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Who are America's Star Firms?

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Abstract

There is wide spread concern about a growing gap between top-performing publicly listed firms and the rest of the economy and the implications of this for rising inequality in the U.S. Using conventional return calculations, there is indeed a widening gap between star firms (defined as those in top 10 percent of return on invested capital in any year) and the rest of the economy over time, especially in industries that rely on a skilled labor force. However, once measurement error in intangible capital is accounted for, this gap shrinks dramatically and has not been widening over time. While pricing power, as measured by markups, predicts star firm status, a large fraction of star firms have low markups and there is no evidence that star firms are cutting output or investment more than other firms for the same markup. The effect of star status is persistent. Five years later, star firms have higher growth, profits, and Tobin's Q. A small subset of exceptional firms may pose more pressing policy concerns with much higher returns and the potential to exercise market power in the future.

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Who are America's Star Firms?

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Introduction

A great deal of attention has been paid to two trends: (1) the emergence of star firms that have pulled away from the rest of the economy (Furman and Orszag [2015], Koller, Goedhart, and Wessels [2017], Autor, Dorn, Katz, Patterson, and Van Reenen [2017]) and (2) introduction of new technologies together 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 we have little systematic evidence on the characteristics of the star firms. Questions of interest include: In which industries star firms occur, how long they retain their star status, and if these two trends are related - that is, is the rise of star firms related to the increased dependence on intangible capital?

Determining whether the performance gap between star firms and other firms is the result of luck, market imperfections, or a reflection of successful idiosyncratic firm growth strategies[2] is a public policy priority that will shape policies that promote or regulate high-value firms. The dominant concern is that these firms are gaining their distinction through market power, and relatedly, research has shown an apparent marked increase in concentration in U.S. industries in the last two decades (Gutiérrez and Philippon [2017] and in markups and market power (De Loecker and Eeckhout [2017]; Barkai [2016]).[3] Autor et al. [2017] link concentrated winner-take-all markets with the fall in the labor share in the US economy as an explanation for the rise of star firms. Baker and Salop [2015] directly link a decline in the enforcement of anti-trust statutes to increases in concentration and rising inequality in the U.S.. Grullon, Larkin, and Michaely [2017] and Gutiérrez and Philippon [2017] argue that increased market power may be responsible for a combination of high profits and low investment. There is also concern that star firms may be creating systemic problems and disruptions through the economy. For instance, Van Reenen and Patterson [2017] suggest that the rise of star firms will lead to a fall in economic dynamism and productivity with declining pay and job opportunities for the average worker.

[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]) and other macroeconomic impacts (e.g. Atkeson and Kehoe [2005], McGrattan and Prescott [2010], Eisfeldt and Papanikolaou [2014] and Perez-Orive, Caggese, et al. [2017]).

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

[3] For a strong dissenting view arguing that the observed changes in concentration computed at the national level are economically immaterial, see Shapiro [2018].

In this paper, use a dataset of publicly listed firms in the United States from the Compustat database to identify star firms and the industries in which these firms are more likely to appear in. We examine the role of intangible capital, competition (Herfindahl-Hirschman industry concentration index), and market power in influencing star firm status. 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.[4] Finally, we examine the persistence of the star firms' performance and whether they differ in their investment and output per unit of capital compared to other firms in the economy.

Following Furman and Orszag [2015], we define star firms as firms in the top 10% of Return on Invested Capital (ROIC) in the US in a particular year.[5] Using conventional ROIC measures, in Figure 1, we find that there has indeed been a run-up in the ROIC of the top decile of large, non-financial sector, publicly-listed U.S. firms.[6] Over the period 1965-2015, the ratio of the 90th percentile ROIC firm to the median ROIC firm has increased by over 69%. Importantly, we find that the star firms whose returns are diverging from the rest of the firms are in industries that require high cognitive skills and that in these industries average returns are higher. In industries where the tasks involve routine manual skills and which score low on non-routine cognitive and complex problem solving skills, we see lower returns and don't see the star firms pulling away from the rest.

However, conventional return metrics do not capitalize research and development, brand capital, or other forms of organizational capital. The consequences of not measuring intangible capital are far-reaching because they affect measures of firms' earnings, identification of variable costs, capital investment and estimates of pricing power, outcomes which are subject to controversy. While De Loecker and Eeckhout [2017] show that there is a dramatic rise in firm market power in the

[4] Our implementation of operating markups, which follow the work of De Loecker and Eeckhout [2017] and Traina [2018] is discussed below.

[5] 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).

[6] We restrict our sample to large firms (defined as firms with assets more than $200 Million in 2009 dollars, adjusted for inflation) to replicate the equivalent figure in the previous studies. However, 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.

US 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, there is no rise in markups. To address these issues, we adjust the conventional ROIC measures, measures of capital stock, as well as variable costs and measures of pricing power from De Loecker and Eeckhout [2017] and Traina [2018] to take into account investment in intangible capital.

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. Thus, the differences that we found earlier in firm differentiation between industries are likely attributable, in great part, to not accounting for intangible capital consistently. Industries that rely heavily on complex cognitive skills are likely to have higher amounts of intellectual and organizational capital, which is not measured by ROIC prepared according to generally accepted accounting principles.

Next, we show that once we adjust the markups based on operating expenses for intangible capital, there is indeed a rise in markups over time. We also find that markups are positively related to high profits and greater probability of being a star, especially in industries that rely on low routine manual skills. In the overall sample, higher profits and restrictions of output are positively related to pricing power. However, ROIC stars have higher Output (sales/invested capital) Capex, and R&D investment compared to other firms. In addition, a large fraction of star firms have relatively low markups. We find no evidence that star firms are cutting output or any type of investment compared to other firms, even at high levels of markups.

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 year 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 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. We find that large firms and firms with high markups in industries with high complex problem and analytical skills are more likely to be stars using this alternative definition.

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.[7] 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. All our results hold with these alternative definitions.

A policy implication of our analysis is that while high pricing power is associated with high profits and star firm status, we also see that star firms are not cutting output less than other firms with same markups, and that a significant proportion of star firms do not have high markups. There is also little evidence that extraordinary returns are being realized as a result of high industry concentration or high market share. 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 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, their markups are not necessarily much larger than those of the 90th percentile firm over the sample period. As we discuss 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.

[7] 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.

Our paper contributes to the recent literature on star firms. Several researchers have used alternative definitions of star firms, and have focused on the consequences of the rise in industry concentration. Autor et al. [2017] use a definition of star firms based on productivity and market share and argue that star firms contribute to inequality within the US because they are more profitable and have lower wage to sales ratios, despite paying higher unit wages. Hall [2018] studies mega firms, defined as firms with more than 10,000 workers and finds no evidence that industries with high proportion of these firms have high markups but does find that markups increase in sectors with rising share of mega firms.[8] In contrast to these papers, we use a market based measure of returns on invested capital to characterize star firms, which is also the definition that studies highlighting the emergence of star firms have focused on such as Furman and Orszag [2015], Koller et al. [2017], Council of Economic Advisors [2016].

Our paper is also related to the growing literature on the rise in concentration and markups. Grullon et al. [2017] find that firms in industries that are more concentrated enjoy higher profit margins and positive abnormal stock returns. They proxy price-cost margins by the Lerner Index (operating income after depreciation scaled by total sales) and returns by Return on Assets (ROA) and make no adjustments for intangible capital in their calculations. The focus in their paper is also on increase in industry concentration over time rather than on identifying characteristics of star firms. Barkai [2016] shows that the profit share of the US non-financial corporate sector has increased drastically over the past three decades, enough to offset the decline in both labor and capital shares. Kurz [2017] argues that modern developments in information technology have created higher barriers to entry leading to a rise in market concentration and increasing monopoly power of firms. Gutiérrez and Philippon [2017] link the decline in competition to the decrease in corporate investment. Alexander and Eberly [2018] and Crouzet and Eberly [2018] argue that the rise in intangible investment in retail trade can account for the increase in concentration and decreased investment. By contrast, the focus in our paper is on the characteristics of star firms and providing a link to the rise of intangible capital, increases in market power and industry

[8] There is also an international literature where researchers have looked at export markets or labor productivity to document the rise in market power. De Loecker et al. [2016] examine the effect of tariff reductions on competition and markups. Freund and Pierola [2015] show that much of the exports of many countries can be attributed to a small number of firms which they refer to as export superstars. Andrews et al. [2015] highlight the notion of frontier firms, a small number of firms that are much more efficient than the bulk of their competitors. None of these papers look at returns or the role played by intangible capital.

concentration. We find little evidence for the hypothesis that these firms are restricting investment.

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. [2017] 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 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 also provide breakdowns of our results by high-technology and other industries.

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:

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

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], amongst 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:

$$\begin{aligned} Invested\,Capital_{it} = PPENT_{it} + ACT_{it} + INTAN_{it} - LCT_{it} - GDWL_{it} \\ - max(CHE - 0.02 \times SALE, 0) \end{aligned} \tag{2}$$

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 does not include internal intangible assets like R&D and SG&A. We exclude Goodwill, which are the intangible assets arising out of M&A transactions when

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

one company acquires another for a premium, in the computation of invested capital in equation 2 so that our measure is not distorted by price premiums paid for by acquisitions, allowing for an even comparison of operating performance across companies. Thus, ROIC measures the return that an investment generates for the providers of capital and reflects management's ability to turn capital into profits. In calculating ROIC we 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 but in section 4.2 we undertake robustness tests allowing for varying percentages. Thus, our principal 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 star* as a dummy variable that takes the value 1 if the firm's ROIC is above the 90th 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 and drop firms with negative invested capital. As noted before, Figure 1 shows that there is a large rise in capital returns over the past three decades where the ratio of the 90th percentile ROIC firm to the median ROIC firm has increased by over 69%. We also see that the divergence of the top decile of firms from the rest of the economy really takes off in the 1990s.[10] 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.

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],

[10] In an early version of the paper, we find much higher increases in ROIC (over 190%) for the 90th percentile without the sample restrictions to large firms and firms with positive invested capital.

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, 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 to the Occupational Employment Statistics (OES), a US establishment level dataset 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 an industry-level skill score. We currently use these scores for manufacturing industries.

We separate the manufacturing sample into high and low skill 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, high CPS, and high NRCOG. 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 which reduces total invested capital, thereby inflating ROIC numbers. There is also a large divergence between the ROIC realized by the median cognitively skilled firm (low RMAN) and the median high RMAN firm.

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], Grabowksi and Mueller [1978], 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], $ICAP_{it}$.

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

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.[11]

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:

$$ROIC_{it} = \frac{ADJPR_{it}}{Invested\,Capital^{TOT}_{it-1}} \tag{4}$$

where

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

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].

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 is 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 $PPEGT$)[12]

[11] 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.

[12] 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.

and top and bottom 1% outliers in $ROIC^{TOT}$, we define $ROIC^{TOT}Star$ as a dummy variable that takes the value 1 if the firm's $ROIC^{TOT}$ is above the 90th percentile of $ROIC^{TOT}$ 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 $ROIC^{TOT}$ for the top 10% of firms in Figure 3.[13]

In Figure 4, we present estimates for high skilled versus low skilled industries. The run-up we saw in Figure 2 in high skilled industries disappears once we adjust for intangible capital. In section 4 of the paper, we discuss various robustness tests and alternate definitions of intangible capital to address concerns with the definition of cash holdings. We are agnostic on how to treat the firm's cash holdings. For much of the analysis we adopt the practitioner view and subtract cash positions in excess of 2% of revenue from the firm's invested capital. In section 4.2 we consider alternative treatments of cash and note the outcomes.

2 Estimating Concentration and Market Power

As a measure of competition, we define 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 is 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

[13] As shown in Appendix figure A1, we obtain a similar picture when we restrict the sample to large firms, and extend the time period to 1965 to be consistent with the sample in Figure 1

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 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 (as measured by Cost of Goods Sold) in 1980 to 67% above marginal cost by 2014.

To estimate markups, we rely on the framework by De Loecker and Warzynski [2012] and De Loecker and Eeckhout [2017] that is based on 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. 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 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.

Recent work by Traina [2018] 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 A2 of the Appendix. We differ from Traina [2018] in our adjustment of operating expenses to include the correction for intangible capital.

The derivation of markups follows De Loecker and Eeckhout [2017] and Traina [2018] where the markup is simply defined as the ratio of price for the output good over marginal cost:

$$Markup_{it} = \theta_{it} \times \frac{P_{it}Q_{it}}{P_{it}V_{it}} \tag{7}$$

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*). To estimate this, we consider 3-digit NAICS industry-specific Cobb-Douglas production functions with variable inputs and capital.[14] Thus, for a given industry (3-digit NAICS):

$$SALE_{it} = \beta_v \times OPEX_{it} + \beta_k \times K_{it-1} + \omega_{it} + \epsilon_{it} \tag{8}$$

where $SALE_{it}$ is Log (sales deflated by GDP deflator), *OPEX* is the variable input and is measured as Log(Operating Expenses deflated by GDP deflator), K_{it-1} is Log(Capital Stock), and 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. 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:

$$K_{it} = K_{it-1} + \Delta I_{it} \tag{9}$$

where ΔI_{it} is net investment computed using changes to PPENT and deflated by the investment goods deflator.[15] The coefficient β_v represents the output elasticity of the variable input OPEX.

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. In the first stage, we remove idiosyncratic errors from the production

[14] In our current implementation we do not apply the Olley and Pakes [1996] correction. The effect of that correction is somewhat controversial, as discussed by Ackerberg et al. [2015], Ackerberg [2016], Gandhi et al. [2017], and Frank and Yang and footnote 12 in De Loecker and Eeckhout [2017]. As shown by Yasar et al. [2008], the correction is small on this data set. All our results are materially the same if we were to apply the correction

[15] 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.

process by estimating the following regression:

$$SALE_{it} = \beta_v \times OPEX_{it} + \beta_k \times K_{it-1} + \alpha_i + \gamma_t + \epsilon_{it} \tag{10}$$

where α_i are firm fixed effects and γ_t are year fixed effects. From this we 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:

$$\mathrm{E}\begin{bmatrix} \xi_{it}(\beta) & OPEX_{it-1} \\ & K_{it-1} \end{bmatrix} = 0 \tag{11}$$

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

$$Markup_{it} = \beta_v \times \frac{SALE_{it}}{OPEX_{it}} \tag{12}$$

where the β_v are 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 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 replace OPEX in the above equations with OPEX* where

$$OPEX^* = OPEX - XRD - RDIP - 0.3 \times SGA \tag{13}$$

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 1.2. With these adjustments, we re-estimate markups to be:

$$Markup_{it}^{TOT} = \beta_v^* \times \frac{SALE_{it}}{OPEX_{it}^*} \tag{14}$$

where β_v^* are the output elasticities estimated using OPEX* as the variable input and $Log(CapitalStock + ICAP_{it})$ as the capital input in equation 14.

