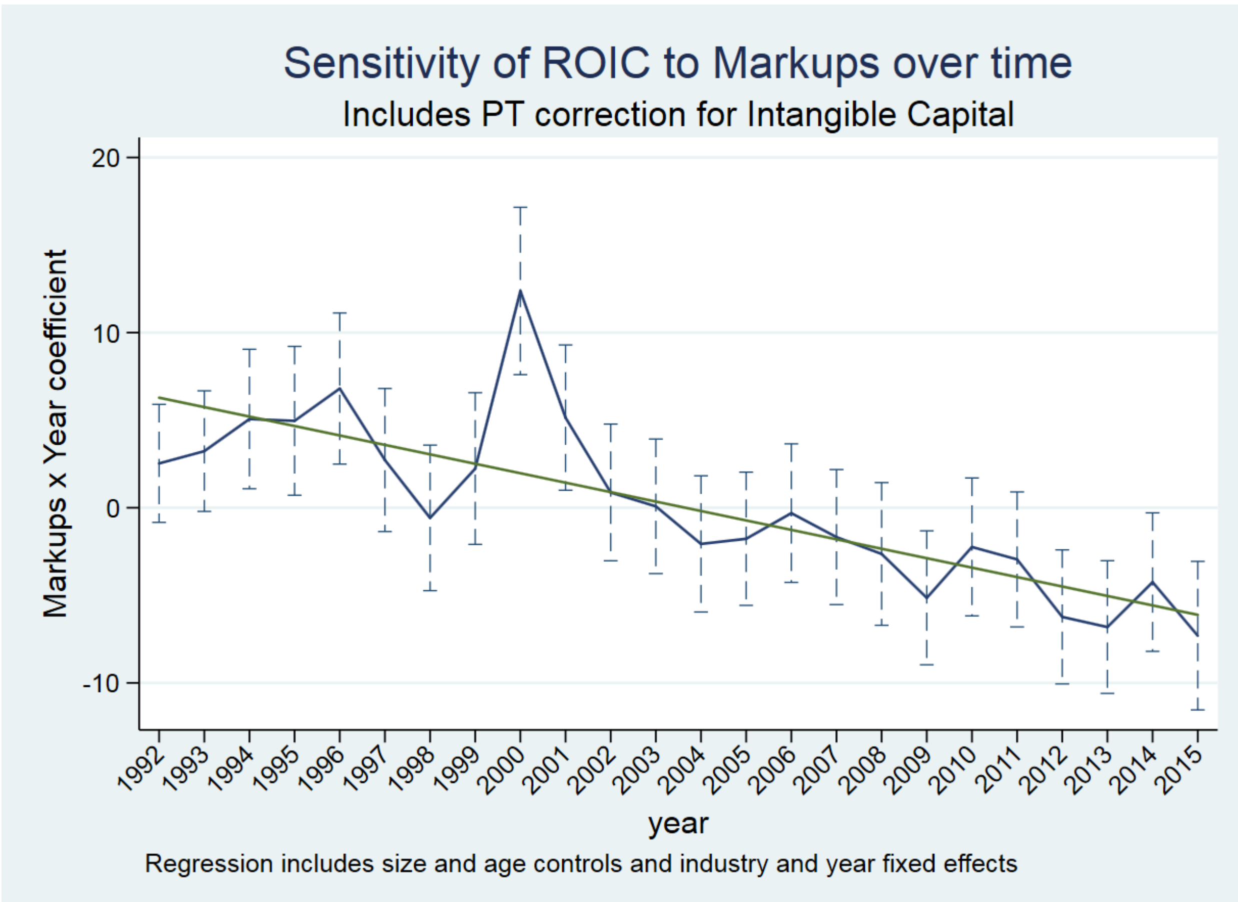


Figure 8: **ROIC and Markups over time - Differences in Human Capital**
This figure plots the interaction coefficient of markups and year dummies from a regression of ROIC on Markups, Log(Assets), Log(Age), Markups x Year, industry and year fixed effects. *ROIC* includes the Peters and Taylor [2017] adjustment for intangible capital. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. The figure shows ROIC-markup sensitivity across industries with low and high intangible capital($ICAP$)/assets ratios. Detailed variable definitions are in the Appendix.

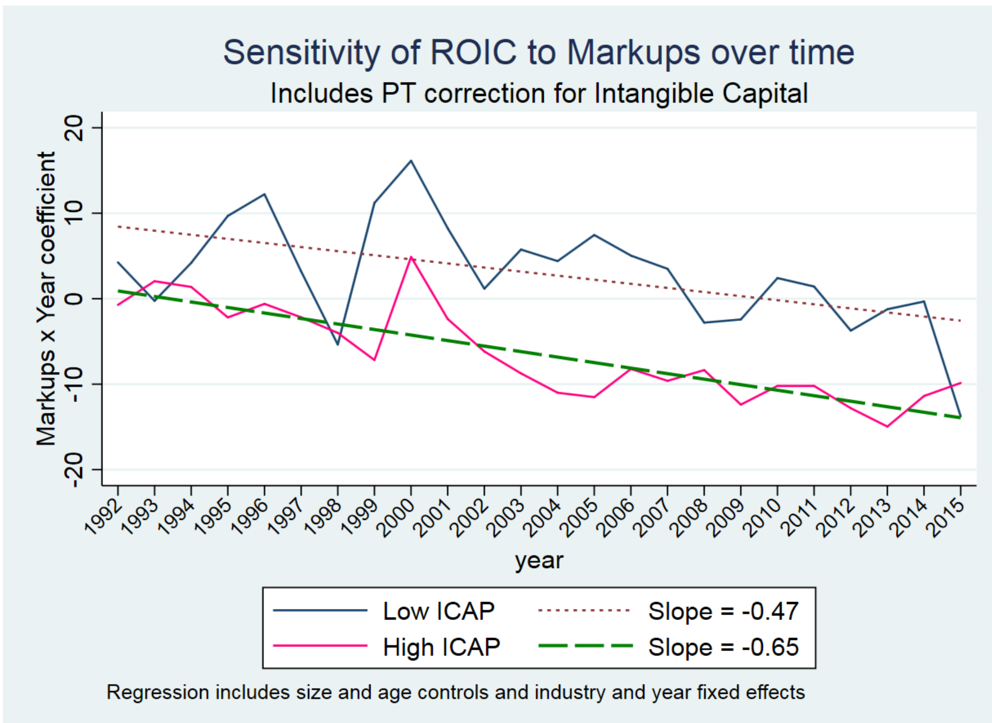


Figure 9: **Markups and Intangible Capital over time**
This figure plots the relation between markups and intangible capital/assets over time from a regression including size and age controls and industry fixed effects. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

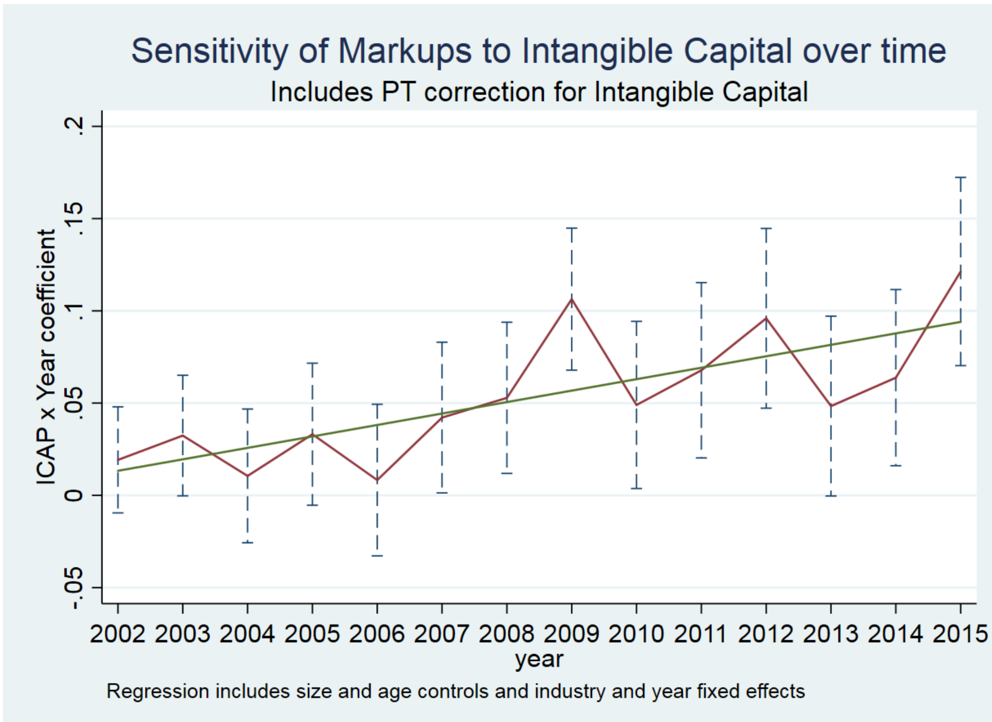


Figure 10: **Distribution of Markups across Star firms and all other firms**
This figure plots the histogram of *Markups* for *ROIC* Stars and all other firms. The figure also shows the smoothed values of a kernel-weighted local polynomial regression of *ROIC* on *Markups*. *ROIC* stars are firms that are in the top 10% of *ROIC* in a particular year. *ROIC* includes the Peters and Taylor [2017] adjustment for intangible capital. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

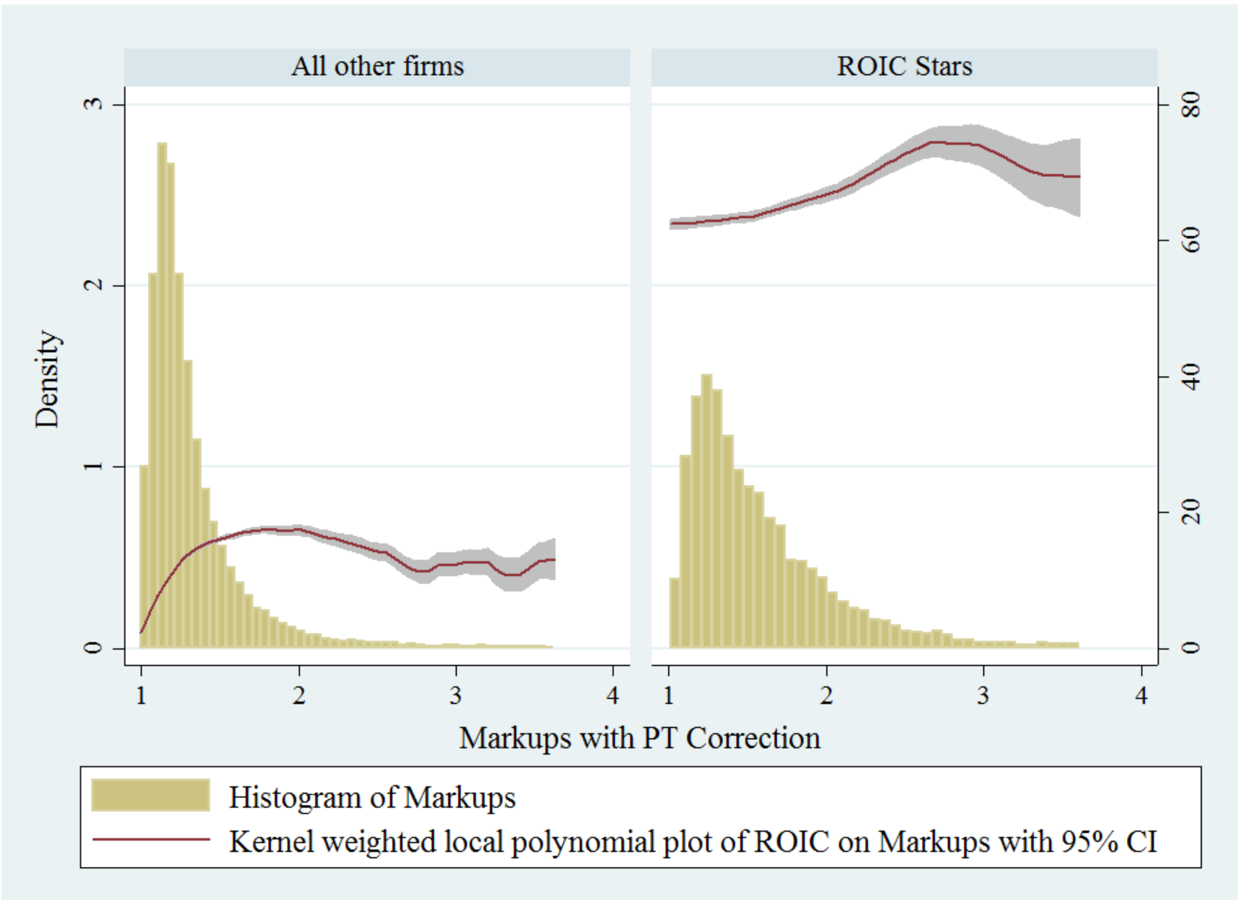
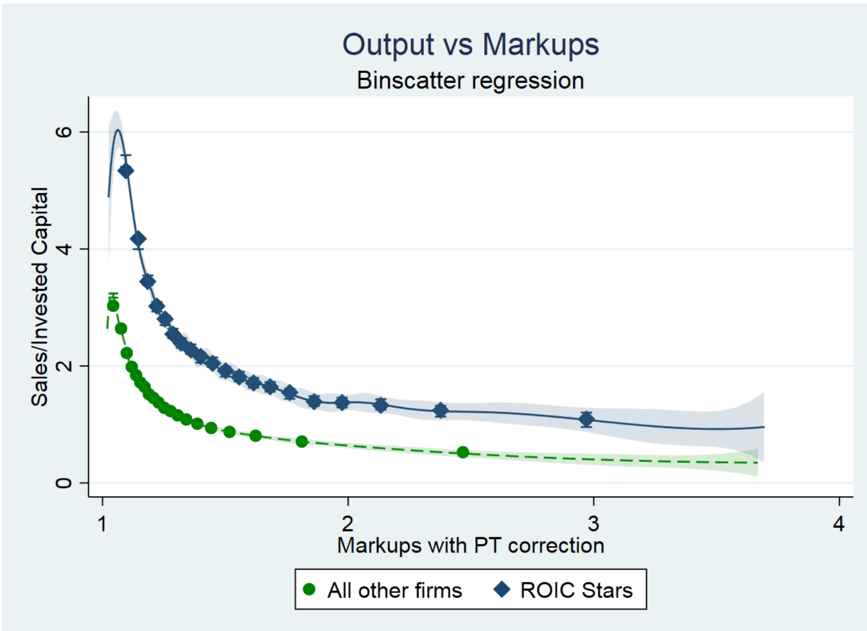