Table 1 presents summary statistics of the main variables in our analysis. 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 according to conventional metrics is -32.3% and for just large firms (unreported in the table) it is 24.3. Once we adjust for intangible capital, the mean $ROIC^{TOT}$ is 13%. By definition, 10% of our sample are classified as star firms according to both the ROIC measures, $ROIC$ Star and $ROIC^{TOT}$ Star. Once we take into account intangible capital, the average markup is 1.18. The average Herfindahl industry concentration is 0.09 and the average firm market share is 0.014.

3 Empirical Findings

3.1 Is there a rise in Markups?

There has been a great deal of controversy on the rise in market power in the US. 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. [2017] and Autor et al. [2017]).

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 5, we plot the sales-weighted average markups each year estimated using COGS, OPEX, and OPEX* 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]. 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 Figure 6, we estimate the evolution of markups using capital adjustments, $Markups^{TOT}$, in the US economy over our sample period. We see an upward trend only for the 90th 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 in Figure 7 and find that markups are higher in high skilled industries (low RMAN) than low skilled industries for the top 10% of firms.

Overall, this section shows 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 highest markups and the rest of the economy, we see these differences amplified in high skilled industries where the measurement of intangible capital is even more important.

3.2 Explaining the Rise of Star Firms

To explore the incidence of star firms, for firm i in industry j in year t, we estimate the following regression:

$$Star_{ijt} = a + \beta_1 \times Log(Assets)_{it} + \beta_2 \times Log(Age)_{it} + \beta_3 \times Market\ Share_{it} + \beta_4 \times Markups_{it} + \beta_5 \times HHI_{jt} + \phi_j + \gamma_t + \epsilon_{ijt} \quad (15)$$

where *Star* is a dummy variable that takes the value 1 if the firm is a star firm and 0 otherwise. We first estimate the equation using *ROIC Star* as the definition of a star firm and using *Markups* based on operating expenses, OPEX. We then re-estimate the equation using corrections for intangible capital using $ROIC^{TOT}$ *Star* and $Markups^{TOT}$. *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. The regressions include industry (3-digit NAICS level) fixed effects, and year fixed effects and all standard errors are clustered at the firm level. All the regressions are estimated using ordinary least squares (linear probability models) but we get similar results using Logit estimation. We don't 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. Instead, we employ year and industry dummies and 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.

In Table 2, we estimate specification 15 to examine firm and industry characteristics that are associated with star status. In columns 1-5 we focus on the full sample of firms, in column 6 we look at only manufacturing firms for which we have data on skills, in column 7 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 8 we focus on young firms (defined as firms that are less than five years of age). We drop firms with negative invested capital in all regressions.

The results in Table 2 show that ROIC Star firms are on average larger, younger, have higher

markups and higher market share than rest of the firms in the economy. Industry concentration does not seem to affect star status. Given the concerns with mis-measurement of intangible capital, we repeat the specifications in Table 2 with the new measures of ROIC and Markups, $ROIC^{TOT}$ and $Markups^{TOT}$, that include adjustments for intangible capital from Peters and Taylor [2017].

Next, we repeat the estimation in Table 2 using $ROIC^{TOT}$ and $Markups^{TOT}$. The results in columns 1-5 of Table 3 show that after correcting for intangible capital, we find strong evidence that high markups predict $ROIC^{TOT}$. 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 $ROIC^{TOT}$ firms are on average large and young. These results on size, age, and markups hold in the different sub-samples in columns 6-8 for manufacturing, large firms, and young firms respectively. We find limited evidence that firm level market share or industry concentration at the 3-digit NAICS level predicts star status. HHI is never significant in any of the specifications and market share comes in significant only for large firms. In unreported tests, we find similar results if we use logit estimation for all the regressions instead of linear probability models.

It is likely that the effect of market power indicators may vary across levels of $ROIC^{TOT}$. In panel B of Table 3, we re-estimate the full model (column 5 of panel A) 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. A possible advantage of this approach may be that the estimates are not sensitive to the extreme outliers, that is firms with very little invested capital due to write-offs and/or atypical revenue windfalls. The results show that the profitability of firms at the top of the distribution of $ROIC^{TOT}$ appears more sensitive to markups than that at the bottom.

Henceforth, in all regression specifications we use the new definitions of ROIC and Markups ($ROIC^{TOT}$ and $Markups^{TOT}$) that incorporate intangible capital.

To explore the impact of human capital, we interact industry indices of human capital skill with

the key variables of interest as shown in the equation below:

$$Star_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{it} + \beta_2 \times Log(Age)_{it} + \beta_3 \times Market\,Share_{it} + \beta_4 \times Markups_{it}$$
$$+ \beta_5 \times HHI_{jt} + \beta_6 \times Log(Assets)_{it} \times Industry\,Skill_j + \beta_7 \times Market\,Share_{it} \times IndustrySkill_j$$
$$+ \beta_8 \times Markups_{it} \times Industry\,Skill_j + \beta_9 \times HHI_{jt} \times Industry\,Skill_j$$
$$+ \phi_j + \gamma_t + \epsilon_{ijt} \quad (16)$$

In Table 4, we examine the role of industry skill in predicting star status. We have the industry skills data only for manufacturing following Ayyagari and Maksimovic [2017] and hence these regressions are based on just the manufacturing industries. Across all regressions, the main effects on size and markups are positive and significantly associated with predicting superstar status. In columns 1-4 we look at the role of RMAN, in columns 5-8 we look at the role of CPS, and in columns 9-12 we look at the role of NRCOG. The interaction of RMAN with size, markups and HHI are all significant at the 1% level in columns 1-3 suggesting that in industries that rely heavily on routine manual skills (low skilled industries), large firms, firms with high markups and those in concentrated industries are less likely to be in the top 10% of ROIC firms in a year. We find similar results with industries that rely on high complex problem solving skills in columns 5-8 where large firms and firms with high markups in these industries are more likely to star firms. In columns 9-12 we see that in industries that rely on high non-routine cognitive analytical skills, large firms are more likely to be ROIC stars.

In unreported tests, we estimate unconditional quantile effects of the interaction of skill and markups (models 2, 6, and 10 of panel A) and find that the impact of skill and markups is stronger at higher levels of quantiles, especially for large firms.

3.3 Future Performance of ROIC Stars

Thus far, we have defined 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 the

first part of 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 superstar is associated with higher average performance in the subsequent five year period. Specifically, the regression we estimate is as follows:

$$\begin{aligned} Performance_{ijt} = \alpha_0 + \beta_1 \times Log(Assets)_{it-5} + \beta_2 \times Log(Age)_{it-5} + \beta_3 \times HHI_{jt-5} \\ + \beta_4 \times Market\,Share_{it-5} + \beta_5 \times Markups_{it-5} + \beta_6 \times ROIC^{TOT}Star_{it-5} \\ + \beta_7 \times ROIC^{TOT}_{it-5} + \phi_j + \gamma_t + \epsilon_{ijt} \end{aligned} \quad (17)$$

We look at the following five performance measures: 5-year average $ROIC^{TOT}$, *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, 5-year average *Labor Productivity*, and 5-year average Tobin's Q^{TOT} over these periods. 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, age, market share, HHI, and markups at the beginning of each panel. All regressions also include industry and year fixed effects.

Column 1 of Table 5 shows that while higher $ROIC^{TOT}$ is on average positively associated with higher average $ROIC^{TOT}$ in the subsequent five year period, star firms have lower $ROIC^{TOT}$ suggesting a regression to the mean. The predicted value of average 5-year $ROIC^{TOT}$ for firms that were superstars five years ago is 55.3 compared to 20.5 for firms that were not superstars five years ago. Column 2 shows that while past $ROIC^{TOT}$ is not associated with sales growth, past $ROIC^{TOT}$ stars have higher sales growth in the future but not necessarily higher employment growth in column 3. In column 4, $ROIC^{TOT}$ is associated with higher average labor productivity whereas star firms are not necessarily more productive than other firms in the economy. Column 5 shows that firms that are classified as $ROIC^{TOT}$ stars five years ago have high average Tobin's Q in the 5 years hence.

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 ROIC stars five years ago have

higher average returns over the subsequent five-year period than firms that were not ROIC stars.

3.4 Markups, Output, and Investment in Star Firms

A central policy question is whether high profits, and in particular, star firm status, are the result of monopoly power. This possibility is suggested by De Loecker and Eeckhout [2017] who calculate that markups in the US increased from 18% above marginal cost in 1980 to over 67% in 2014. Markups could rise due to outright monopoly or due to monopolistic competition where with high markups but also high fixed costs, firms actually earn low profits. Grullon et al. [2017] also argue that the increase in industry concentration in the US is related to high return on assets and this is mainly driven by firm's higher profit margins rather than asset utilization. [16]

Our results above are more nuanced. We find that a measure of pricing power, a high markup, statistically predicts star status for a firm, but there has been little increase in markups over the past several decades. To gain further intuition about the role of markups, we explore the relation between markups, ROIC, and a measure of output - the ratio of sales to invested capital - graphically for star firms and for all other U.S. public firms in general.

In Figure 8 we present a histogram of markups for firms that were classified as $ROIC^{TOT}$ stars and for all other firms and for each of those sub-samples, a non-parametric smoothed scatter plot of $ROIC^{TOT}$ 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 $ROIC^{TOT}$ 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 $ROIC^{TOT}$ within the sample of firms that have passed the threshold to be classified as star firms. In addition, in Figure 9, when we define superstars as firms that have $ROIC^{TOT}$ in the top decile in 3 or more years over this period or 5 or more years over the period, we find the

[16] Blonigen and Pierce [2016] study mergers and show that mergers are not necessarily associated with increase in efficiency but rather with an increase in market power as seen in the 15-50% increase in markups associated with mergers.

scatter plot for superstars to be similar to that of the star firms.[17]

In Figure 10, we present non-parametric smoothed scatter plot of Sales/Invested Capital against markups using kernel weighted local polynomial smoothing over the period 1990 to 2015 for all firms in the economy and for ROIC stars. We find that the relation between sales/invested capital in non-monotonic for both sets of firms. Beyond a certain level of markups, there is a decline in Sales/Invested Capital. Such an association of high markups and low output might arise if firms with market power restrict output to increase markups. 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.

In Table 6, we explore the relation between star status, markups, output and investment more formally in a multivariate regression framework controlling for *Log Assets*, *Log Age*, profitability (*Tobin's Q*), industry and 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. Columns 1, 3, and 5 shows that $ROIC^{TOT}$ star firms have higher Sales/Invested Capital and greater investment, both CAPEX, and Intangible (R&D) Investment compared to all other firms. Higher markups are associated with lower Sales/Invested Capital, higher CAPEX, and lower R&D Investment in these regressions. We find these results to be robust to a number of checks including industry x year fixed effects, scaling *CAPEX* by *PPENT* and *XRD* by intangible capital (*ICAP*). Given the skewness in the R&D variable, we also find similar results if we were to use both the dependent and independent variables in terms of logs.

When we focus on the the interaction of $ROIC^{TOT}$ and markups, we find the interaction to be negative and significant for *Sales/Invested Capital*. The economic significance of these interaction terms can be seen in the predictive margin plots. Figure 11 shows that $ROIC^{TOT}$ star firms have steeper declines in Sales/Invested Capital with markups but their investments do not seem to be

[17] We obtain similar outcomes when we define superstar status more narrowly by requiring five years of star status in the period 2005 to 2015.

very significantly different from that of the non-star firms. These results are also robust to using firm and year fixed effects in all regressions. In all cases, we find no evidence that the star firms are cutting output or investment more than the other firms in the economy.

The analyses thus far jointly show that the evidence attributing high profits of star firms to market power is modest. Moreover, the concern raised by Gutiérrez and Philippon [2017] that the decline *CAPEX* is attributable to increasing market power is not supported. Overall, our results indicate that while markups strongly predict high profits, not all star firms have high mark-ups and that star firms are restricting output or investment less than other firms with the same markups.

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 12 shows that these firms (especially Apple) have abnormally high returns to capital which exceed even the top 10% of $ROIC^{TOT}$ firms. Their markups in Figure 13 are however not abnormally high (except for Facebook) and are below the 90th percentile of markups in our sample for most of the sample period.

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)[18]

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 12 and 13, 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 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

[18]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

market dominance.

4 Robustness

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 by 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 Table 4. All our results are materially similar suggesting that our results are robust to smaller adjustments to intangible capital.

4.1 Alternate Classification of Superstars

We next narrow our definition of star firms to see whether the role of market power and size differs for the most profitable firms. Appendix Figure A3 plots the mean ROIC for the Top 100 and Top 150 firms each year and confirms that there is no run-up in ROIC over time for even the top 100 or 150 firms. In unreported robustness tests, we vary our definition of star firms to the Top 100 firms and Top 150 firms in terms of ROIC and repeat our estimations from Table 4. Although we do not have as much power in these tests, the results confirm that in high skilled industries, large firms are more likely to be in the top 100 or 150 firms earning super normal returns.

While the above definitions are based on returns to equity, as an alternate definition, we define stars in terms of Tobin's Q. Again following Peters and Taylor [2017], we define Q^{TOT} as the ratio of Firm value to $TOTCAP$ which is the sum of physical ($PPENT$) and intangible capital ($ICAP$):

$$Q_{it}^{TOT} = \frac{V_{it}}{TOTCAP_{it}} \tag{18}$$

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^{TOT}, we define Q *star* as a dummy variable that takes the value 1 if the firm's Q^{TOT} is above the 90th percentile of Q^{TOT} across all firms in the US economy in a particular year and 0 otherwise.

While Q^{TOT} 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. Novy-Marx [2007]). Thus, it may not measure current product market performance, and we do not use it as the primary metric of star status.

In Table 7, we use the alternate definition of star status based on Tobin's Q defined in equation (14). The estimates in Table 7 confirm our previous results on the role of industry skill as a determinant of star status. In high skilled industries (high complex problem solving skill, high non-routine cognitive skills, and low routine manual skills), large firms and those with high markups are more likely to be top performers in terms of Tobin's Q.

4.2 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 economically rational (see Martin and Santomero [1997]; 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 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 amongst 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

$$Invested\,Capital_{it}^{CASH} = PPENT_{it} + ACT_{it} + ICAP_{it} - LCTit - GDWL_{it} \tag{19}$$

Analogously we define ROIC with this new adjustment as:

$$ROIC_{it}^{CASH} = \frac{ADJPR_{it}}{Invested\,Capital_{it}^{CASH}} \tag{20}$$

In Figure 16, we present four $ROIC^{TOT}$ graphs where $ROIC^{TOT}$ 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 $ROIC^{TOT}$ for the top 10% of firms as in Figure 3.

In Table 8, we repeat the specifications in Table 4 but re-estimating $ROIC^{TOT}$ using different treatment of cash. We consider excess cash to be any cash over 1% of sales in panel A and over 10% of sales in panel B. In Panel C, we use the firm's total cash holdings in computing ROIC, which we term $ROIC^{CASH}$. Across the three panels, we obtain similar results wherein large firms and those with high markups in high skilled industries are more likely to be superstar firms.

5 Conclusion

In this paper, we assess publicly-listed star firms in the U.S. We we use financial statement data as conventionally presented, a small percentage of star firms seem to be pulling away from other firms in the economy over time in terms of their return on capital. In particular, star firms in highly skilled industries 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, we see that the differences in firm returns in highly skilled and other industries shrink dramatically and the gap between star firms and other firms does not widen over time. Furthermore, once we adjust markups based on operating expenses for investment in intangible capital, we do find an 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. In a companion paper Ayyagari et al. [2018], we examine the influences of market power and human capital in an international sample of firms.

Overall, our results indicate that there islittle evide nce that the most profitable 10% of firms are pulling away from the rest of the economy. However, there is 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. However, 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.

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Figure 1: **Rise in Star Firms**
This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital (ROIC) in each year across all public firms in the US economy.Detailed variable definitions are in the Appendix.

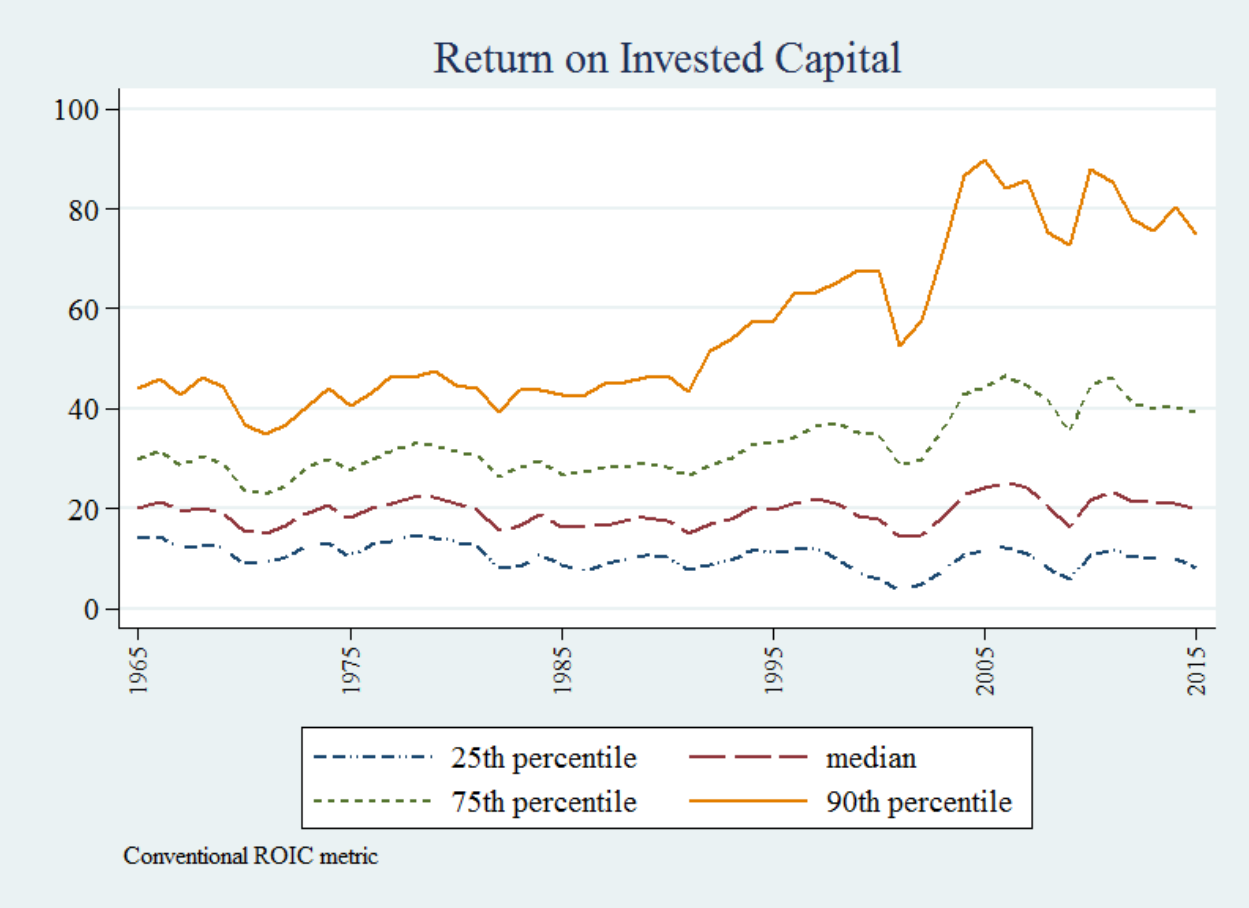

Figure 2: **Differences in Human Capital**
This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital (ROIC) in each year in low and high routine manual (RMAN) manufacturing industries. Detailed variable definitions are in the Appendix.

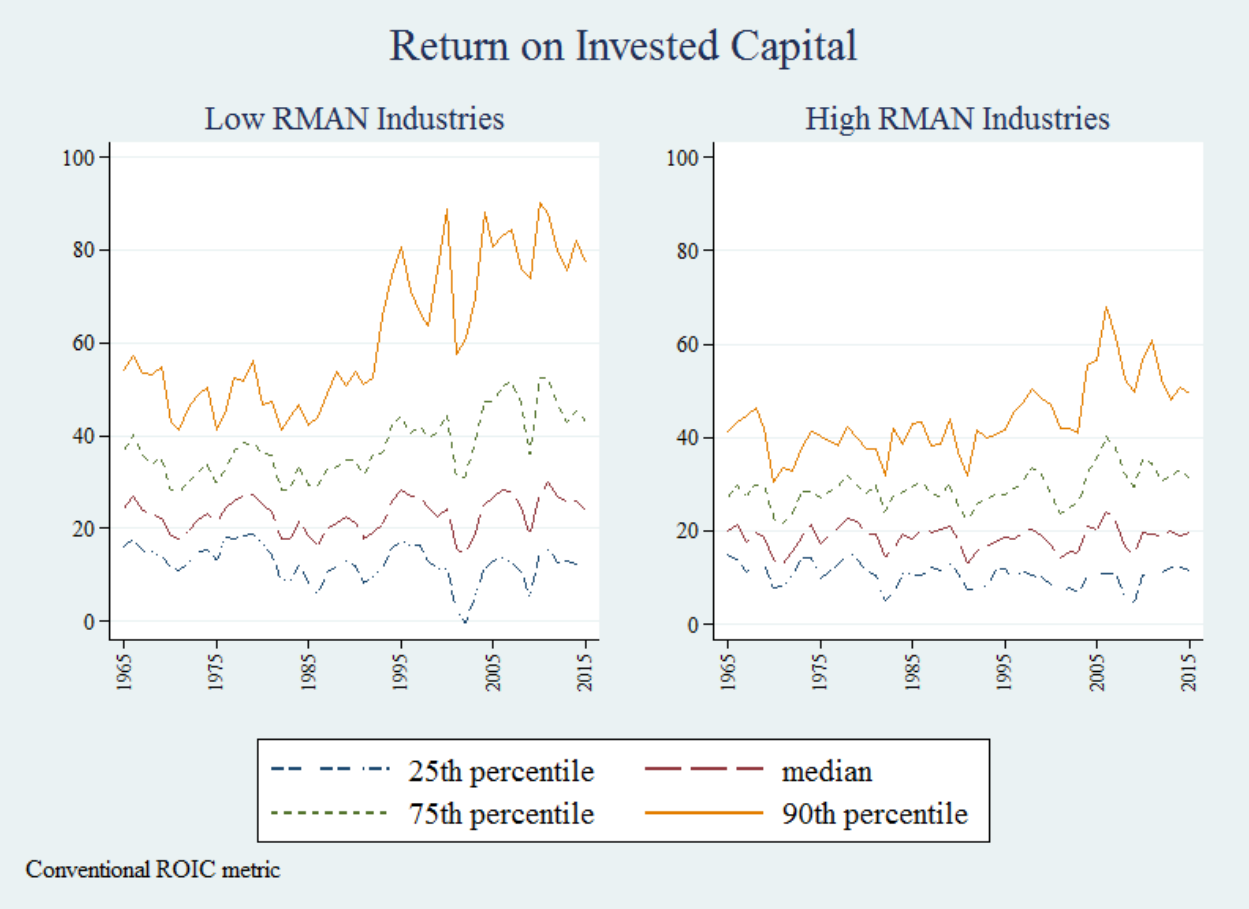

Figure 2: **Differences in Human Capital (Continued....)**
This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital (ROIC) in each year in low and high complex problem solving skill (CPS), and low and high cognitive skilled (NRCOG) manufacturing industries. Detailed variable definitions are in the Appendix.

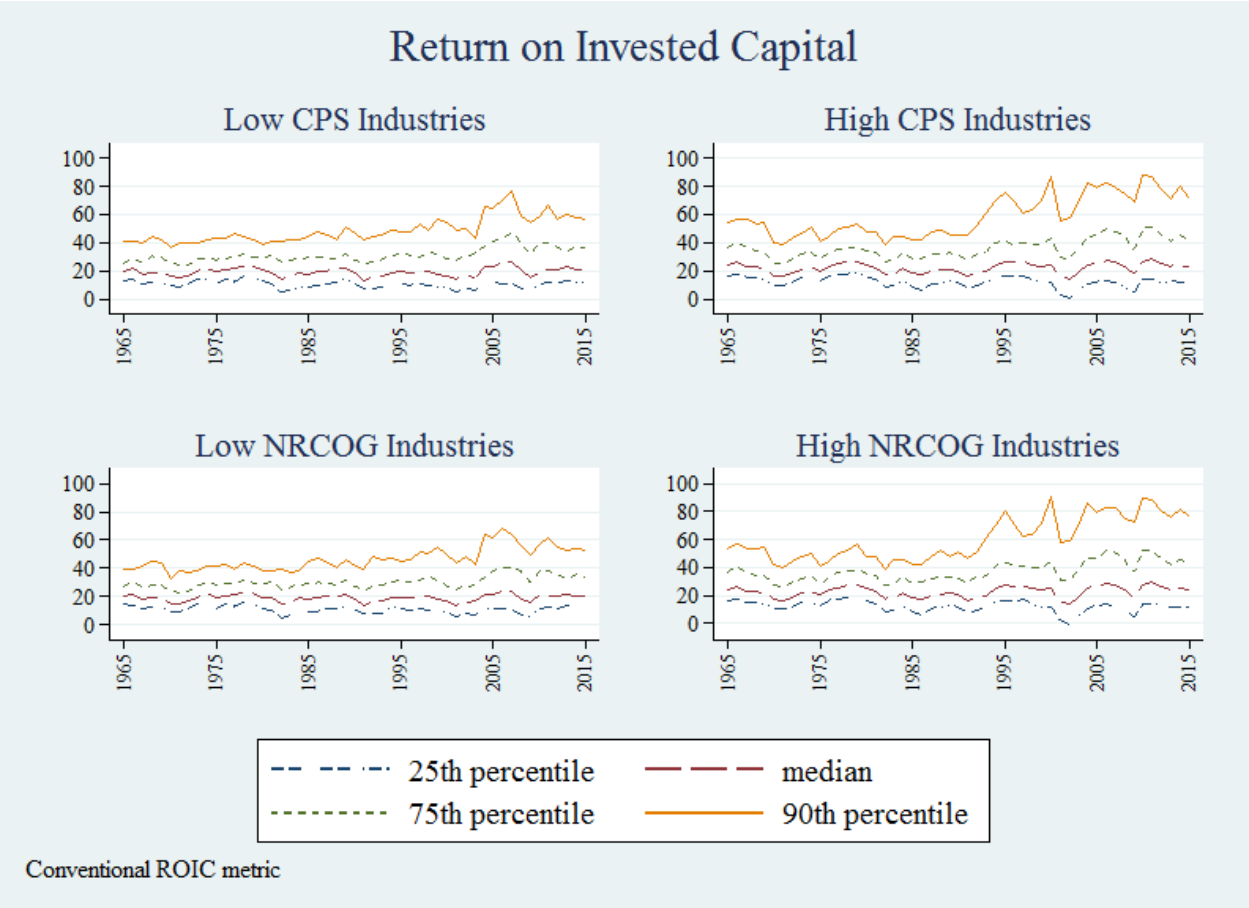

Figure 3: **Rise in Star Firms - correcting for intangible capital**
This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital ($ROIC^{TOT}$) in each year across all public firms in the US economy. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible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