Figure 11: **Output and Markups over time**
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Sales/Invested Capital on $Markups$ for $ROIC$ stars and all other firms. The first figure does not control for covariates whereas the second figure controls for Firm size, age, industry and year fixed effects.$ROIC$ stars are firms that are in the top 10% of $ROIC$ in a particular year. $ROIC$ includes the Peters and Taylor [2017] adjustment for intangible capital. $Markups$ are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.



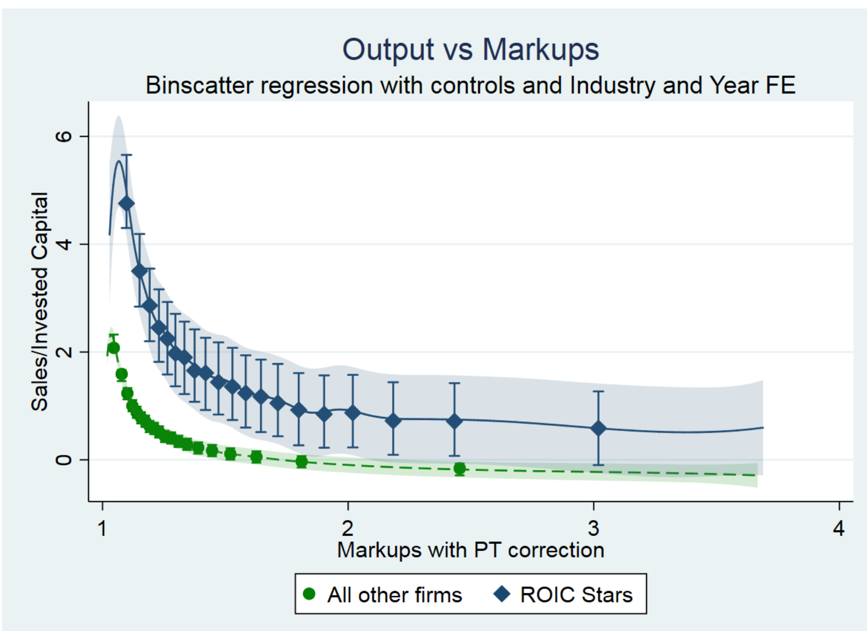
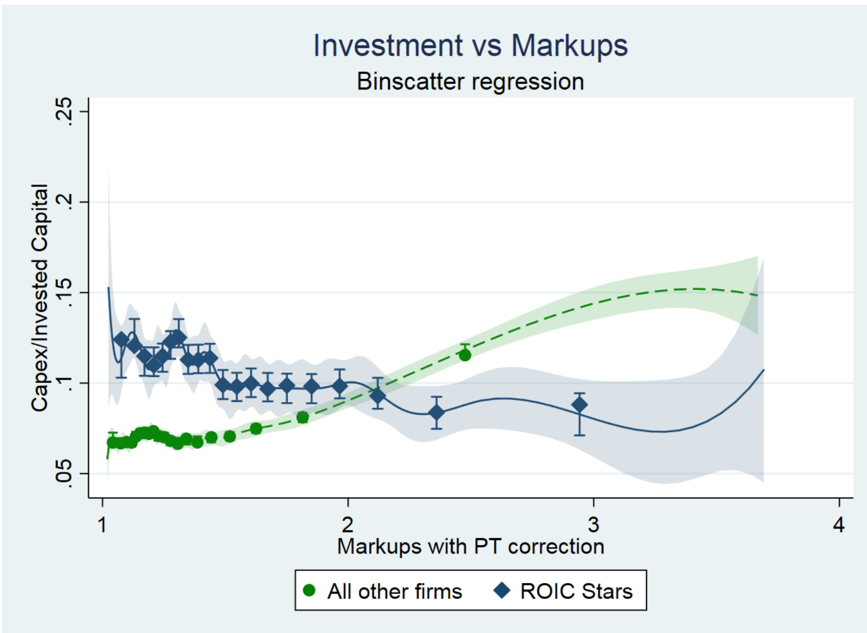


Figure 12: **Investment and Markups over time**
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Capex/Invested Capital and R&D Investment/Invested Capital on *Markups* for *ROIC* stars and all other firms.*ROIC* stars are firms that are in the top 10% of *ROIC* in a particular year. *ROIC* includes the Peters and Taylor [2017] adjustment for intangible capital. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.



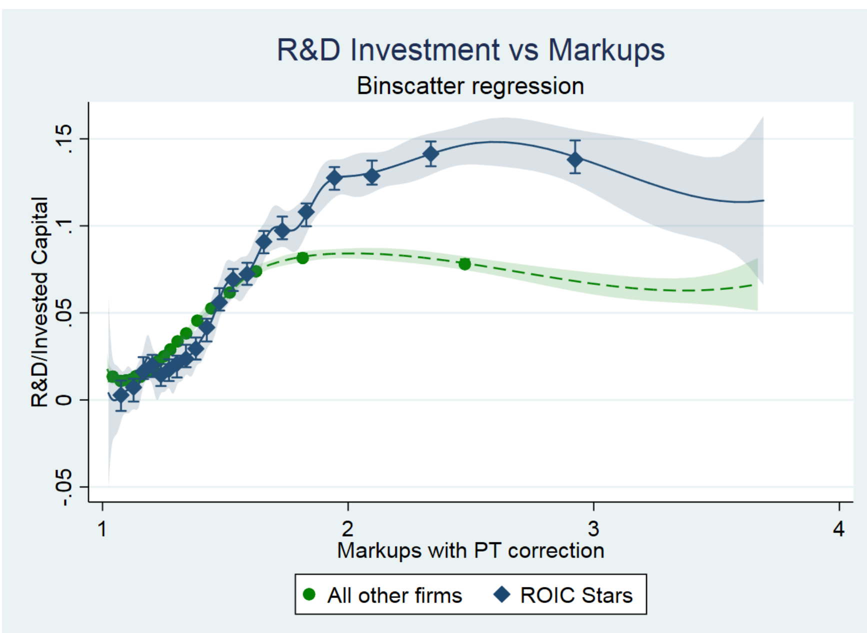


Figure 13: **Output, Investment and Markup - Differences in Human Capital**
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Sales/Invested Capital, Capex/Invested Capital, and R&D Investment/Invested Capital on *Markups* for *ROIC* stars and all other firms in low and high ICAP industries. *ROIC* stars are firms that are in the top 10% of *ROIC* in a particular year. *ROIC* includes the Peters and Taylor [2017] adjustment for intangible capital. *Markups* are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

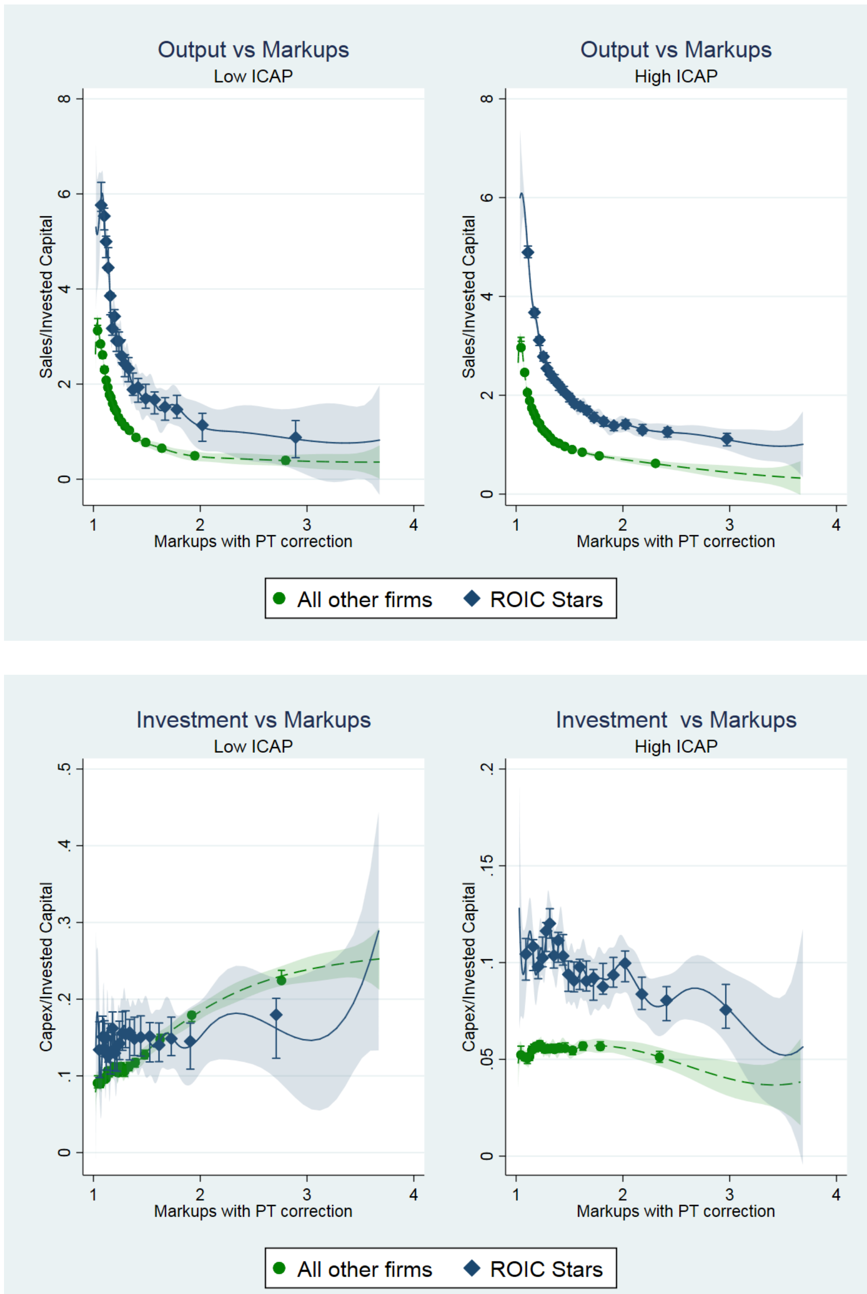


Figure 13: **Output, Investment and Markup - Differences in Human Capital (Continued..)**

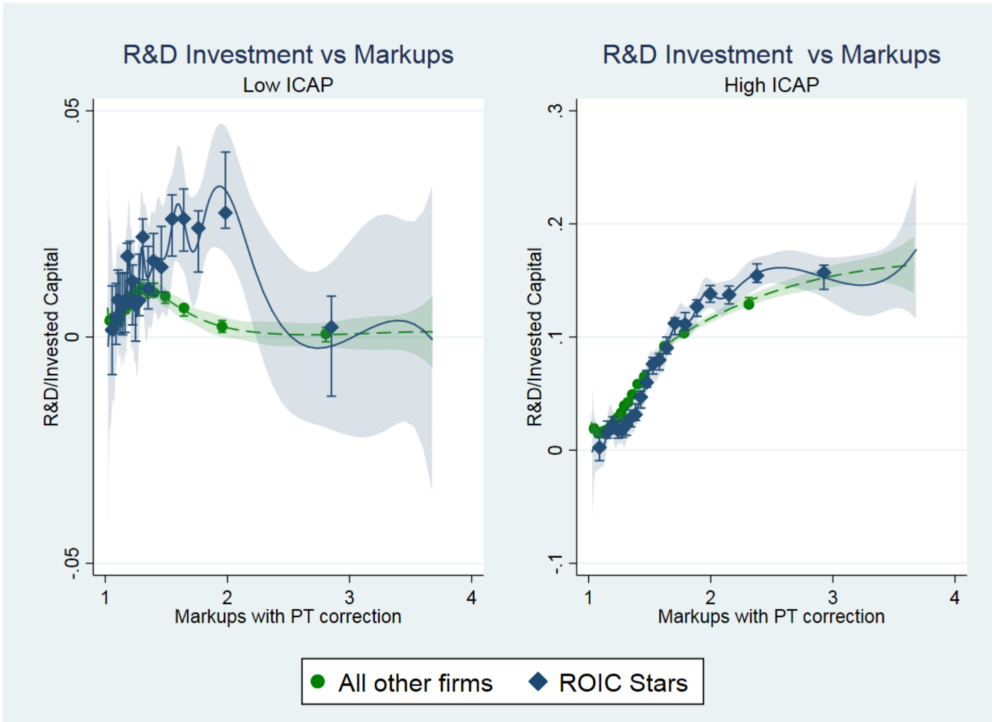


Figure 14: **ROIC of Elite Firms (Apple, Facebook, Amazon, Microsoft, Google)**
This figure plots the 90^{th} percentile of Return on Invested Capital ($ROIC$) in each year across all public firms in the US economy as well as the $ROIC$ for five firms referred to as superstars anecdotally. $ROIC$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

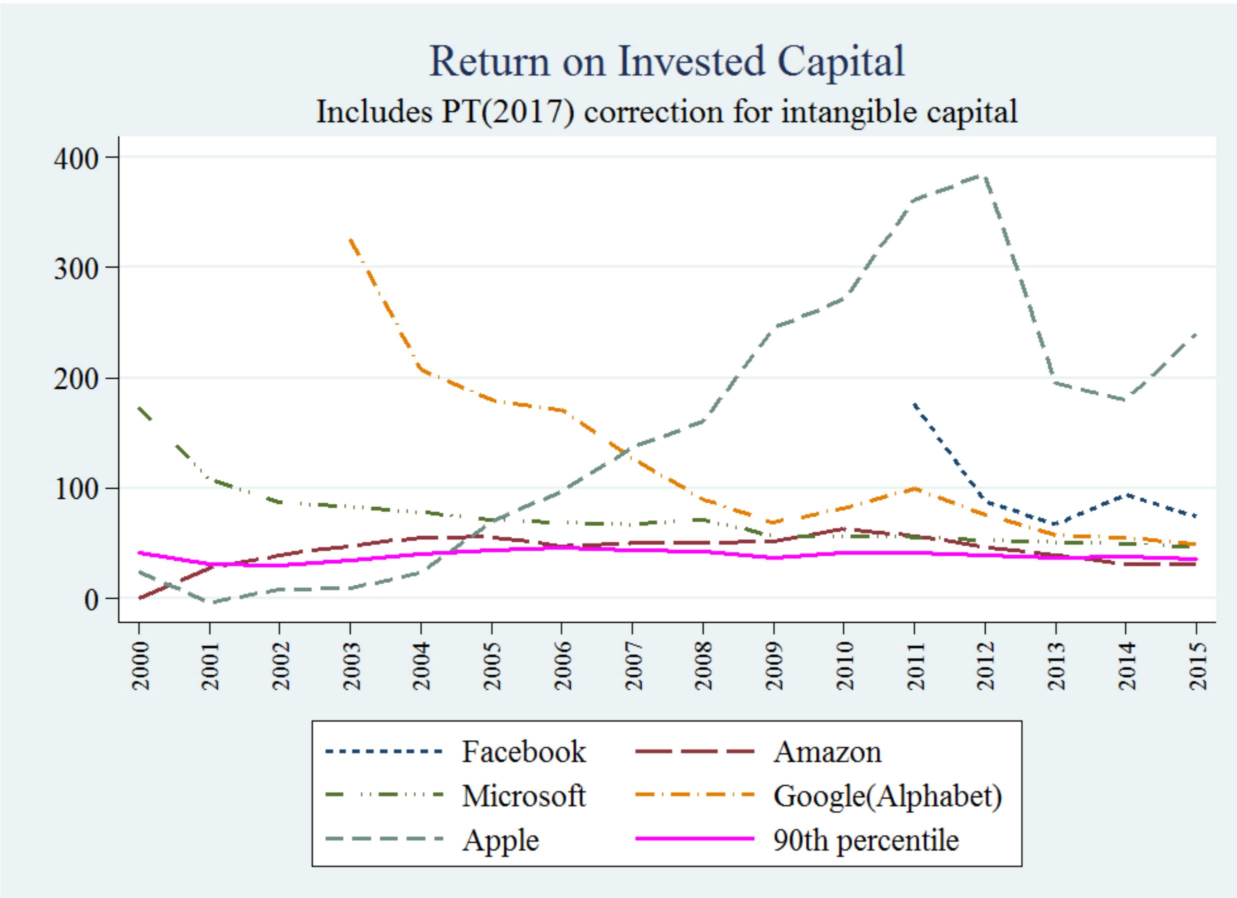


Figure 15: **Markups of Elite Firms (Apple, Facebook, Amazon, Microsoft, Google)**
This figure plots the 90^{th} percentile of $Markups$ in each year across all public firms in the US economy as well as the $Markups$ for five firms referred to as superstars anecdotally. $Markups$ are defined as Sales/Variable Cost where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

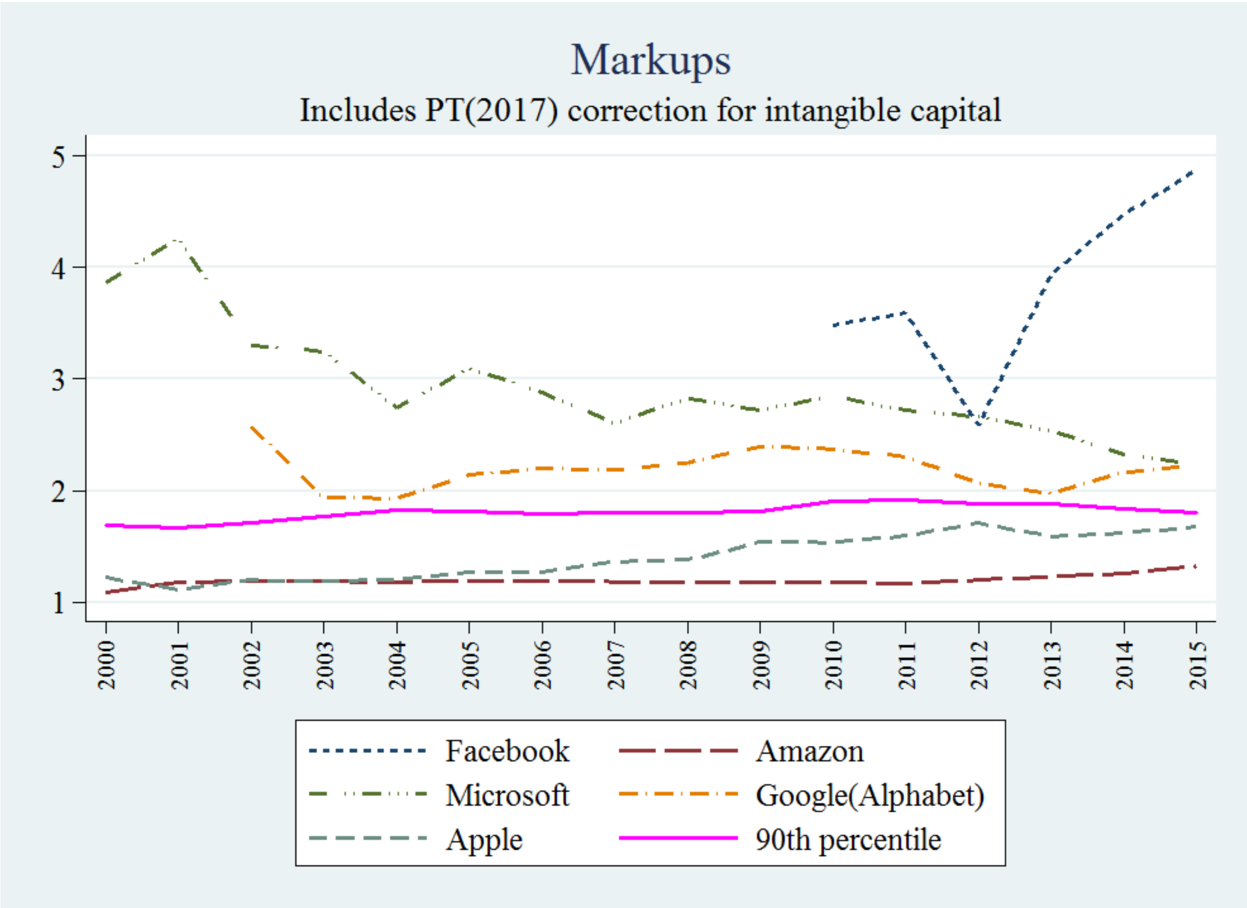


Table 1: **Are Star Firms Persistent Performers?**
This table reports estimates from the following panel regression model:

$$Performance_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{ijt-5} + \beta_2 \times Log(Age)_{ijt-5} + \beta_3 \times ROIC_{ijt-5} + \beta_4 \times Star_{ijt-5} + \phi_{jt} + \varepsilon_{ijt}$$

Performance is Sales growth/Employment growth (each defined as the 5-year log difference in sales or employment respectively divided by 5), Labor Productivity, or $ROIC$ averaged over 5 years. Log(Assets) is the 5-year lagged value of the logarithm of total assets. Log(Age) is the 5-year lagged value of the firm age. $Markups$ is the 5-year lagged value of Markups computed using operating expenses as a variable input of production and includes correction for intangible capital. Star is a dummy variable that takes the value 1 if firm is 5-year lagged $ROIC$ was above the 90th percentile of $ROIC$ respectively across all firms 5 years back and 0 otherwise. The regressions are 5-year stacked panel regressions: 1990-1995, 1995-2000, 2000-2005, 2005-2010, and 2010-2015 and include industry x year fixed effects with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROIC	ROIC	Sales Growth	Sales Growth	Emp Growth	Emp Growth	Labor Productivity	Labor Productivity
L5.Log(Assets)	3.359***	0.972***	-0.005***	-0.005***	-0.005***	-0.008***	36.204***	30.382***
	(0.092)	(0.059)	(0.001)	(0.001)	(0.001)	(0.001)	(2.003)	(2.053)
L5.Log(Age)	0.068	0.492***	-0.032***	-0.034***	-0.023***	-0.022***	-35.186***	-33.991***
	(0.226)	(0.139)	(0.002)	(0.002)	(0.002)	(0.002)	(4.404)	(4.350)
L5.ROIC Star	34.310***		0.033***		0.053***		85.715***	
	(0.623)		(0.005)		(0.005)		(8.850)	
L5.ROIC		0.639***		0.000		0.001***		1.596***
		(0.007)		(0.000)		(0.000)		(0.107)
N	18224	18224	11867	11867	11422	11422	17768	17768
Adj. R-sq	0.396	0.733	0.083	0.080	0.077	0.085	0.405	0.413
Fixed Effects	Industry x Year							

Table 2: **Who are America's Stars? Correcting for intangible capital**
This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{ijt-1} + \beta_2 \times Log(Age)_{ijt-1} + \beta_3 \times HHI_{jt-1} + \beta_4 \times Market\ share_{ijt-1} + \beta_5 \times Markups_{ijt-1} + \phi_j + \gamma_t + \varepsilon_{ijt}$$