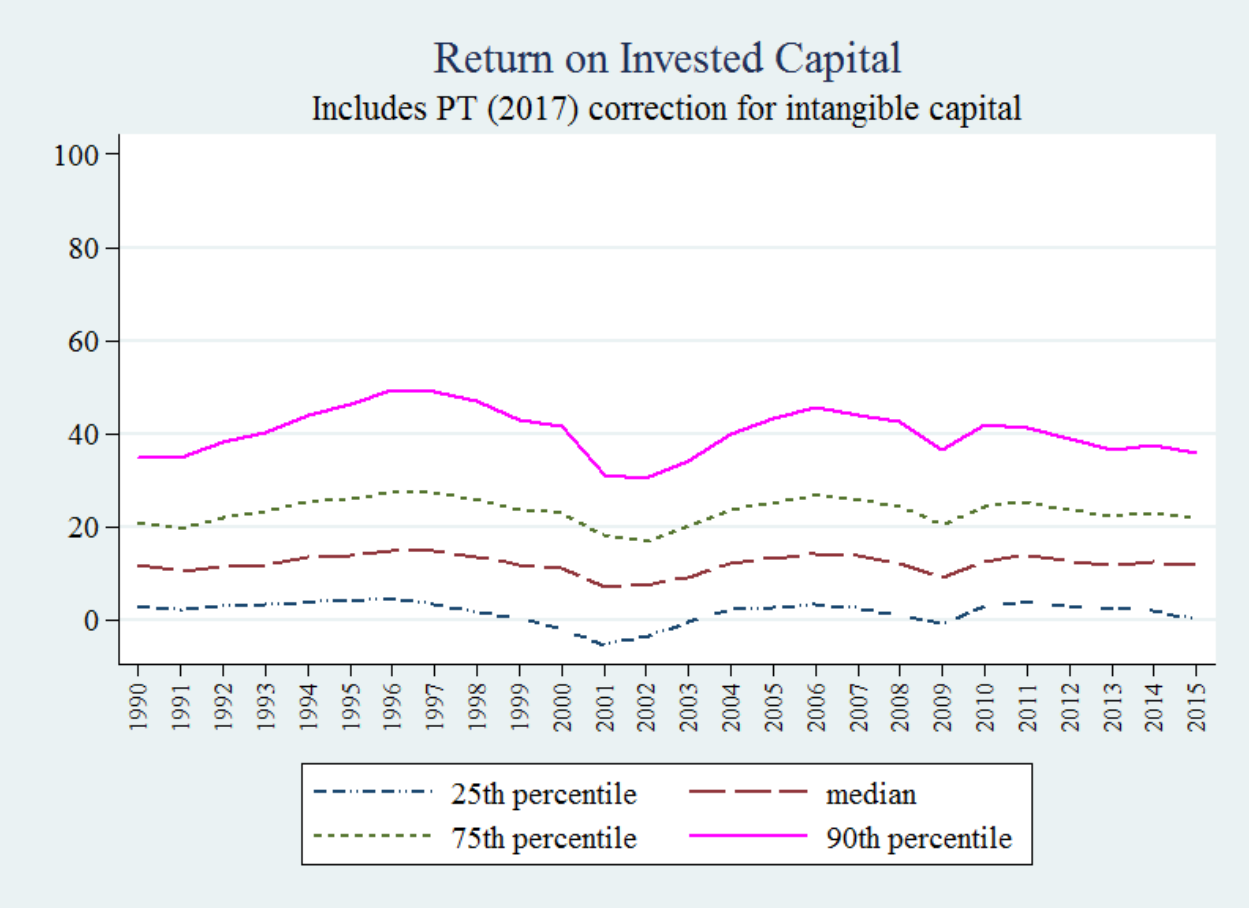

Figure 4: **Differences in Human Capital - correcting for intangible capital**
This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital ($ROIC^{TOT}$) in each year in low and high routine manual (RMAN) manufacturing industries. $ROIC^{TOT}$ includes the Peters and Taylor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

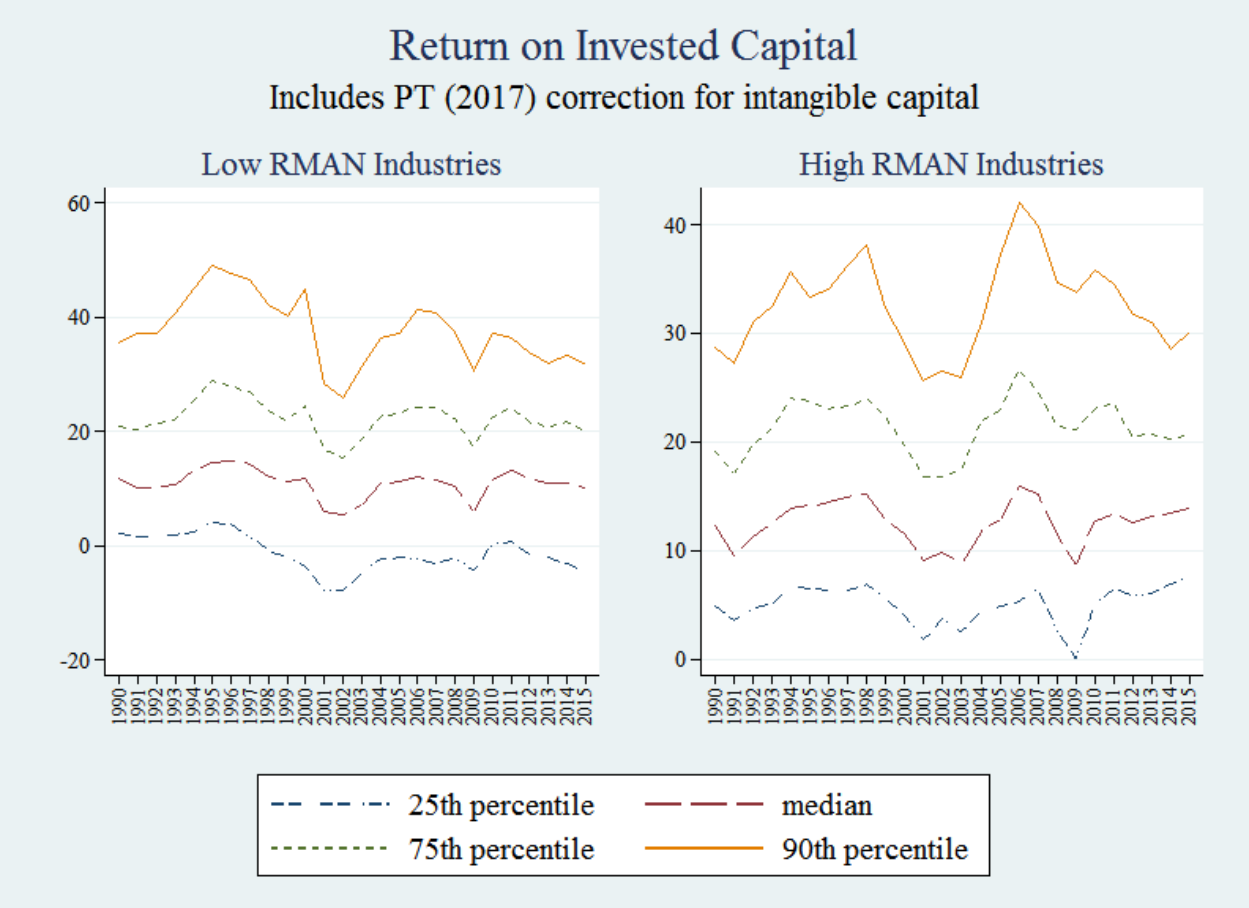

Figure 4: **Differences in Human Capital - correcting for intangible capital (Continued....)** This figure plots the 25th, 50th, 75th, and 90th percentile of Return on Invested Capital ($ROIC^{TOT}$) in each year in low and high complex problem solving skill (CPS), and low and high cognitive skilled (NRCOG) manufacturing industries. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

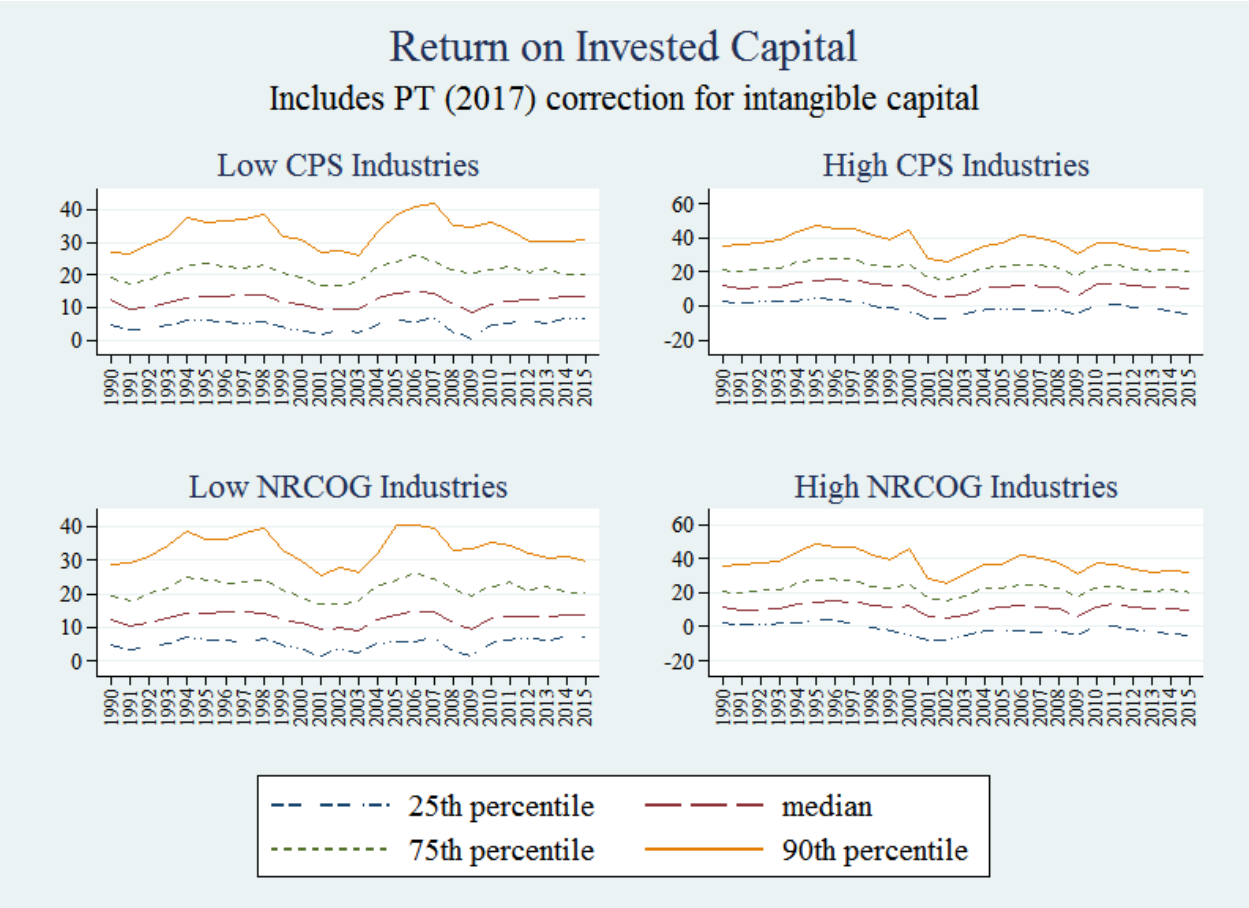

Figure 5: **Markups based on different variable inputs**
OPEX* Markups are $Markups^{TOT}$ which use operating expenses with intangible capital adjustments as a measure of variable cost. OPEX Markups are $Markups$ which use operating expenses without intangible capital adjustments as a measure of variable cost. COGS Markups use cost of goods sold (COGS) as a measure of variable cost.

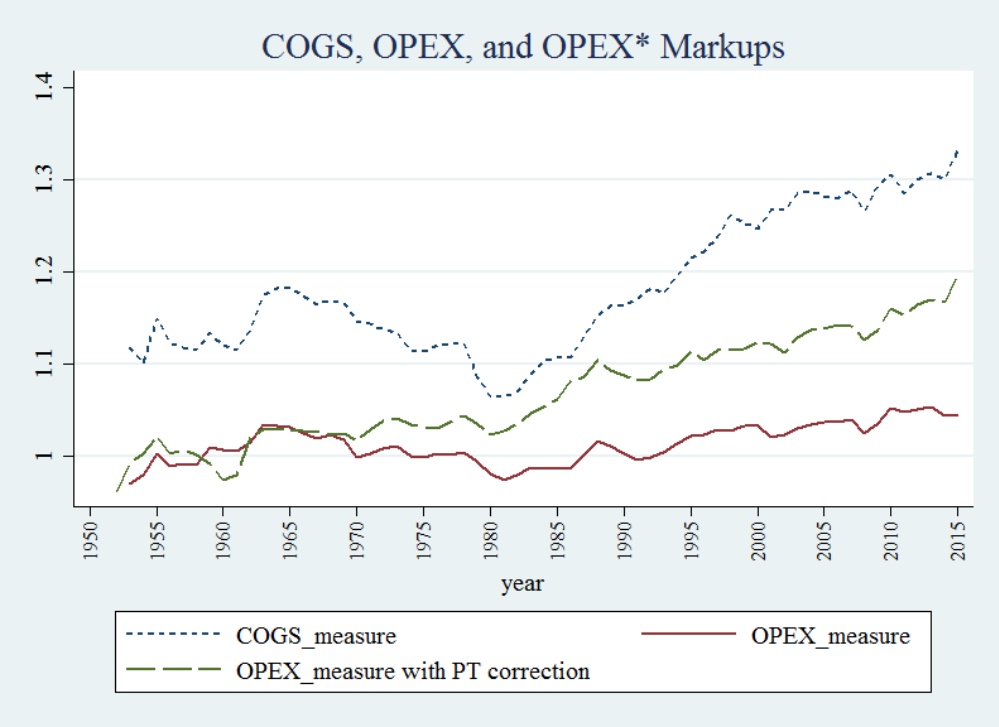

Figure 6: **Markups in the US Economy**
This figure plots the 25th, 50th, 75th, and 90th percentile of $Markups^{TOT}$ in each year across all public firms in the US economy. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost. Detailed variable definitions are in the Appendix.

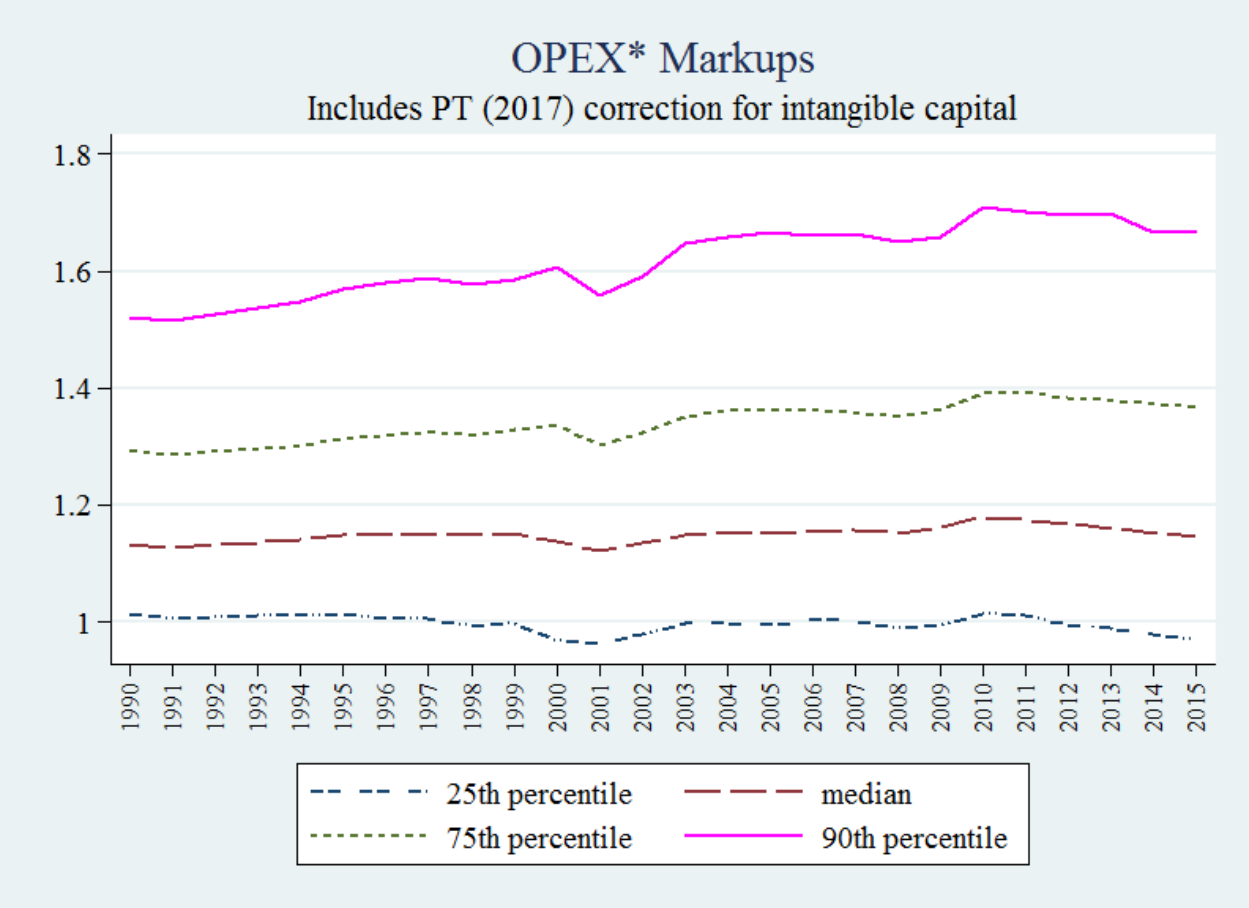

Figure 7: **Markups in the US Economy - Differences in Human Capital**
This figure plots the 25th, 50th, 75th, and 90th percentile of $Markups^{TOT}$ in each year in low and high routine manual (RMAN) manufacturing industries.$Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

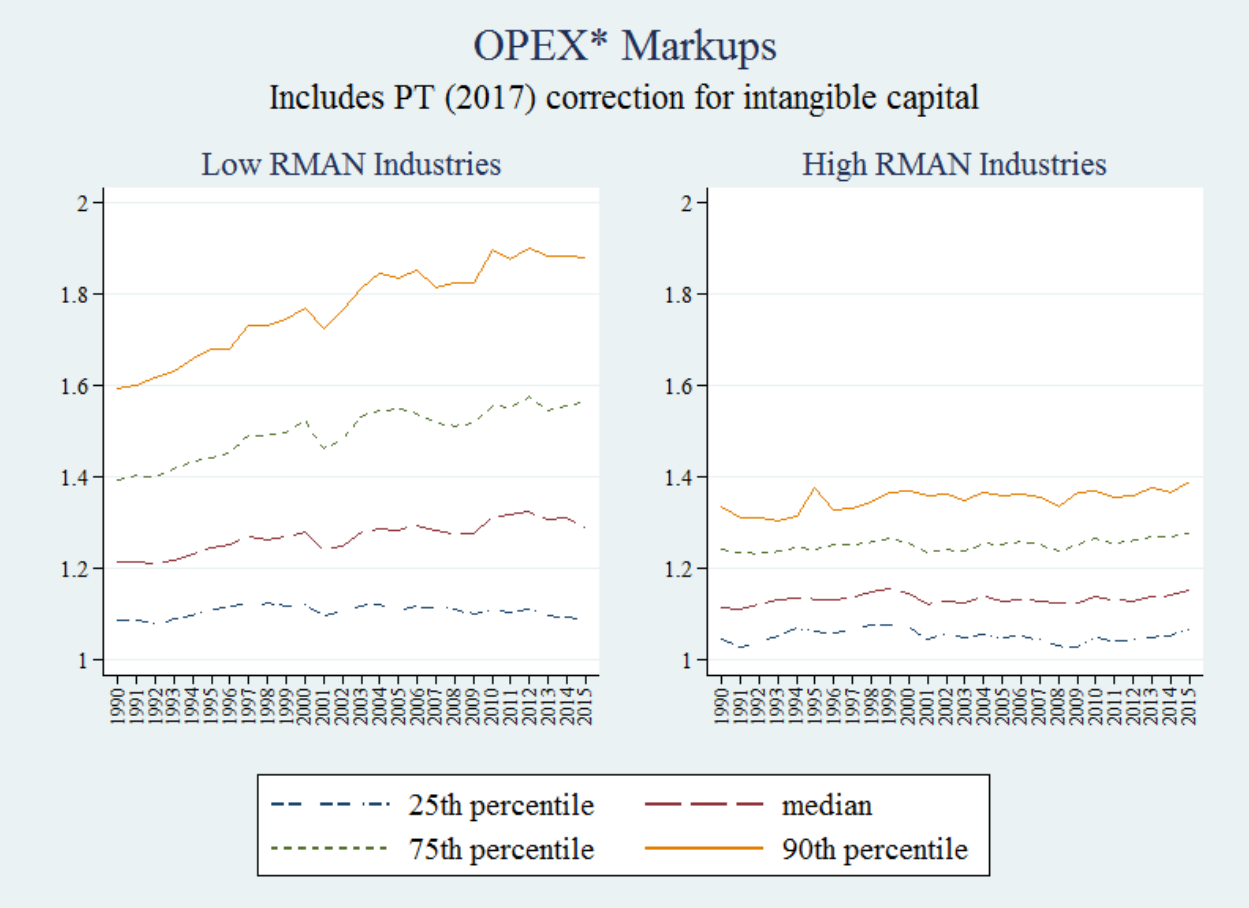

Figure 8: **Distribution of Markups across Star firms and all other firms**
This figure plots the histogram of $Markups^{TOT}$ for $ROIC^{TOT}$ Stars and all other firms. The figure also shows the smoothed values of a kernel-weighted local polynomial regression of $ROIC^{TOT}$ on $Markups^{TOT}$. $ROIC^{TOT}$ stars are firms that are in the top 10% of $ROIC^{TOT}$ in a particular year. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

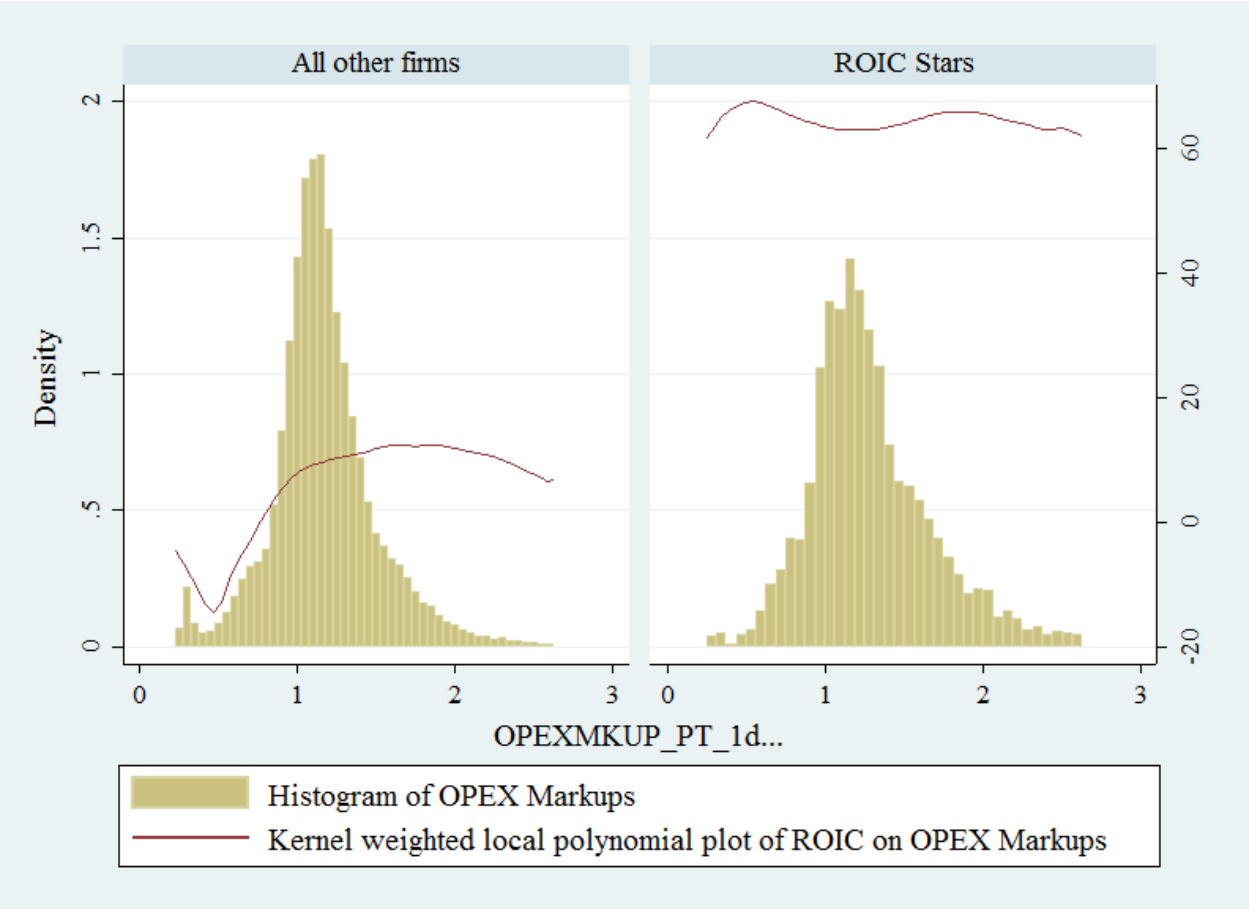

Figure 9: **ROIC and Markups**
This figure plots the smoothed values of a kernel-weighted local polynomial regression of $ROIC^{TOT}$ on $Markups^{TOT}$ for $ROIC^{TOT}$ stars, all other firms, for firms that are $ROIC^{TOT}$ stars for at least three years over the period 2000-2015 and for firms that are $ROIC^{TOT}$ stars for at least five years over the period 2000-2015. $ROIC^{TOT}$ stars are firms that are in the top 10% of $ROIC^{TOT}$ in a particular year. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

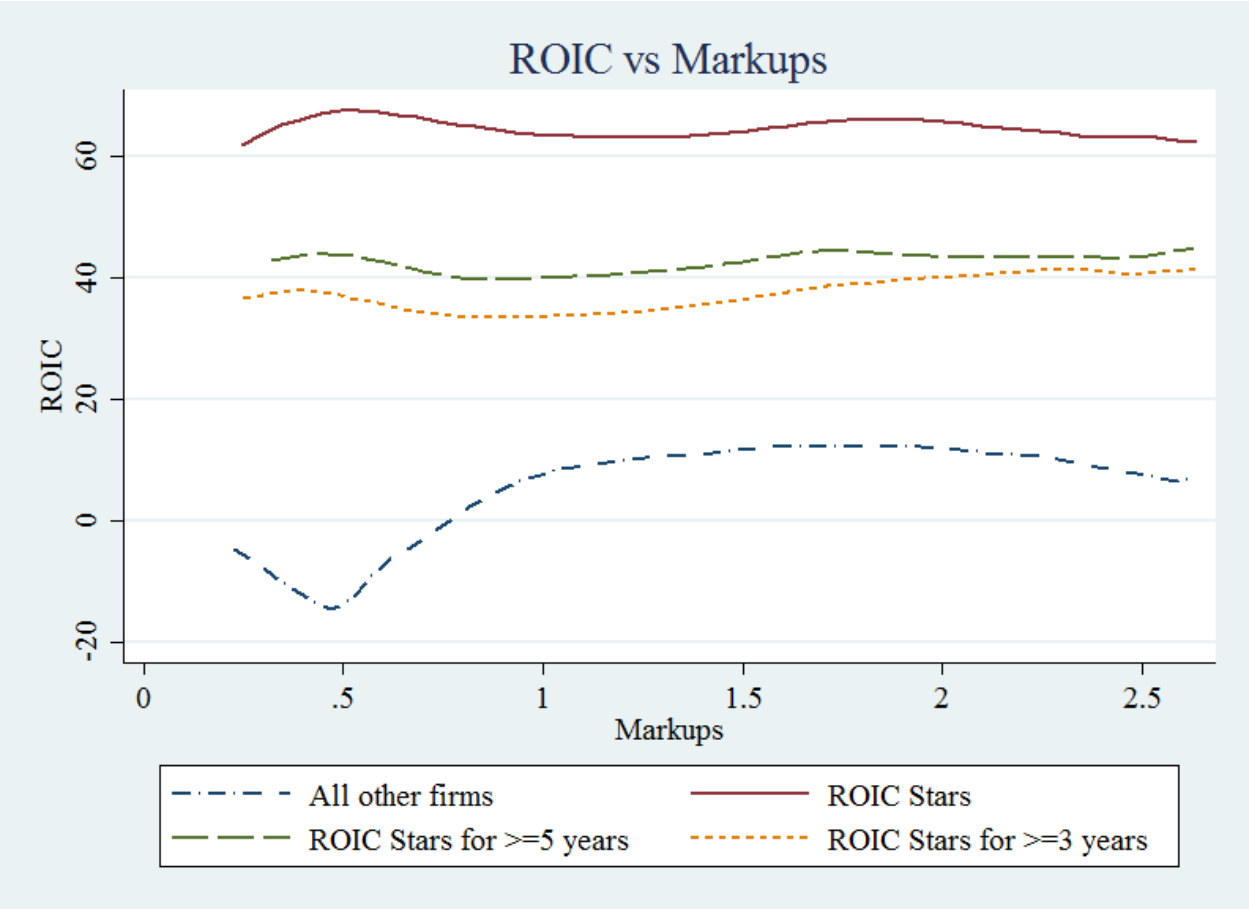

Figure 10: **Sales over Invested Capital - Stars vs all other firms**
This figure plots the smoothed values of a kernel-weighted local polynomial regression of Sales/Invested Capital on $Markups^{TOT}$ for $ROIC^{TOT}$ stars and all other firms. $ROIC^{TOT}$ stars are firms that are in the top 10% of $ROIC^{TOT}$ in a particular year. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