Star is a dummy variable that takes the value 1 if the firm i's $ROIC$ is above the 90^{th} percentile of $ROIC$ respectively across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is logarithm of firm age. HHI is Herfindahl Index of market share in each industry in each year. $Markups$ are estimated using operating expenses as a variable input of production and includes correction for intangible capital. Market Share is the ratio of firm i's sales to total industry js sales in a particular year. Panel A presents results using industry and year fixed effects and panel B reports results using industry x year fixed effects. In both panels, the large firm sample is identified by firms with Real value of assets $\geq$ USD 200Mil and the young firm sample is determined by firms of Age $\leq$ 5years. All regressions in both panels are estimated using ordinary least squares with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	Q Star
Sample	Full	Full	Full	Full	Manuf	Large	Young	Full
L.Log(Assets)	0.017***	0.017***	0.016***	0.009***	0.007***	-0.001	-0.008**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)
L.Log(Age)	-0.065***	-0.064***	-0.066***	-0.063***	-0.058***	-0.059***	-0.150***	-0.057***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.019)	(0.003)
L.HHI		-0.032						
		(0.041)						
L.Market Share			0.108					
			(0.085)					
L.Markups				0.145***	0.143***	0.167***	0.205***	0.094***
				(0.007)	(0.010)	(0.011)	(0.012)	(0.007)
N	83120	81762	81612	81631	41854	46057	8747	78734
Adj. R-sq	0.074	0.074	0.074	0.107	0.081	0.139	0.129	0.064
Fixed effects		———	———	——— Industry, Year	———	———	———	

Table 2: **Who are America's Stars? Correcting for intangible capital (Continued...)**

	(1)	(2)	(3)	(4)	(5)	(6)
	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	Q Star
Sample	Full	Full	Manuf	Large	Young	Full
L.Log(Assets)	0.017***	0.010***	0.007***	0.000	-0.005	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)
L.Log(Age)	-0.066***	-0.063***	-0.057***	-0.059***	-0.144***	-0.057***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.022)	(0.003)
L.Markups		0.144***	0.143***	0.169***	0.193***	0.094***
		(0.007)	(0.010)	(0.011)	(0.012)	(0.008)
N	83014	81525	41854	45925	8367	78632
Adj. R-sq	0.079	0.112	0.086	0.140	0.136	0.066
Fixed effects	Industry x Year					

Table 3: **Skill, Intangible Capital and Star Status**

This table reports estimates from the following panel regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{ijt-1} + \beta_2 \times Log(Age)_{ijt-1} + \beta_3 \times ICAP/TotalAssets_{ijt-1} + \beta_4 \times Markups_{ijt-1} +$$
$$\beta_5 \times LogAssets_{ijt-1} \times RMAN_j \text{ or } ICAP/TotalAssets_{ijt-1} + \beta_6 \times Markups_{ijt-1} \times RMAN_j \text{ or } ICAP/TotalAssets_{ijt-1} + \phi_{jt} + \varepsilon_{ijt}$$

Star is a dummy variable that takes the value 1 if the firm i's ROIC or (Tobin's Q) is above the 90^{th} percentile of ROIC (or Tobin's Q) respectively across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is the logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. ICAP/Total Assets is the ratio of intangible capital to total assets. RMAN is industry-level measure of routine manual skills employed by the workforce in manufacturing industries. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	1	2	3	4	5	6	7	8
	ROIC Star	ROIC Star	Q Star	Q Star	ROIC Star	ROIC Star	Q Star	Q Star
Sample	Manuf	Manuf	Manuf	Manuf	Full	Full	Full	Full
L.Log(Assets)	0.010***	0.007***	-0.001	-0.003*	0.010***	0.004***	0.002	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
L.Log(Age)	-0.057***	-0.057***	-0.050***	-0.050***	-0.056***	-0.056***	-0.050***	-0.051***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
L.Markups	0.141***	0.142***	0.130***	0.134***	0.151***	0.197***	0.098***	0.127***
	(0.010)	(0.010)	(0.012)	(0.011)	(0.007)	(0.010)	(0.008)	(0.011)
L.ICAP/Assets					-0.026***	0.011	-0.008	-0.008
					(0.007)	(0.007)	(0.008)	(0.008)
L.Log(Assets) x RMAN	-0.006**		-0.005**					
	(0.003)		(0.003)					
L.Markups x RMAN		0.002		-0.016				
		(0.014)		(0.016)				
L.Log(Assets) x L.ICAP/Assets					-0.012***		-0.013***	
					(0.002)		(0.002)	
L.Markups x L.ICAP/Assets						-0.067***		-0.044***
						(0.006)		(0.007)
N	41440	41440	40206	40206	80194	80194	77395	77395
Adj. R-sq	0.087	0.086	0.070	0.070	0.126	0.129	0.078	0.078
Fixed Effects	— Industry x Year —							

Table 4: **Output and Investment in Star Firms**
This table reports estimates from the following panel regression model:

$$Output\ or\ Investment_{ijt} = \alpha_0 + \beta_1 \times LogAssets_{ijt-1} + \beta_2 \times LogAge_{ijt-1} + \beta_3 \times Star_{ijt-1} + \phi_{jt} + \varepsilon_{ijt}$$

The dependent variable is Output (Sales/Invested Capital) or Investment which is measured by CAPEX/Invested Capital or R&D Expenses/Invested Capital. Star is a dummy variable that takes the value 1 if the firm i's ROIC or Tobins Q is above the 90^{th} percentile of ROIC or Tobins Q respectively across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is the logarithm of firm age. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Output	Output	Investment	Investment	R&D	R&D
L.Log(Assets)	0.031***	0.044***	0.004***	0.005***	0.000	0.000
	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
L.Log(Age)	0.002	-0.039***	-0.013***	-0.013***	-0.015***	-0.014***
	(0.013)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)
L.ROIC Star	0.632***		0.030***		0.008***	
	(0.026)		(0.002)		(0.001)	
L.Q Star		0.130***		0.035***		0.029***
		(0.025)		(0.002)		(0.002)
N	80805	76530	80618	76279	81929	77571
Adj. R-sq	0.306	0.277	0.345	0.353	0.416	0.423
Fixed Effects				Industry x Year		

Table 5: **Who are America's Stars? Role of Productivity**
This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{ijt-1} + \beta_2 \times Log(Age)_{it-1} + \beta_3 \times Productivity_{ijt-1} + \beta_4 \times Markups_{ijt-1} + \phi_{jt} + \varepsilon_{ijt}$$

Star is a dummy variable that takes the value 1 if the firm i's ROIC or (Tobin's Q) is above the 90^{th} percentile of ROIC (or Tobin's Q) respectively across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. Columns (1) and (5) include the full sample; columns (2) and (6) is manufacturing sub-sample, columns (3) and (7) is large firm sample (Real value of assets is $\geq$ USD 200Mil) and columns (4) and (8) is young firm sample (Age $\leq$ 5years). All regressions iare estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROIC Star	ROIC Star	ROIC Star	ROIC Star	Q Star	Q Star	Q Star	Q Star
	Full	Manuf	Large	Young	Full	Manuf	Large	Young
L.Log(Assets)	0.008***	0.007***	-0.000	-0.000	-0.002*	-0.005***	-0.014***	-0.022***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)	(0.005)
L.Log(Age)	-0.055***	-0.048***	-0.057***	-0.104**	-0.051***	-0.047***	-0.040***	0.027
	(0.003)	(0.004)	(0.004)	(0.043)	(0.003)	(0.004)	(0.004)	(0.045)
L.Markups	0.111***	0.101***	0.118***	0.147***	0.064***	0.086***	0.087***	0.034*
	(0.007)	(0.009)	(0.011)	(0.015)	(0.007)	(0.011)	(0.010)	(0.018)
L.Productivity	0.105***	0.110***	0.200***	0.155***	0.109***	0.145***	0.257***	0.177***
	(0.010)	(0.015)	(0.021)	(0.020)	(0.012)	(0.019)	(0.023)	(0.027)
N	73428	38396	41565	5158	71061	37385	40195	5001
Adj. R-sq	0.114	0.086	0.151	0.141	0.066	0.078	0.119	0.070
Fixed Effects	—————————- Industry x Year —————————							

Table 6: **Who are America's Stars? Role of Import Competition**
This table reports estimates from the following instrumental variable regression model:

$$Y_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{ijt-1} + \beta_2 \times Log(Age)_{ijt-1} + \beta_3 \times Imports_{jt-1} + \beta_4 \times Star_{ijt-2} + \beta_5 \times Star_{ijt-2} \times Imports_{jt-1} + \phi_{jt} + \varepsilon_{ijt}$$

Y is one of the following variables: Markups, ROIC, Output (Sales/Invested Capital) or Investment which is measured by CAPEX/Invested Capital or R&D Expenses/Invested Capital. Star is a dummy variable that takes the value 1 if the firm i's ROIC is above the 90^{th} percentile of ROIC respectively across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. Imports is the value of Chinese Imports in each industry in the US scaled by initial absorption in that industry in 2005, instrumented by the value of Chinese imports in each industry in eight other developed countries scaled by initial absorption in that industry in 2000. Initial Industry Absorption is defined as Shipments + Imports Exports. Panel A shows results without interaction terms and panel B reports results including the interaction of Imports and past ROIC star status. Both the main effect of Imports and the interaction terms are instrumented in panel B. In panel A, we report the first stage F-statistic and in panel B we report the Weak ID test, which is the Stock-Yogo weak identification test with critical values: 10% maximal IV size=7.03 15%=4.58 20%=3.95 25%=3.63. All regressions are estimated using industry and year fixed effects and standard errors clustered at the industry level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A:

	(1)	(2)	(3)	(4)	(5)
	Markups	ROIC	Output	Investment	R&D
L.Log(Assets)	0.071***	4.050***	0.052***	0.003***	0.002**
	(0.020)	(0.347)	(0.014)	(0.001)	(0.001)
L.Log(Age)	0.000	-1.763*	-0.034	-0.013***	-0.019***
	(0.015)	(0.983)	(0.031)	(0.002)	(0.006)
L.Imports	-0.841**	-74.215**	-1.637**	0.061	0.041
	(0.351)	(32.801)	(0.814)	(0.067)	(0.093)
N	12576	12805	12666	12758	12777
Adj. R-sq	0.102	0.114	0.015	0.030	0.052
First Stage F-Test	56.96	56.33	56.62	56.03	56.62
Fixed Effects	——- Industry, Year ——				

Table 6: **Who are America's Stars? Role of Import Competition (Continued...)**

Panel B:

	(1)	(2)	(3)	(4)	(5)
	Markups	ROIC	Output	Investment	R&D
L.Log(Assets)	0.066***	3.418***	0.037***	0.003***	0.002**
	(0.020)	(0.271)	(0.012)	(0.001)	(0.001)
L.Log(Age)	0.018	0.946	0.016	-0.009***	-0.019***
	(0.019)	(0.887)	(0.033)	(0.002)	(0.005)
L.Imports	-0.528*	-78.062**	-1.323	0.092*	0.024
	(0.267)	(36.147)	(0.948)	(0.053)	(0.068)
L.Imports x L2.ROIC Star	0.070	-0.216	-0.670	-0.003	0.011
	(0.320)	(22.339)	(0.669)	(0.045)	(0.054)
L2. ROIC Star	0.222***	24.747***	0.463***	0.020***	0.002
	(0.049)	(2.322)	(0.094)	(0.005)	(0.011)
N	10403	10595	10486	10540	10570
adj. R-sq	0.123	0.238	0.037	0.038	0.048
Weak ID Test	17.037	16.939	16.966	17.006	16.962
Fixed Effects	——- Industry, Year ——				

Table 7: **Skill, Intangible Capital and Star Status: Measurement of Excess Cash**

This table reports estimates from the following panel regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times LogAssets_{ijt-1} + \beta_2 \times LogAge_{ijt} + \beta_3 \times ICAP/TotalAssets_{ijt-1} + \beta_4 \times Markups_{ijt-1} +$$
$$\beta_5 \times LogAssets_{ijt-1} \times ICAP/TotalAssets_{ijt-1} + \beta_6 \times Markups_{ijt-1} or ICAP/TotalAssets_{ijt-1} + \phi_{jt} + \varepsilon_{ijt}$$

Star is a dummy variable that takes the value 1 if the firm i's ROIC is above the 90^{th} percentile of ROIC respectively across all firms in a particular year and 0 otherwise. In columns 1-3, we use the firm's total cash holdings in computing ROIC, $ROIC^{CASH}$, in columns 4-6, we consider excess cash to be any cash over 1% of sales in computing ROIC, $ROIC^{1per}$ and in columns 7-9 we consider excess cash to be any cash over 10% of sales in computing ROIC, $ROIC^{10per}$. Log(Assets) is the logarithm of total assets and Log(Age) is the logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. ICAP/Total Assets is the ratio of intangible capital to total assets. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$ROIC^{CASH}$ Star	$ROIC^{CASH}$ Star	$ROIC^{1per}$Star	$ROIC^{1per}$ Star	$ROIC^{10per}$ Star	$ROIC^{10per}$ Star
L.Log(Assets)	0.011***	0.007***	0.008***	0.002*	0.007***	0.002*
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
L.Log(Age)	-0.053***	-0.053***	-0.066***	-0.065***	-0.068***	-0.067***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.ICAP/Assets	-0.024***	-0.001	-0.038***	-0.003	-0.042***	0.001
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
L.Markups	0.114***	0.140***	0.145***	0.187***	0.149***	0.192***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)
L.Log(Assets) x L.ICAP/Assets	-0.006***		-0.010***		-0.008***	
	(0.002)		(0.002)		(0.002)	
L.Markups x L.ICAP/Assets		-0.039***		-0.060***		-0.061***
		(0.005)		(0.005)		(0.005)
N	80599	80599	83786	83786	83941	83941
adj. R-sq	0.095	0.096	0.129	0.131	0.128	0.131
Fixed Effects	Industry x Year					

Table A1: **Summary Statistics**
This table reports the summary statistics of the key variables used in our analysis. All variable definitions are in the Appendix.

Variable	Obs	Mean	Std. Dev.	Min	Max
ROIC Star	83,120	0.1	0.285	0	1
ROIC	83,120	12.798	24.988	-129.511	150.069
Log(Assets)	83,120	5.578	1.975	-6.908	12.906
Log(Age)	83,120	2.746	0.700	1.386	4.205
HHI	81,804	0.093	0.082	0.028	0.596
Market Share	81,634	0.015	0.036	0.000	0.316
Markups	81,694	1.315	0.395	0.006	3.628
Markups_prodfn	78,225	1.221	0.278	0.204	2.627
ICAP/Assets	81,551	0.647	0.547	0.000	4.049
Industry-level Variables					
Skill (CPS)	254	0.003	0.441	-1.159	1.228
Skill (NRCOG)	254	-0.352	0.347	-1.321	0.628
Skill (RMAN)	254	0.219	0.430	-0.938	1.432
ImportsUSA	808	0.071	0.138	5.88E-05	0.92799
ImportsOTH	808	0.060	0.103	0.000208	0.809136

Table A2: **Variable Definitions**

Variables	*Definition*
Invested Capital$^{\text{unadj}}$	Invested Capital = PPENT + ACT + INTAN - LCT - GDWL - max(CHE-0.02 x SALE, 0) where PPENT is Net Property, Plant, and Equipment, ACT is Current Assets, INTAN is Total Intangible Assets, LCT is Current Liabilities, GDWL is Goodwill that represents the excess cost over equity of an acquired company, CHE is Cash and Short-term Investments, and SALE is net sales/turnover. This definition does not include the Peters and Taylor [2017] correction for intangible capital.
ROIC$^{\text{unadj}}$	(EBIT$_{\text{t}}$+AM$_{\text{t}}$)/Invested Capital$^{\text{unadj}}{}_{\text{t-1}}$ where EBIT is Earnings before Interest and Taxes and AM is Amortization of Intangibles. This definition does not include the Peters and Taylor [2017] correction for intangible capital.
ROIC Star$^{\text{unadj}}$	Dummy variable that takes the value 1 if the firms ROIC$^{\text{unadj}}$ is above the 90th percentile of ROIC$^{\text{unadj}}$ across all firms in the US economy in a particular year and 0 otherwise. This definition does not include the Peters and Taylor [2017] correction for intangible capital.
Invested Capital	Invested Capital = PPENT + ACT + ICAP - LCT - GDWL - max(CHE-0.02 x SALE, 0) where PPENT is Net Property, Plant, and Equipment, ACT is Current Assets. ICAP is defined as the sum of externally purchased intangible capital (INTAN) and internally purchased intangible capital, both measured at replacement cost. Internally purchased intangible capital is in turn measured as the sum of knowledge capital (K_int_know) and organization capital (K_int_org). LCT is Current Liabilities, GDWL is Goodwill that represents the excess cost over equity of an acquired company, CHE is Cash and Short-term Investments, and SALE is net sales/turnover.
ROIC	ROIC = (EBIT + AM + XRD + 0.3 x SGA - δ_{RD} x K_int_know - δ_{SGA} x K_int_org)/Invested Capital$_{\text{t-1}}$ where EBIT is Earnings before Interest and Taxes, AM is Amortization of Intangibles, XRD is Research and Development Expense, SGA is Selling, General, and Administrative Expense defined below, δ_{RD} is the depreciation rate associated with knowledge capital and is set to 15% following Peters and Taylor (2017) and δ_{SGA} is the depreciation rate associated with organization capital and is set to 20% following Falato, Kadyrzhanova, and Sim (2013) and Peters and Taylor (2017). K_int_know and K_int_org are the firms intangible capital replacement cost and organization capital replacement cost respectively from Peters and Taylor [2017]
SGA	SGA= XSGA-XRD-RDIP where XRD is Research and Development Expense, RDIP is in-process R&D expense, XSGA is Selling, General, and Administrative Expense. This definition of SGA follows Peters and Taylor [2017].
ROIC Star	Dummy variable that takes the value 1 if the firms ROIC is above the 90th percentile of ROIC across all firms in the US economy in a particular year and 0 otherwise.
OPEX*	Operating expenses adjusted for intangible capital given by $OPEX^* = OPEX - XRD - RDIP - 0.3 \times SGA$ where OPEX is Total Operating Expenses, XRD is Research and Development Expense, RDIP is in-process R&D expense, SGA is Selling, General, and Administrative Expense
Markups	Markups following the cost share approach = Sales/Variable Input where Operating Expenses* (OPEX*) is used as a variable input.
Markups_prodfn	Markups following the estimation in De Loecker and Eeckhout (2017) using Operating Expenses* (OPEX*) as a variable input.
COGS Markups	Markups following the estimation in De Loecker and Eeckhout (2017) using Cost of Goods Sold (COGS) as a variable input.

Table A2: **Variable Definitions**

Variables	***Definition***
Log(Assets)	Logarithm of total assets.
Log(Age)	Log(1+Firm Age) where Firm Age is the number of years the firm has appeared in Compustat.
Market share	Ratio of firm i's sales to total industry j's sales in a particular year.
HHI	Herfindahl-Hirschman Index defined as the sum of squares of the market shares of the firms within each 3-digit NAICS industry.
Output	Sales/Invested Capital.
Investment	Capital Expenditures/Invested Capital.
R&D	R&D Expenses/Invested Capital.
Tobin's Q	Q = V/TOTCAP where V is the market value of the firm defined as the market value of equity (=total number of common shares outstanding (Compustat item CSHO) times closing stock price at the end of the fiscal year (Compustat item PRCC_F) plus the book value of debt (Compustat items DLTT + DLC) minus the firms current assets (Compustat item ACT) which includes cash, inventory, and marketable securities. TOTCAP is sum of Property, Plant and Equipment (Compustat item PPENT) and Intangible Capital (ICAP). ICAP is defined as the sum of externally purchased intangible capital (INTAN) and internally purchased intangible capital, both measured at replacement cost. Internally purchased intangible capital is in turn measured as the sum of knowledge capital (K_int_know) and organization capital (K_int_org). Q is provided by Peters and Taylor [2017].
Skill(CPS)	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.Source: O*NET
Skill(NRCOG)	Mathematical Reasoning + Inductive Reasoning + Developing Objectives and Strategies + Making Decisions and Solving Problems. Source: O*NET
Skill(RMAN)	Spend time making repetitive motions + Pace Determined by Speed of Equipment + Manual Dexterity + Finger Dexterity. Source: O*NET
ImportsUSA	Total value of Chinese imports into the US in each 4-digit NAICS industry j scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ minus total exports, $E_{j,2005}$ in that industry in 2005. Source: US Census Bureau
ImportsOTH	Total value of Chinese imports into 8 other developed economies in each 4-digit NAICS industry j scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ minus total exports, $E_{j,2005}$ in that industry in 2005. Source: UN Comtrade Database

The Rise of Star Firms: Intangible Capital and Competition INTERNET APPENDIX

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1 Estimation of Market Power

In this section, we describe the production function approach used to estimate markups, which is different from the cost shares approach used in the paper. As discussed in De Loecker et al. [2018], both approaches have their own advantages and disadvantages and in this section we show that our results are robust to using the production function approach to using markups.

The standard derivation of markups follows De Loecker and Eeckhout [2017] where the markup is simply defined as the ratio of price for the output good over marginal cost:

$$Markup\_prodfn_{it} = \theta_{it} \times \frac{P_{it}Q_{it}}{P_{it}V_{it}} \tag{1}$$

where θ_{it} is output elasticity of the variable input, and $\frac{P_{it}Q_{it}}{P_{it}V_{it}}$ is the revenue share of the variable input (or simply $SALE/OPEX$).

As in Traina [2018] and De Loecker and Eeckhout [2017], we consider 3-digit NAICS industry-specific Cobb-Douglas production functions with variable inputs and capital. Thus, for a given industry (3-digit NAICS):

$$SALE_{it} = \beta_v \times v_{it} + \beta_k \times K_{it-1} + \omega_{it} + \epsilon_{it} \tag{2}$$

where $SALE_{it}$ is Log (sales deflated by GDP deflator) and K_{it-1} is Log(Capital Stock) and v_{it} is the variable input deflated by GDP deflator. There is a debate in the literature on what is the right measure of variable inputs and while De Loecker and Eeckhout [2017] use Cost of Goods Sold (Compustat *COGS*), Traina [2018] argues that *SGA* are increasingly a lion's share of variable costs for US firms (as also seen in Appendix Figure A6) and should be included in the calculation of marginal costs. Consistent with Traina [2018], we base our measure of variable inputs on Operating expenses (Compustat item *OPEX*) which includes SGA expenses whereas *COGS* only includes costs of production such as material, labor, and overhead and does not include SGA expenses. We make two additional modifications to the above. First, since we treat research expenditures as an intangible investment, and the Peters and Taylor [2017] adjustment treats a portion of the SGA as an organizational investment, our calculations of firm markups differs from that in Traina [2018]. Expenditures on R&D and the full amount of the SGA are included in OPEX and treated as variable costs. However, our measure of the firm's capital stock includes both tangible and intangible capital. This, in turn implies that intangible investments such as R&D and a portion of

SGA are subtracted from OPEX in order to obtain our measure of variable costs, *OPEX**. Thus we use *OPEX** as our measure of variable input where

$$OPEX^{*} = OPEX - XRD - RDIP - 0.3 \times SGA \tag{3}$$

Second, we re-define K to include intangible capital as $Log(CapitalStock + ICAP_{it})$ where $ICAP_{it}$, is the sum of externally and internally purchased intangible capital defined in section **??**.

We use the perpetual inventory method to construct measures of capital stock. We first initialize the capital stock using the first available entry of gross PPE and then iterate forward on capital using the accumulation equation:

$$K_{it} = K_{it-1} + \Delta I_{it} \tag{4}$$

where ΔI_{it} is net investment computed using changes to PPENT and deflated by the investment goods deflator.[1] The coefficient β_v represents the output elasticity of the variable input OPEX. ω_{it} is Log Productivity which is assumed to follow an AR(1) process $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$. The parameter ξ_{it} is the innovation to the firm's productivity process.

To estimate the above, we follow the literature and adopt a control function approach to address endogeneity concerns due to the potential simultaneity between unobserved productivity shocks and the demand for inputs. If the demand for an input increases with productivity shocks, that input's demand function can be inverted and the unobserved productivity shocks can be derived as a function of observables.

We first estimate equation (2) using firm and year fixed effects following Traina [2018] and obtain sales estimates which are used to derive implied productivity ω_{it} as a function of elasticity parameters β. This function is projected onto its lag which is then used to recover the innovations in the productivity process ξ_{it}, again as a function of industry-specific output elasticities, β. Under the assumption that the variable input use responds to productivity shock but its lagged values do not, the elasticity parameters β can be obtained using a standard GMM procedure from the following moment conditions:

$$\mathrm{E}\begin{bmatrix} \xi_{it}(\beta) & OPEX^{*}_{it-1} \\ & K_{it-1} \end{bmatrix} = 0 \tag{5}$$

Finally, based on these output elasticity estimates, we re-write the equation for markups as

$$Markup\_prodfn_{it} = \beta_v \times \frac{SALE_{it}}{OPEX^{*}_{it}} \tag{6}$$

where the β_v are the output elasticities at the industry level and $\frac{SALE_{it}}{OPEX^{*}_{it}}$ are varying at the firm level. Following De Loecker and Warzynski [2012], we correct the markup estimates for measurement error in sales obtained in the first stage.