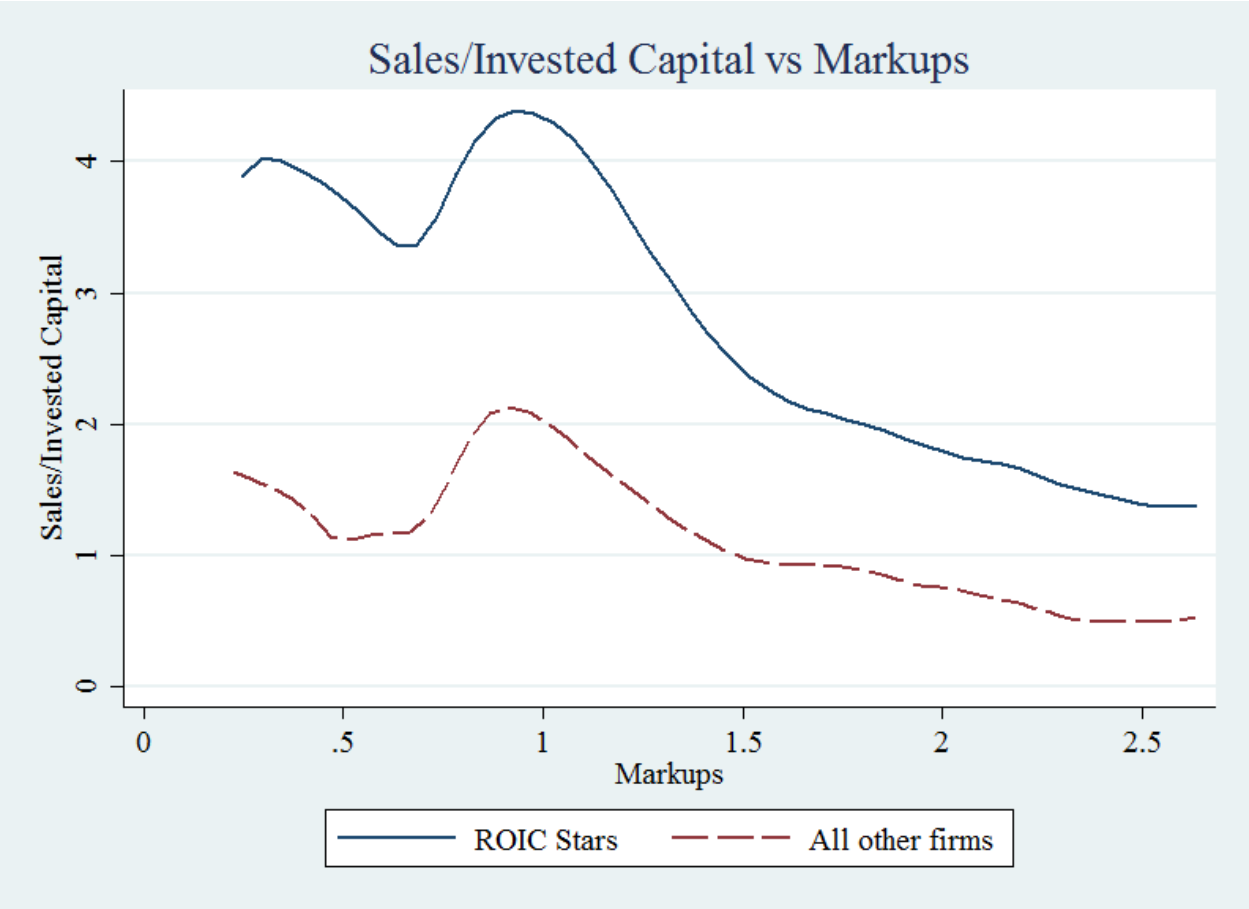

Figure 11: **Output and Investment - ROIC Stars x Markups**
This figure plots the predicted margin graphs of the interaction effects in Table 6. $ROIC^{TOT}$ stars are firms that are in the top 10% of $ROIC^{TOT}$ in a particular year. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

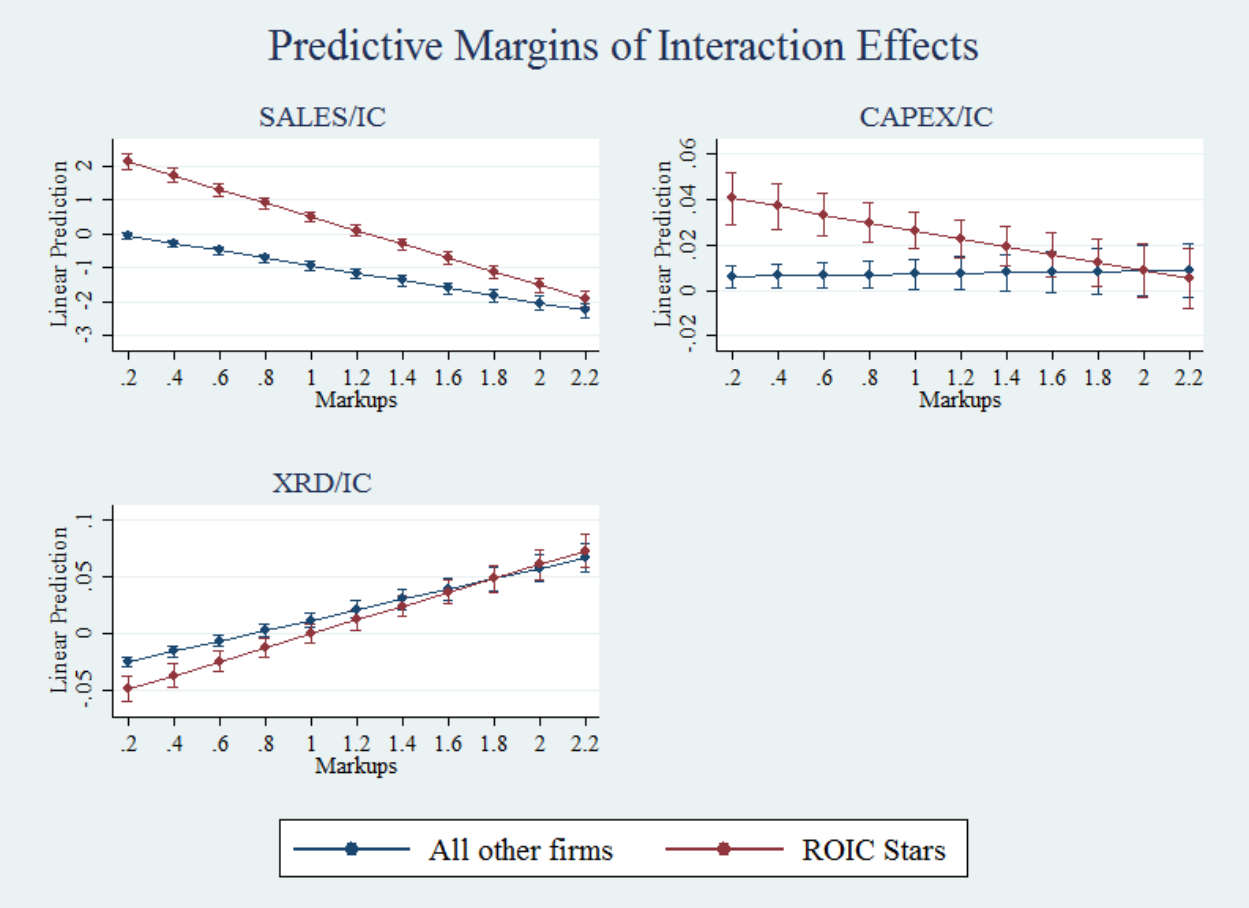

Figure 12: **ROIC of Elite Firms (Apple, Facebook, Amazon, Microsoft, Google)**
This figure plots the 90th percentile of Return on Invested Capital ($ROIC^{TOT}$) in each year across all public firms in the US economy as well as the $ROIC^{TOT}$ for five firms referred to as superstars anecdotally. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

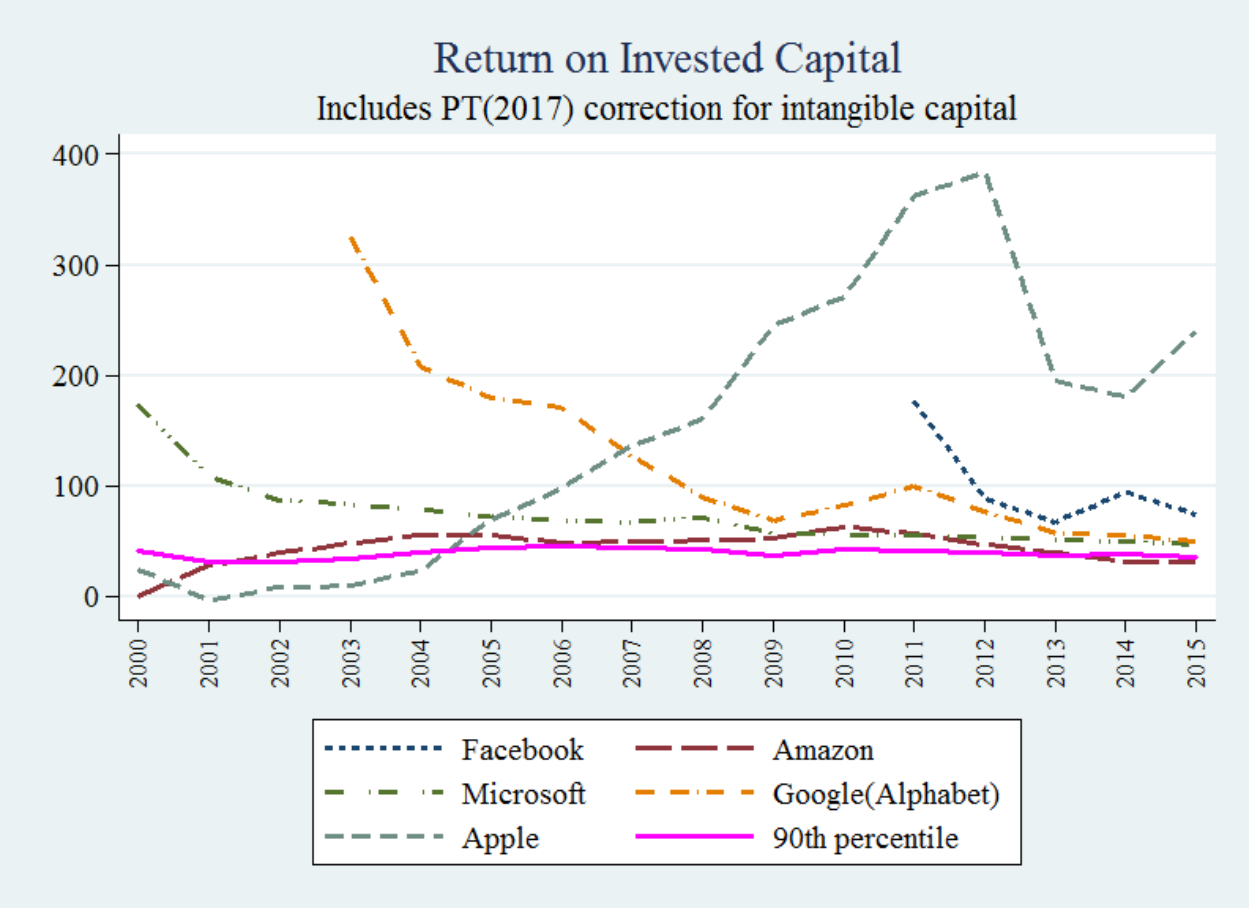

Figure 13: **Markups of Elite Firms (Apple, Facebook, Amazon, Microsoft, Google)** This figure plots the 90th percentile of $Markups^{TOT}$ in each year across all public firms in the US economy as well as the $Markups^{TOT}$ for five firms referred to as superstars anecdotally. $Markups^{TOT}$ use operating expenses with intangible capital adjustments as a measure of variable cost in estimation of markups. Detailed variable definitions are in the Appendix.