We begin by comparing markups generated using different measures of marginal costs - *COGS* as in De Loecker and Eeckhout [2017], *OPEX* as in Traina [2018], and our own measure of operating expenses adjusted for investments in intangible capital following Peters and Taylor [2017], *OPEX**. In Figure A7 of the Internet Appendix, we plot the sales-weighted average markups each year estimated using these three measures as variable inputs. We plot the markups over the period 1950-2015 for comparison to the evidence in De Loecker and Eeckhout [2017] and Traina [2018].

[1] GDP deflator is given by line 1 of NIPA Table 1.1.9 and the Non-residential fixed investment good deflator is given by line 9 of Table 1.1.9.

The figure confirms that the rise in markups exists only when we define variable costs in terms of $COGS$ rather than $OPEX$. The rise in $COGS$ markups in the figure mimics the rise in markups shown in De Loecker and Eeckhout [2017]. Our magnitudes are smaller because unlike in their paper, we do not include financials, real estate, and utilities in our sample and also drop foreign incorporated firms. The rise in COGS markups are even higher with the inclusion of these other sectors and foreign incorporated firms. However, importantly the figure also shows that once we correct the definition of $OPEX$ for intangible capital and use $OPEX^*$ as an input, we get a similar rise in markups.

In Table A3 of the Appendix, we show that using the above production function approach to estimate Markups, $Markups\_prodfn$ yields a similar association between these markups and star status as using the cost shares approach.

Figure A1: **Differences in Human Capital-Robustness**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital (ROIC) in each year in low and high complex problem solving skill (CPS), and low and high cognitive skilled (NRCOG) manufacturing industries.

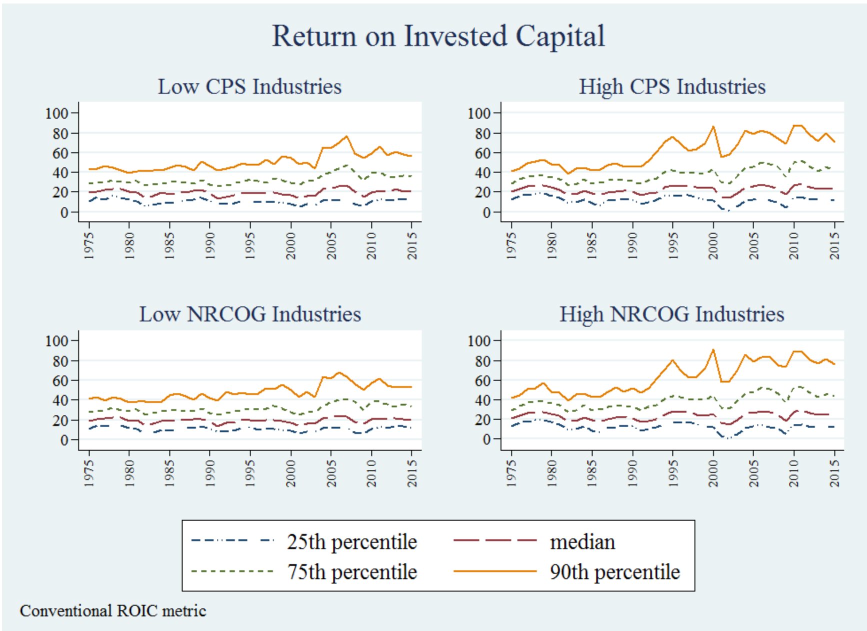


Figure A2: **Rise in Star Firms - Large Firm Sample**

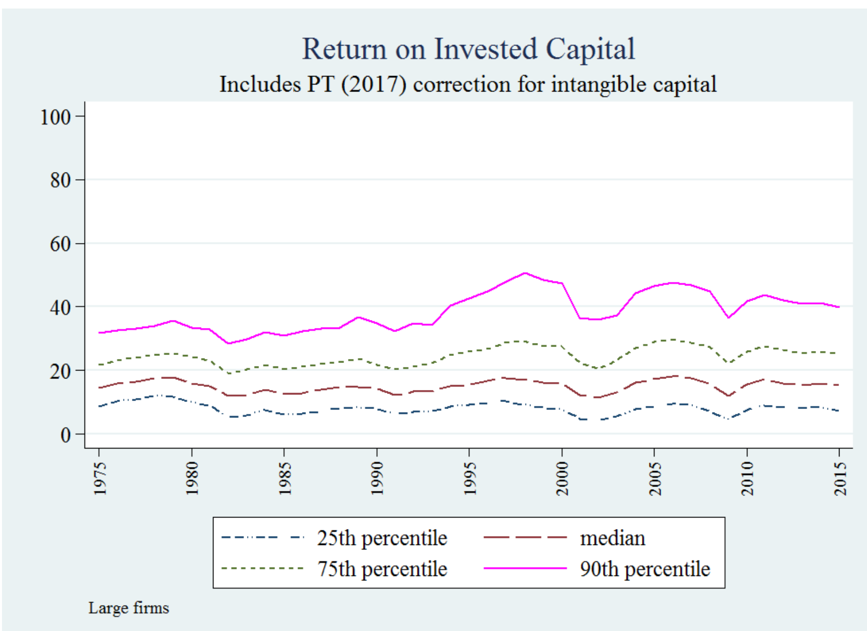


Figure A3: **Rise in Star Firms - Without excluding goodwill**

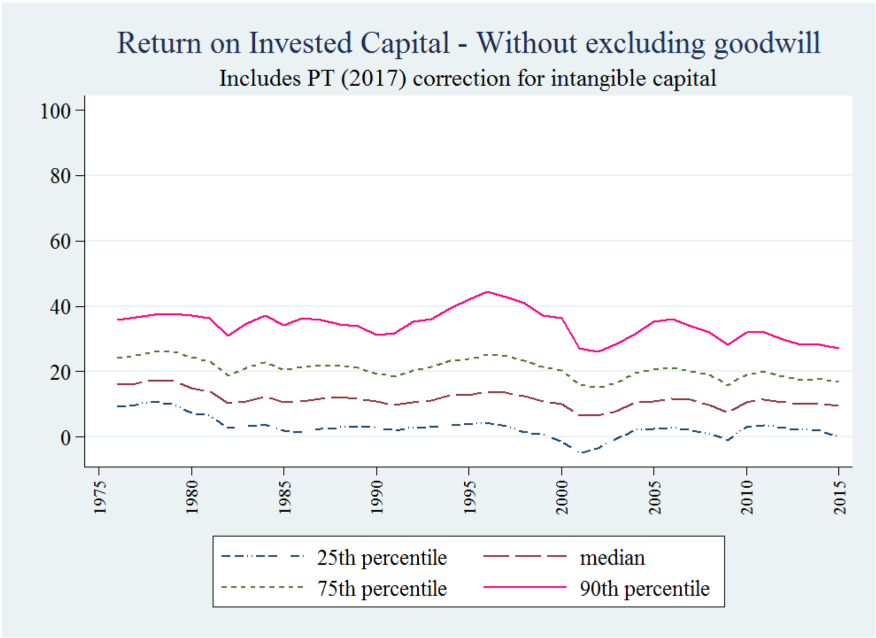


Figure A4: *ROIC* **of Top 100 and Top 150 firms**

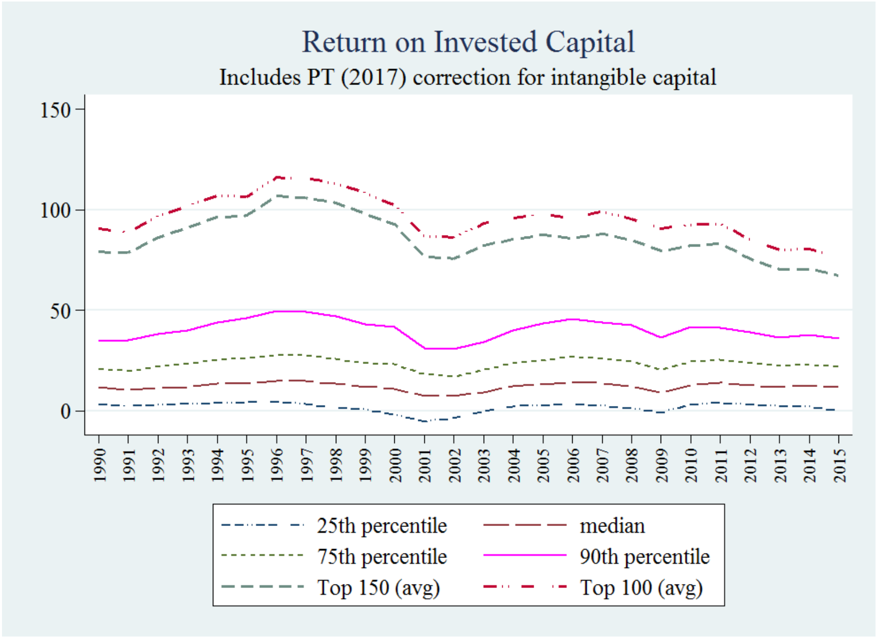


Figure A5: **Differences in Human Capital-Robustness**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of Return on Invested Capital ($ROIC$) in each year in low and high complex problem solving skill (CPS), and low and high cognitive skilled (NRCOG) manufacturing industries. $ROIC$ includes the adjustment for intangible capital. Detailed variable definitions are in the Appendix.

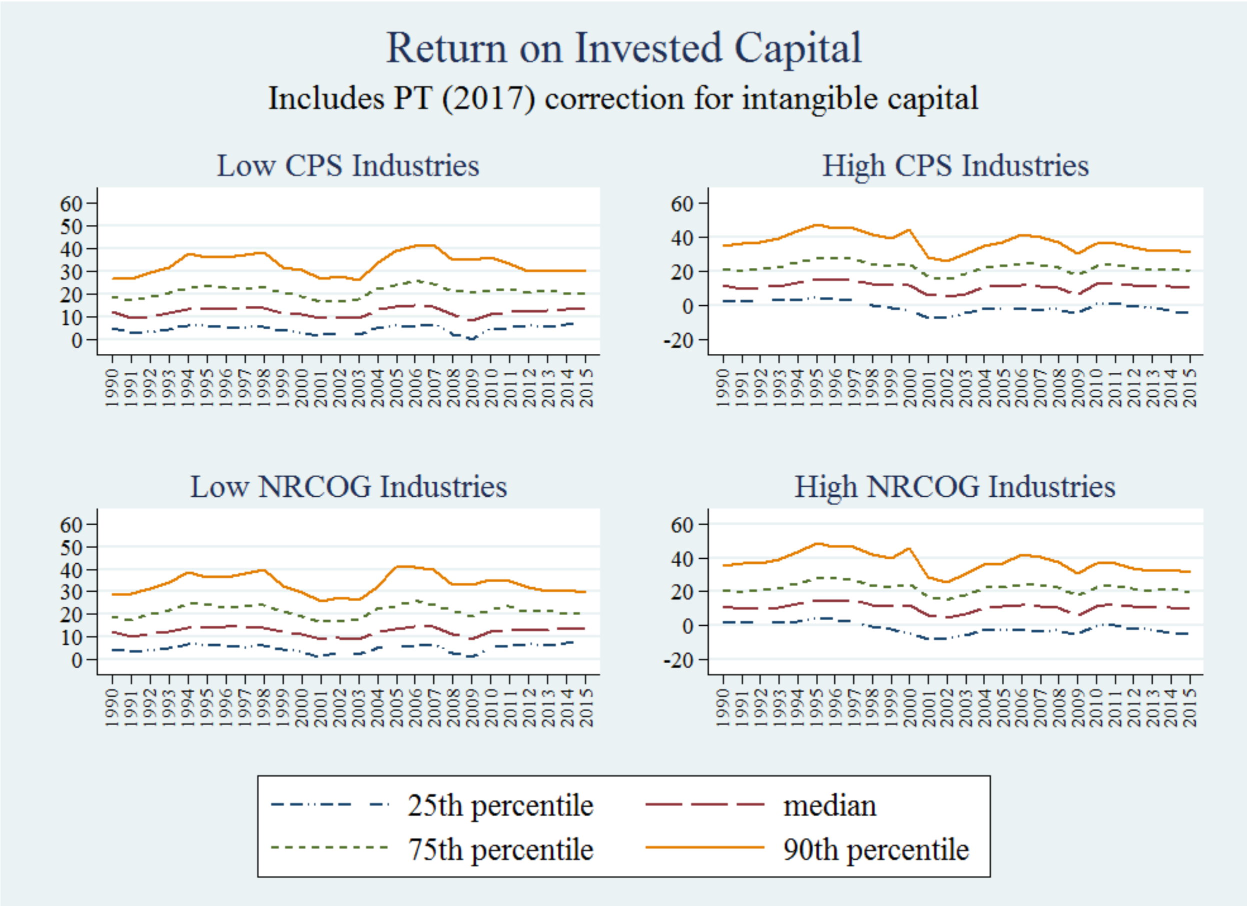


Figure A6: **COGS are a declining share of firm variable costs**

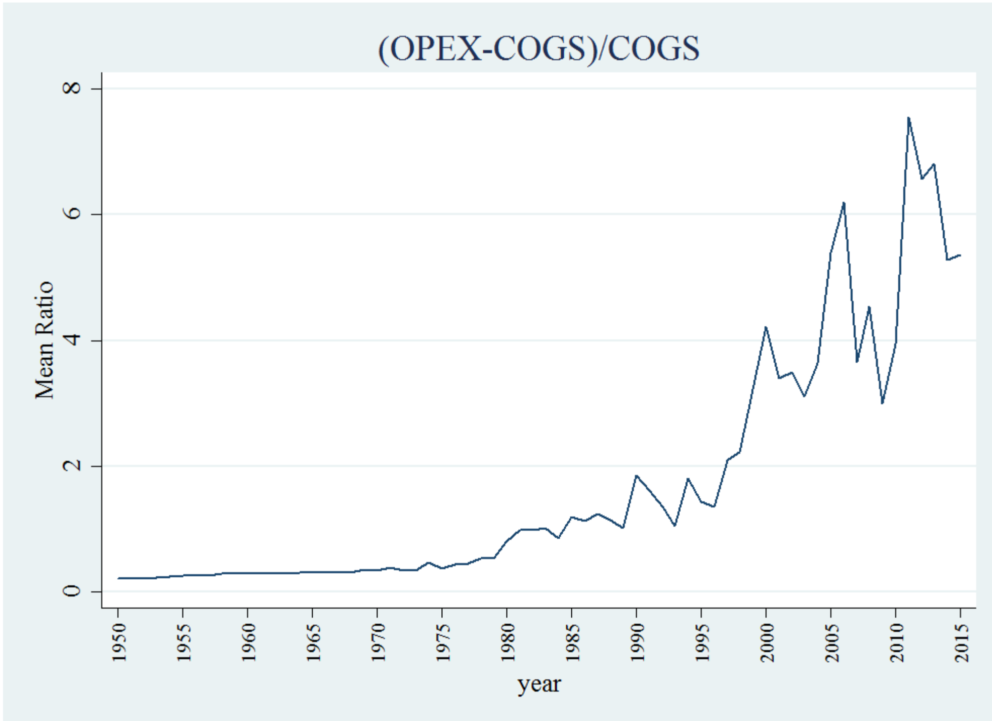


Figure A7: **Markups based on different variable inputs**
This figure plots the sales weighted average markups in each year across all public firms in the US economy. Markups are defined as Sales/Variable Cost where we use three different measures of variable cost - Cost of Goods Sold, Operating Expenses, Operating Expenses with intangible capital adjustments. Detailed variable definitions are in the Appendix.

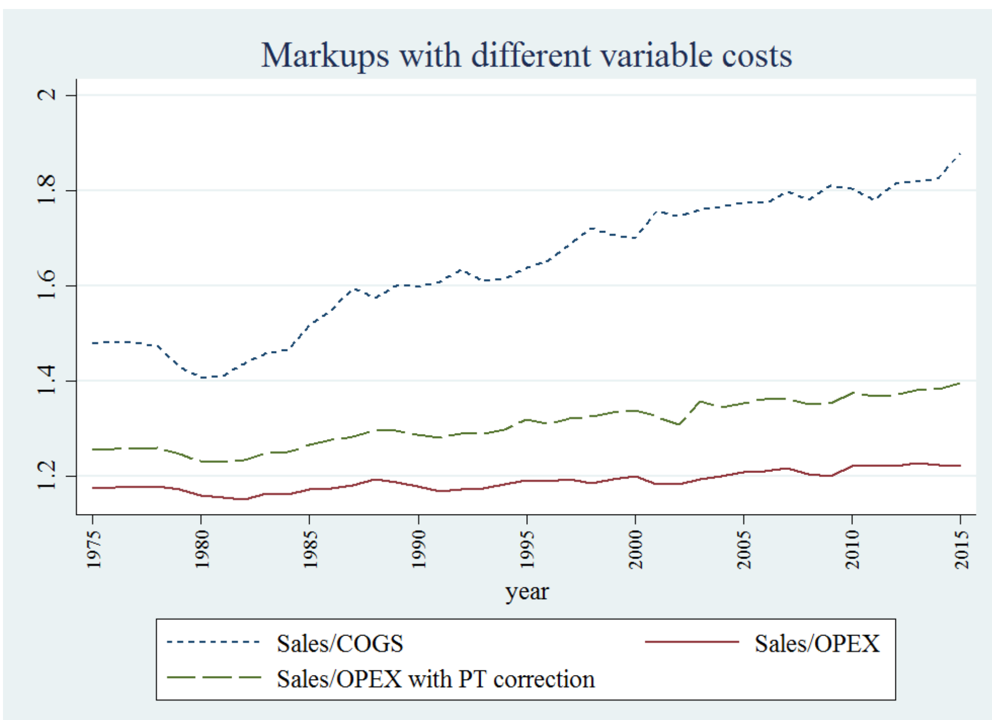
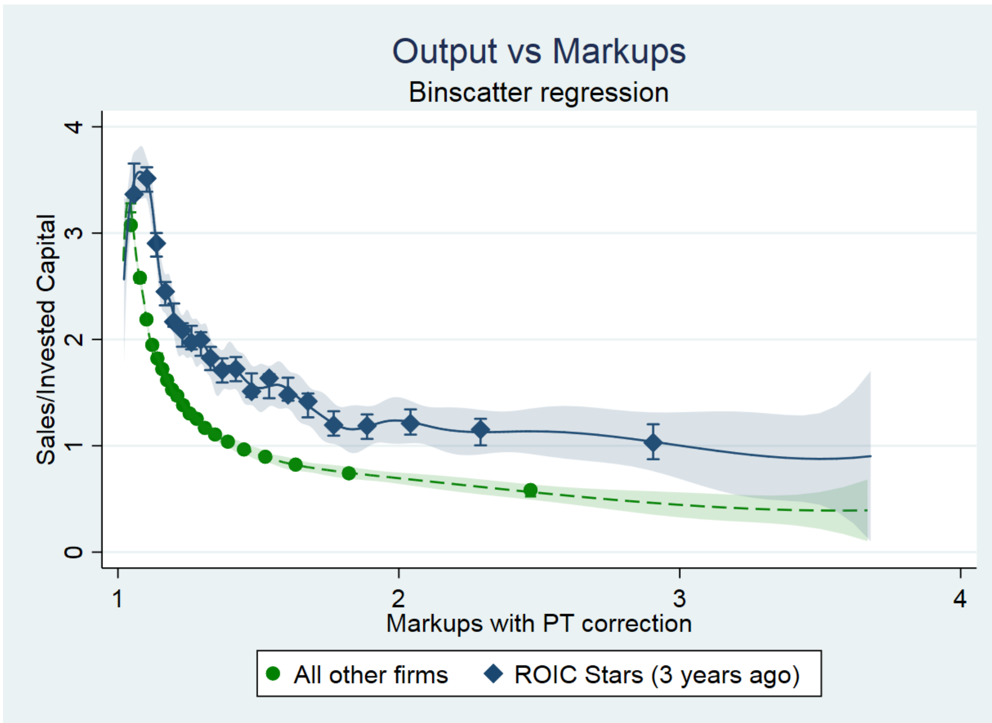


Figure A8: **Output vs Markups - Robustness of Figure 11 in the paper**
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Sales/Invested Capital on *Markups* for *ROIC* stars and all other firms. The first figure defines Stars three years ago and the second figure defines stars 5 years ago.



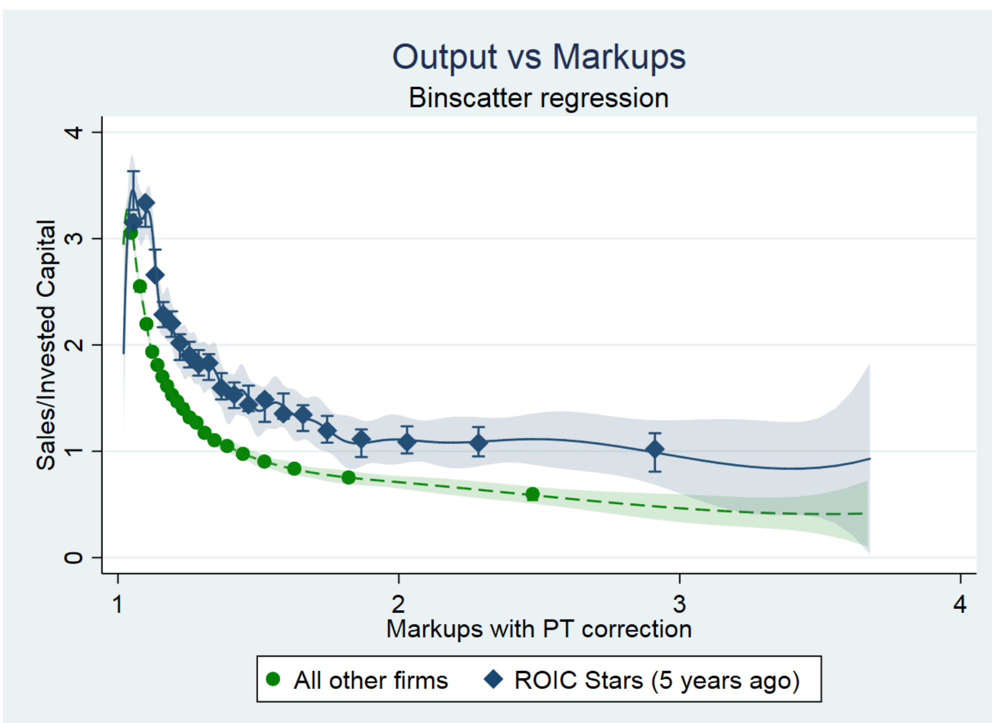


Figure A9: **Output vs Markups - Q stars vs other firms**
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Sales/Invested Capital on $Markups$ for Q stars and all other firms.

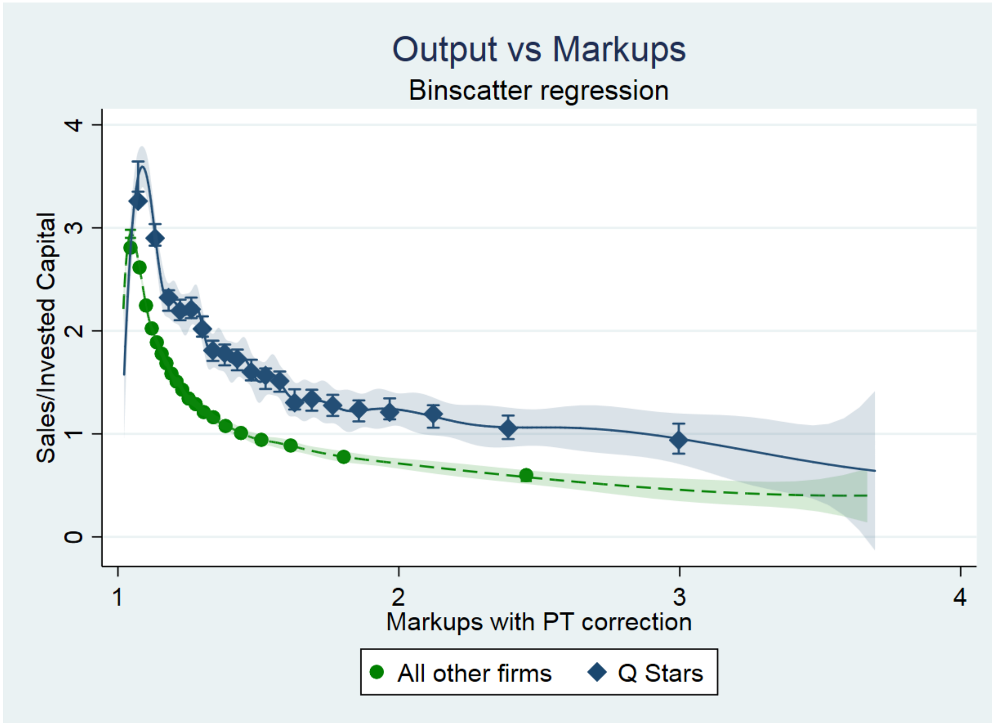


Figure A10: **Markups (Production Function) of Elite Firms (Apple, Facebook, Amazon, Microsoft, Google)**
This figure plots the 90^{th} percentile of $Markups$ in each year across all public firms in the US economy as well as the $Markups$ for five firms referred to as superstars anecdotally. $Markups$ are computed using the production function approach and use operating expenses with intangible capital adjustments as a measure of variable cost. Detailed variable definitions are in the Appendix.