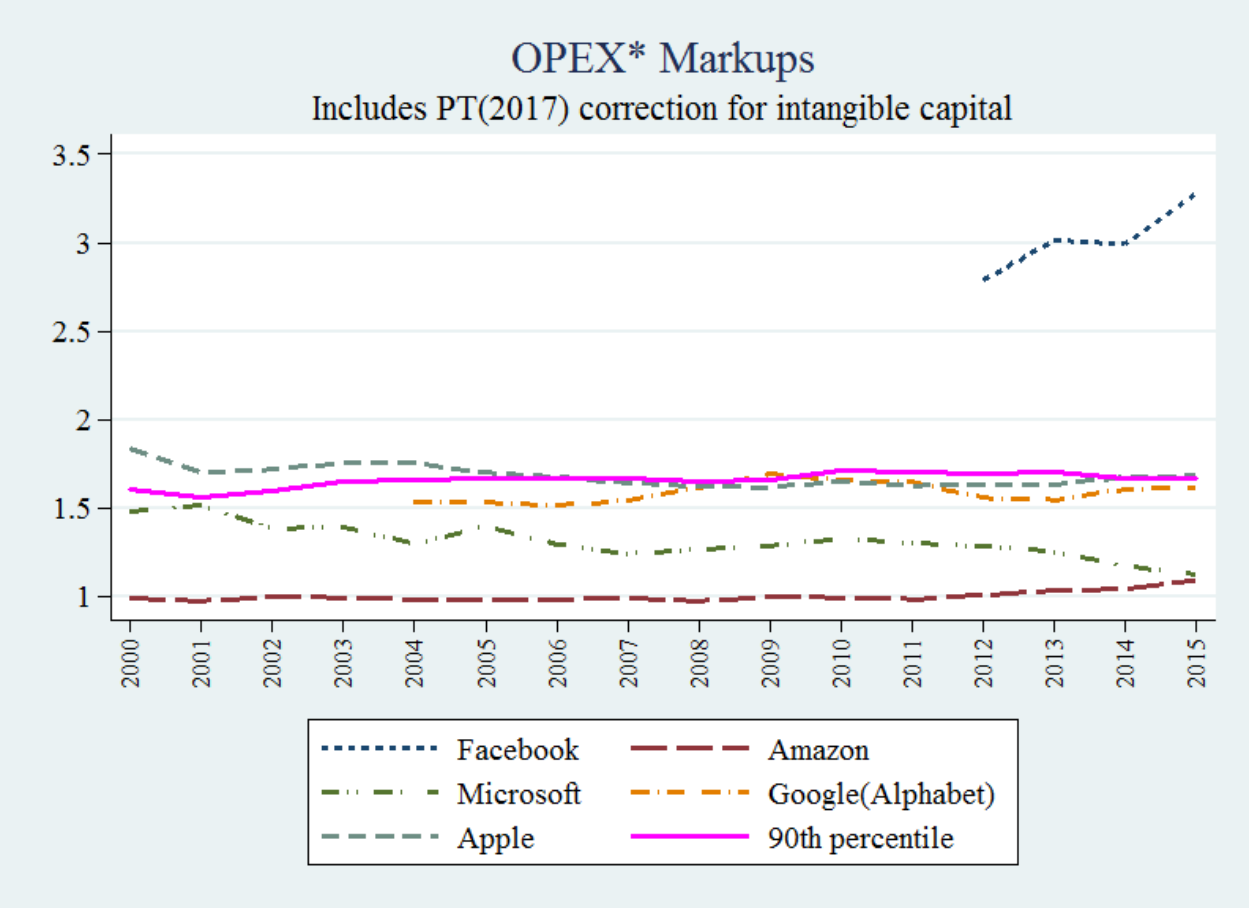

Figure 14: **Measurement of Excess Cash - Robustness**
This figure plots the 25th, 50th, 75th, and 90th percentile of alternate definitions of $ROIC^{TOT}$ in each year across all public firms in the US economy. The alternate definitions correspond to using cash above 1% of sales, 5% of sales, 10% of sales, and 20% of sales respectively as excess cash rather than the 2% of sales used in the rest of the paper. $ROIC^{TOT}$ includes the Peters and Taylor [2017] adjustment for intangible capital. Detailed variable definitions are in the Appendix.

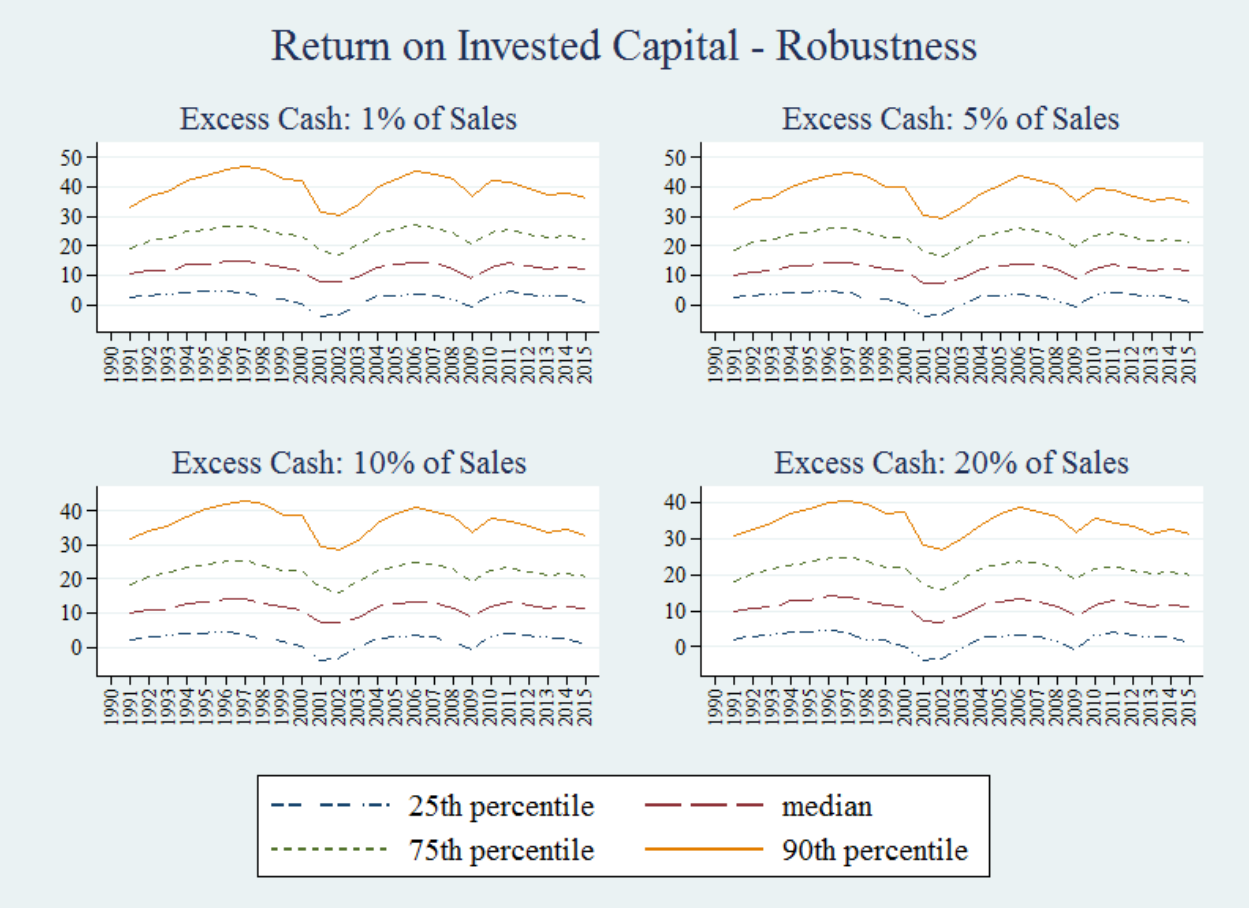

Table 1: **Summary Statistics**
This table reports the summary statistics of the key variables used in our analysis. All variable definitions are in the Appendix.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ROIC Star	97,241	0.100	0.300	0.000	1.000
ROIC	97,241	-32.354	250.464	-2955.128	443.913
Markups	78,668	0.971	0.227	0.150	1.763
ROIC^{TOT} Star	93,438	0.100	0.300	0.000	1.000
ROIC^{TOT}	93,438	12.943	27.207	-129.511	150.167
Log(Assets)	93,438	5.448	1.988	-6.908	12.906
Log(Age)	93,438	2.666	0.744	1.099	4.205
$\text{Markups}^{\text{TOT}}$	83,842	1.182	0.338	0.226	2.635
Market Share	91,683	0.014	0.036	0.000	0.323
HHI	91,966	0.093	0.082	0.028	0.596
RMAN	46,997	0.382	0.323	-0.050	1.380
CPS	46,997	0.318	0.352	-0.706	0.962
NRCOG	46,997	-0.181	0.300	-1.076	0.281

Table 2: **Who are America's Stars?**
This table reports estimates from the following regression model:

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

ROIC Star is a dummy variable that takes the value 1 if the firm i's ROIC is above the 90th percentile of ROIC across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is the number of years the firm is in the database. 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. Market Share is the ratio of the firm i's sales to total industry j's sales in a particular year. Columns (1)-(5) include the full sample; column (6) is manufacturing sub-sample, column (7) is large firm sample (Real value of assets is $\geq$ USD 200million) and column (8) is sample of young firms (Age$\leq$5 years). All regressions 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	ROIC Star
	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Manufac	Large Firms	Young Firms
Log(Assets)	0.013***	0.013***	0.004***	0.014***	0.002	0.000	0.001	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)
Log(Age)	-0.037***	-0.037***	-0.030***	-0.038***	-0.032***	-0.034***	-0.028***	-0.175***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.036)
HHI		-0.022			-0.011	-0.026	0.056	-0.097
		(0.031)			(0.038)	(0.087)	(0.056)	(0.089)
Markups			0.280***		0.287***	0.348***	0.325***	0.301***
			(0.015)		(0.016)	(0.024)	(0.027)	(0.023)
Market Share				-0.025	0.248***	0.413**	0.374***	0.297
				(0.084)	(0.096)	(0.186)	(0.119)	(0.251)
N	97241	97241	78668	96237	77875	41100	39539	6703
Adj. R-sq	0.059	0.059	0.081	0.058	0.082	0.061	0.120	0.089
Fixed Effects	Industry, Year							

Table 3: **Who are America's Stars? Correcting for intangible capital**
This table reports estimates from the following regression model in panel A:

$$ROIC_{ijt}^{TOT} = \alpha_0 + \beta_1 \times LogAssets_{ijt} + \beta_2 \times LogAge_{it} + \beta_3 \times HHI_{jt} + \beta_4 \times Market\,share_{ijt} + \beta_5 \times Markups_{ijt} + \phi_j + \gamma_t + \varepsilon_{ijt}$$

$ROIC^{TOT}$ Star is a dummy variable that takes the value 1 if the firm i's $ROIC^{TOT}$ is above the 90th percentile of $ROIC^{TOT}$ across all firms in a particular year and 0 otherwise. Log(Assets) is the logarithm of total assets and Log(Age) is the number of years the firm is in the database. HHI is Herfindahl Index of market share in each industry in each year. $Markups^{TOT}$ are estimated using operating expenses as a variable input of production and include correction for intangible capital. Market Share is the ratio of firm i's sales to total industry js sales in a particular year. In panel A, columns (1)-(5) include the full sample; column (6) is manufacturing sub-sample, column (7) is large firm sample (Real value of assets is $\geq$ USD 200Mil and column (8) is young firm sample (Age $\leq$ 5years). All regressions in Panel A are estimated using ordinary least squares with standard errors clustered at the firm level. Panel B presents generalized quantile regressions for the 25th, 50th, 75th, and 90th of $ROIC^{TOT}$ for specification (5) of panel A. Detailed variable definitions are in the Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A: OLS Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star	ROIC^{TOT} Star
	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Manufac	Large Firms	Young Firms
Log(Assets)	0.022***	0.022***	0.018***	0.022***	0.017***	0.017***	0.006**	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Log(Age)	-0.086***	-0.086***	-0.077***	-0.088***	-0.078***	-0.069***	-0.075***	-0.206***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.023)
HHI		-0.021			-0.050	-0.000	-0.030	0.078
		(0.038)			(0.040)	(0.109)	(0.053)	(0.127)
Markups			0.149***		0.149***	0.124***	0.175***	0.198***
			(0.010)		(0.010)	(0.012)	(0.015)	(0.017)
Market Share				0.056	0.131	-0.107	0.374***	-0.146
				(0.081)	(0.085)	(0.104)	(0.104)	(0.320)
N	93438	91966	83842	91683	81950	41887	44611	9652
Adj. R-sq	0.089	0.089	0.099	0.089	0.099	0.068	0.129	0.105
Fixed Effects	Industry, Year							

Table 3: **Who are America's Stars? Correcting for intangible capital (Continued...)**

Panel B: Generalized Quantile Estimation of Model (5) in Panel A

	(1)	(2)	(3)	(4)
	ROIC^{TOT}	ROIC^{TOT}	ROIC^{TOT}	ROIC^{TOT}
Quantile	25	50	75	90
Markups	18.079***	17.665***	25.242***	38.081***
	(0.894)	(1.103)	(1.570)	(1.920)
N	83842	83842	83842	83842
Fixed Effects		Industry, Year		

Table 4: **Human Capital and Star Status**

This table reports estimates from the following panel regression model:

$$ROIC_{ijt}^{TOT} = \alpha_0 + \beta_1 \times LogAssets_{ijt} \times Skill_j + \beta_2 \times LogAge_{it} + \beta_3 \times HHI_{jt} \times Skill_j + \beta_4 \times Market\ share_{ijt} \times Skill_j + \beta_5 \times Markups_{ijt} \times Skill_j + \phi_j + \gamma_t + \varepsilon_{ijt}$$