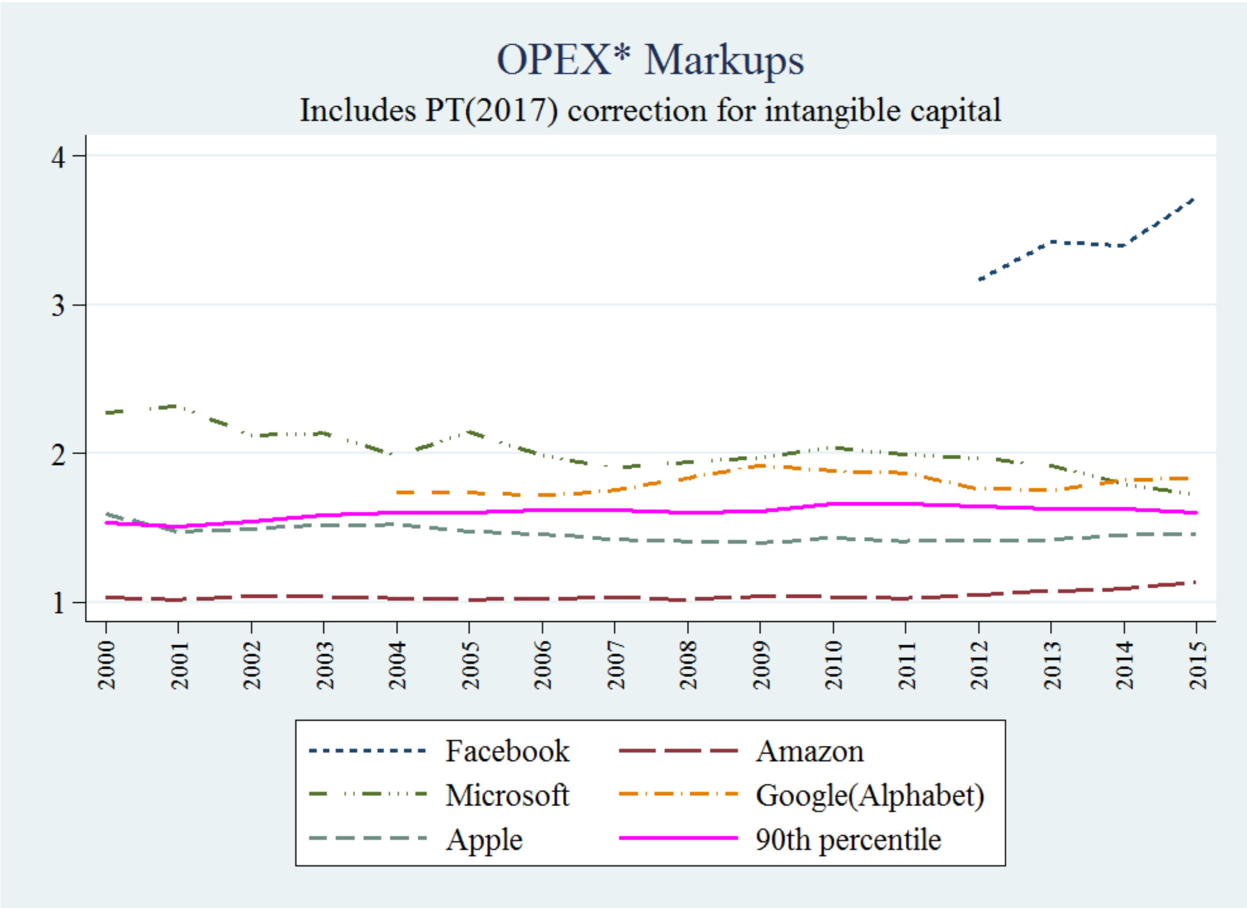


Figure A11: **Measurement of Excess Cash - Robustness**
This figure plots the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of alternate definitions of $ROIC$ in each year across all public firms in the US economy. The alternate definitions correspond to using cash above 1% of sales, 5% of sales, 10% of sales, and 20% of sales respectively as excess cash rather than the 2% of sales used in the rest of the paper. $ROIC$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

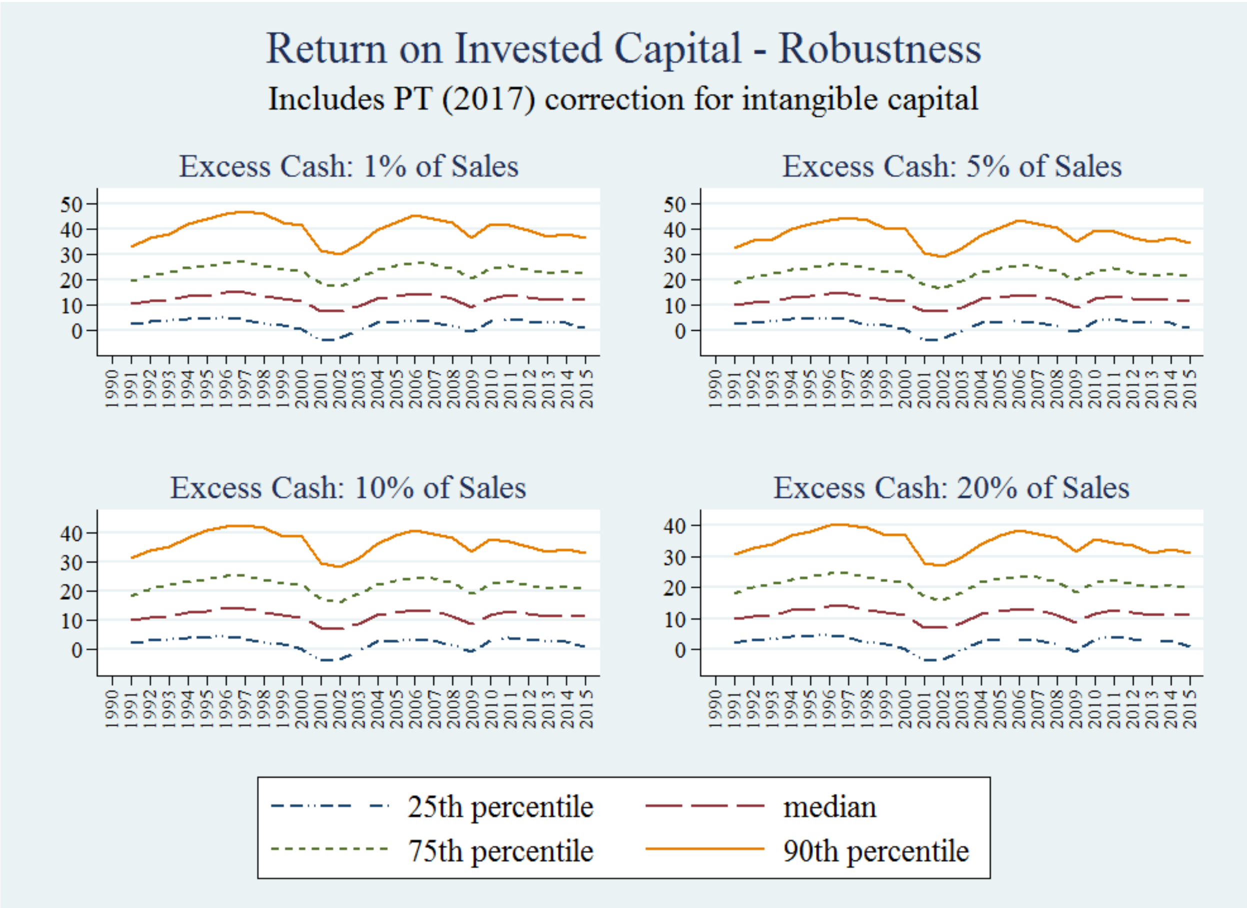


Table A1: **Are Star Firms Persistent Performers? Robustness using Q**

This table reports estimates from the following panel regression model:

$$Performance_{ijt} = \alpha_0 + \beta_1 \times LogAssets_{ijt-5} + \beta_2 \times LogAge_{ijt-5} + \beta_3 \times QStar_{ijt-5} + \beta_4 \times Q_{ijt-5} + \phi_{jt} + \varepsilon_{ijt}$$

Performance is Sales growth/Employment growth/Growth in Intangible Capital (each defined as the 5-year log difference in sales or employment respectively divided by 5), Labor Productivity, Tobin's Q (Q) or $ROIC$ averaged over 5 years. Log(Assets) is the 5-year lagged value of the logarithm of total assets. Log(Age) is the 5-year lagged value of the firm age. $Markups$ is the 5-year lagged value of Markups computed using operating expenses as a variable input of production and includes correction for intangible capital. Q Star is a dummy variable that takes the value 1 if firm i's 5-year lagged Q was above the 90th percentile of Tobin's Q respectively across all firms 5 years back and 0 otherwise. The regressions are 5-year stacked panel regressions: 1990-1995, 1995-2000, 2000-2005, 2005-2010, and 2010-2015 and include industry x year fixed effects with standard errors clustered at the firm level. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobins Q	Tobins Q	Sales Growth	Sales Growth	Emp Growth	Emp Growth	Labor Productivity	Labor Productivity
Lassets_5yrago	0.069***	0.019***	-0.004***	-0.005***	-0.003***	-0.005***	38.308***	37.515***
	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(2.023)	(2.044)
Lage_5yrago	-0.117***	0.006	-0.027***	-0.023***	-0.022***	-0.018***	-40.377***	-38.572***
	(0.012)	(0.009)	(0.002)	(0.002)	(0.002)	(0.002)	(4.470)	(4.497)
L5. Q Star	2.417***		0.076***		0.070***		40.294***	
	(0.051)		(0.006)		(0.005)		(9.047)	
L5. Tobins Q		0.581***		0.019***		0.018***		9.245***
		(0.010)		(0.001)		(0.001)		(1.890)
_cons	0.683***	0.203***	0.160***	0.143***	0.102***	0.086***	211.520***	204.443***
	(0.035)	(0.027)	(0.007)	(0.007)	(0.006)	(0.006)	(12.588)	(12.665)
N	17282	17282	11289	11289	10986	10986	16933	16933
Adj. R-sq	0.451	0.665	0.098	0.113	0.089	0.105	0.395	0.396
Fixed Effects	— Industry x Year —							

Table A2: **Who are America's Stars? Correcting for intangible capital - Firm Fixed Effects**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star	ROIC Star
Sample	Full	Full	Full	Full	Full	Manuf	Large
L.Log(Assets)	-0.022***	-0.022***	-0.023***	-0.029***	-0.031***	-0.028***	-0.055***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
L.Log(Age)	-0.139***	-0.139***	-0.140***	-0.139***	-0.139***	-0.140***	-0.134***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)
L.HHI		-0.074			-0.078*	-0.183	-0.039
		(0.045)			(0.047)	(0.122)	(0.059)
L.Market Share			0.215*		0.306***	0.225	0.544***
			(0.115)		(0.117)	(0.219)	(0.127)
L.Markups				0.108***	0.106***	0.101***	0.127***
				(0.007)	(0.007)	(0.009)	(0.011)
N	82145	80778	80655	80673	78584	40830	44200
Adj. R-sq	0.377	0.380	0.377	0.386	0.387	0.309	0.437
Fixed Effects	— ——— Firm, Year ———-—						

Table A3: **Who are America's Stars? Correcting for intangible capital - Robustness**

	(1)	(2)	(3)	(4)	(5)
	Q Star	ROIC	Tobins Q	ROIC Star	Q Star
Sample	Full	Full	Full	Full	Full
L.Log(Assets)	-0.004***	2.609***	0.041***	0.012***	-0.002*
	(0.001)	(0.116)	(0.008)	(0.001)	(0.001)
L.Log(Age)	-0.059***	-3.672***	-0.414***	-0.058***	-0.052***
	(0.003)	(0.231)	(0.016)	(0.003)	(0.003)
L.Market Share	0.417***	8.748	1.938***	0.173*	0.342***
	(0.089)	(5.637)	(0.468)	(0.090)	(0.087)
L.Markups	0.099***	24.429***	0.662***		
	(0.008)	(0.632)	(0.041)		
L.Markups_prodfn				0.165***	0.165***
				(0.011)	(0.012)
N	77796	80615	77796	73370	71060
Adj. R-sq	0.068	0.283	0.136	0.097	0.067
Fixed Effects	Industry x Year				

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