$ROIC^{TOT}$ Star is a dummy variable that takes the value 1 if the firm is $ROIC^{TOT}$ is above the 90th percentile of $ROIC^{TOT}$ across all firms in a particular year t and 0 otherwise. Log(Assets) is the logarithm of total assets. HHI is Herfindahl Index of market share in each 3-digit NAICS industry in each year. $Markups^{TOT}$ are based on the estimation in De Loecker and Eeckhout (2017) using operating expenses as a variable input of production and include correction for intangible capital. Market Share is the ratio of the firm is sales to total industry js sales in a particular year. Skill is industry-level measure of routine manual skills (RMAN) in columns 1-4, complex problem solving skills (COMPLEXPS) in columns 5-8 and non-routine cognitive analytical skills (NRCOG) in columns 9-12. All regressions include industry and year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Panel B presents generalized quantile regressions of models 2,6, and 10 of panel A for the 25th, 50th, 75th, and 90th quantile of $ROIC^{TOT}$. 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)	(9)	(10)	(11)	(12)
	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star
Skill	RMAN				CPS				NRCOG			
Log(Assets)	0.020***	0.017***	0.017***	0.017***	0.014***	0.017***	0.017***	0.017***	0.018***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Age)	-0.069***	-0.069***	-0.069***	-0.070***	-0.069***	-0.070***	-0.070***	-0.070***	-0.069***	-0.070***	-0.070***	-0.070***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HHI	0.034	0.036	0.363*	0.034	0.036	0.038	0.021	0.037	0.040	0.035	-0.096	0.037
	(0.080)	(0.080)	(0.207)	(0.080)	(0.081)	(0.081)	(0.082)	(0.083)	(0.081)	(0.080)	(0.143)	(0.082)
Market Share	-0.058	-0.122	-0.126	0.017	-0.037	-0.109	-0.110	-0.111	-0.078	-0.107	-0.106	-0.138
	(0.108)	(0.104)	(0.103)	(0.197)	(0.105)	(0.104)	(0.104)	(0.106)	(0.104)	(0.105)	(0.105)	(0.162)
Markups	0.122***	0.129***	0.124***	0.125***	0.123***	0.115***	0.125***	0.125***	0.122***	0.126***	0.126***	0.125***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Log(Assets) x Skill	-0.009***				0.008***				0.006*			
	(0.002)				(0.003)				(0.003)			
Markups x Skill		-0.024*				0.019*				-0.009		
		(0.013)				(0.012)				(0.016)		
HHI x Skill			-0.466*				-0.095				-0.216	
			(0.238)				(0.181)				(0.210)	
Market Share x Skill				-0.212				-0.005				-0.062
				(0.234)				(0.303)				(0.335)
N	42355	42355	42355	42355	42355	42355	42355	42355	42355	42355	42355	42355
Adj. R-sq	0.070	0.069	0.070	0.069	0.070	0.069	0.069	0.069	0.069	0.069	0.069	0.069
Fixed Effects	Industry, Year				Industry, Year				Industry, Year			

Table 5: **Are Star Firms Persistent Performers?**

This table reports estimates from the following panel regression model:

$$Performance_{ijt} = \alpha_0 + \beta_1 \times LogAssets_{ijt-5} + \beta_2 \times LogAge_{ijt-5} + \beta_3 \times HHI_{jt-5} + \beta_4 \times Market\ share_{ijt-5}$$
$$+\beta_5 \times Markups_{ijt-5} + \beta_6 \times ROIC^{TOT} Star_{[}ijt-5]\phi_j + \gamma_t + \varepsilon_{ijt}$$

Performance is Sales growth/Employment growth (each defined as the 5-year log difference in sales or employment respectively divided by 5), Labor Productivity, Tobins Q (Q^{TOT}) or $ROIC^{TOT}$ averaged over 5 years. Log(Assets) is the 5-year lagged value of the logarithm of total assets. HHI is 5-year lagged value of Herfindhal Index of market share in each 3-digit NAICS industry. $Markups^{TOT}$ is the 5-year lagged value of Markups based on the estimation in De Loecker and Eeckhout (2017) using operating expenses as a variable input of production and include correction for intangible capital. Market Share is the 5-year lagged value of the ratio of the firm is sales to total industry js sales in a particular year. $ROIC^{TOT}$ Star is a dummy variable that takes the value 1 if firm is 5-year lagged $ROIC^{TOT}$ was above the 90th percentile of $ROIC^{TOT}$ 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 and 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
	5-year average $ROIC^{TOT}$	5-year change in Log(Sales)	5-year change in Log(Empl)	5-year average Labor Productivity	5-year average Tobin's Q^{TOT}
L5.ROICTOT Star	-2.780***	0.038***	0.003	0.897	0.985***
	(0.611)	(0.007)	(0.007)	(10.998)	(0.060)
L5.ROICTOT	0.633***	-0.000***	0.001***	1.459***	0.003***
	(0.009)	(0.000)	(0.000)	(0.144)	(0.001)
L5.Market share	-1.675	0.030	0.079**	-4.537	0.734**
	(1.900)	(0.040)	(0.037)	(83.102)	(0.299)
L5.MarkupsTOT	9.592***	0.130***	0.087***	41.803**	0.793***
	(0.546)	(0.009)	(0.007)	(17.092)	(0.058)
L5.Log(Assets)	0.733***	-0.006***	-0.009***	28.268***	0.033***
	(0.067)	(0.001)	(0.001)	(2.157)	(0.007)
L5.Log(Age)	0.276*	-0.025***	-0.018***	-39.109***	-0.191***
	(0.144)	(0.002)	(0.002)	(4.735)	(0.015)
L5.HHI	-4.985**	-0.011	0.025	202.495***	0.153
	(2.196)	(0.035)	(0.037)	(60.034)	(0.185)
N	16392	10762	10415	16106	16001
Adj. R-sq	0.732	0.092	0.088	0.402	0.227
Fixed Effects		Industry, Year			

Table 6: **Output and Investment in Star Firms**

This table reports estimates from the following panel regression model:

$$Output\ or\ Performance_{ijt} = \alpha_0 + \beta_1 \times LogAssets_{ijt-1} + \beta_2 \times LogAge_{ijt-1} + \beta_3 \times Markups^{TOT}_{ijt-1}$$
$$+\beta_4 \times ROIC^{TOT} Star_{ijt-1} + \beta_5 \times Markups^{TOT}_{ijt-1} \times ROIC^{TOT} Star_{ijt-1} \phi_j + \gamma_t + \varepsilon_{ijt}$$

The dependent variable is Sales/Invested Capital or CAPEX/Invested Capital or XRD/Invested Capital. $ROIC^{TOT}$ Star is a dummy variable that takes the value 1 if the firm *is* $ROIC^{TOT}$ is above the 90th percentile of $ROIC^{TOT}$ across all firms in a particular year t and 0 otherwise. Log(Assets) is the logarithm of total assets. $Markups^{TOT}$ are based on the estimation in De Loecker and Eeckhout (2017) using operating expenses as a variable input of production and include correction for intangible capital. Q^{TOT} is Tobins Q corrected for intangible capital. All regressions include industry and 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)
	Sales/Invested Capital	Sales/Invested Capital	Capex/Invested Capital	Capex/Invested Capital	XRD/Invested Capital	XRD/Invested Capital
L. ROICTOT Stars	0.804***	1.378***	0.014***	0.038***	-0.008***	-0.028***
	(0.028)	(0.093)	(0.002)	(0.006)	(0.002)	(0.006)
L. MarkupsTOT	-1.052***	-0.992***	-0.001	0.001	0.048***	0.046***
	(0.039)	(0.039)	(0.003)	(0.003)	(0.003)	(0.003)
L. ROICTOT Stars x L.MarkupsTOT		-0.452***		-0.019***		0.016***
		(0.062)		(0.004)		(0.005)
L.Log(Assets)	0.058***	0.057***	0.004***	0.004***	-0.001***	-0.001***
	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
L.Log(Age)	-0.014	-0.013	-0.008***	-0.008***	-0.012***	-0.012***
	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)
L.QTOT	-0.021***	-0.019***	0.008***	0.008***	0.006***	0.006***
	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
N	70094	70094	69582	69582	70667	70667
Adj. R-sq	0.355	0.357	0.359	0.360	0.465	0.466
Fixed Effects	— Industry, Year —					

Table 7: **Human Capital and Star Status Robustness: Tobin's Q**

This table reports estimates from the following panel regression model:

$$Q_{ijt}^{TOT} = \alpha_0 + \beta_1 \times LogAssets_{ijt} \times Skill_j + \beta_2 \times LogAge_{it} + \beta_3 \times HHI_{jt} \times Skill_j + \beta_4 \times Market\,share_{ijt} \times Skill_j + \beta_5 \times Markups_{ijt} \times Skill_j + \phi_j + \gamma_t + \varepsilon_{ijt}$$

Q^{TOT} Star is a dummy variable that takes the value 1 if the firm is Tobin's Q^{TOT} is above the 90th percentile of Q^{TOT} across all firms in a particular year t and 0 otherwise. Log(Assets) is the logarithm of total assets. HHI is Herfindahl Index of market share in each 3-digit NAICS industry in each year. $Markups^{TOT}$ are based on the estimation in De Loecker and Eeckhout (2017) using operating expenses as a variable input of production and include correction for intangible capital. Market Share is the ratio of the firm is sales to total industry js sales in a particular year. Skill is industry-level measure of routine manual skills (RMAN) in columns 1-4, complex problem solving skills (COMPLEXPS) in columns 5-8 and non-routine cognitive analytical skills (NRCOG) in columns 9-12. All regressions include industry and 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	9	10	11	12
	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	Q^{TOT} Star	QTOT Star	Q^{TOT} Star
Skill	RMAN				CPS				NRCOG			
Log(Assets)	0.005***	0.002	0.002	0.002	-0.000	0.002	0.002	0.002	0.004**	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Age)	-0.065***	-0.065***	-0.065***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.065***	-0.066***	-0.066***	-0.066***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HHI	0.083	0.086	0.467**	0.079	0.085	0.087	0.104	0.091	0.092	0.089	0.068	0.088
	(0.074)	(0.075)	(0.190)	(0.074)	(0.076)	(0.075)	(0.077)	(0.077)	(0.075)	(0.075)	(0.142)	(0.076)
Market Share	0.268*	0.203	0.201	0.441	0.279*	0.222	0.219	0.229	0.277*	0.211	0.221	0.132
	(0.153)	(0.149)	(0.148)	(0.309)	(0.149)	(0.149)	(0.149)	(0.153)	(0.150)	(0.151)	(0.149)	(0.188)
Markups	0.162***	0.171***	0.164***	0.165***	0.164***	0.154***	0.165***	0.165***	0.159***	0.164***	0.165***	0.165***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)
Log(Assets) x Skill	-0.009***				0.007***				0.010***			
	(0.002)				(0.003)				(0.003)			
Markups x Skill		-0.032**				0.024*				0.021		
		(0.015)				(0.013)				(0.018)		
HHI x Skill			-0.544**				0.118				-0.027	
			(0.221)				(0.197)				(0.226)	
Market Share x Skill				-0.373				-0.298				-0.202
				(0.306)				(0.409)				(0.387)
N	41085	41085	41085	41085	41085	41085	41085	41085	41085	41085	41085	41085
adj. R-sq	0.072	0.071	0.072	0.071	0.071	0.071	0.071	0.071	0.072	0.071	0.071	0.071
Fixed Effects	Industry, Year				Industry, Year				Industry, Year			

Table 8: **Human Capital and Star Status Robustness: Measurement of Excess Cash**

This table reports estimates from the following panel regression model:

$$ROIC_{ijt}^{TOT} = \alpha_0 + \beta_1 \times LogAssets_{ijt} \times Skill_j + \beta_2 \times LogAge_{it} + \beta_3 \times HHI_{jt} \times Skill_j$$
$$+\beta_4 \times Market\ share_{ijt} \times Skill_j + \beta_5 \times Markups_{ijt} \times Skill_j + \phi_j + \gamma_t + \varepsilon_{ijt}$$

$ROIC^{TOT}$ Star is a dummy variable that takes the value 1 if the firm is $ROIC^{TOT}$ is above the 90th percentile of $ROIC^{TOT}$ across all firms in a particular year t and 0 otherwise. Log(Assets) is the logarithm of total assets. HHI is Herfindahl Index of market share in each 3-digit NAICS industry in each year. $Markups^{TOT}$ are based on the estimation in De Loecker and Eeckhout (2017) using operating expenses as a variable input of production and include correction for intangible capital. Market Share is the ratio of the firm is sales to total industry js sales in a particular year. Skill is industry-level measure of routine manual skills (RMAN) in columns 1-4, complex problem solving skills (COMPLEXPS) in columns 5-8 and non-routine cognitive analytical skills (NRCOG) in columns 9-12. All regressions include industry and year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level.In Panel A, $ROIC^{TOT}$ Star is computed using 1% of sales as excess cash, in panel B $ROIC^{TOT}$ Star is computed using 10% of sales as excess cash and in panel C we use non-cash working capital in computing $ROIC^{TOT}$ Star firms. All regressions include industry and year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star
Skill	RMAN				CPS				NRCOG			
Log(Assets)	0.021***	0.018***	0.018***	0.017***	0.015***	0.018***	0.017***	0.017***	0.019***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Age)	-0.068***	-0.068***	-0.068***	-0.069***	-0.068***	-0.069***	-0.069***	-0.069***	-0.068***	-0.069***	-0.069***	-0.069***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HHI	0.054	0.056	0.394*	0.052	0.055	0.057	0.029	0.056	0.059	0.055	-0.106	0.056
	(0.085)	(0.085)	(0.216)	(0.085)	(0.086)	(0.086)	(0.088)	(0.088)	(0.085)	(0.085)	(0.153)	(0.087)
Market Share	-0.117	-0.183*	-0.189*	0.045	-0.100	-0.170	-0.171	-0.173	-0.139	-0.166	-0.166	-0.141
	(0.113)	(0.110)	(0.108)	(0.213)	(0.110)	(0.110)	(0.109)	(0.112)	(0.110)	(0.110)	(0.110)	(0.174)
Markups	0.123***	0.130***	0.124***	0.126***	0.124***	0.118***	0.126***	0.126***	0.122***	0.127***	0.127***	0.126***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Log(Assets) x Skill	-0.010***				0.008***				0.006*			
	(0.003)				(0.003)				(0.003)			
Markups x Skill		-0.023*				0.016				-0.012		
		(0.014)				(0.012)				(0.017)		
HHI x Skill			-0.481*				-0.161				-0.263	
			(0.249)				(0.190)				(0.222)	
Market Share x Skill				-0.363				0.042				0.070
				(0.250)				(0.331)				(0.362)
N	39651	39651	39651	39651	39651	39651	39651	39651	39651	39651	39651	39651
Adj. R-sq	0.070	0.069	0.069	0.069	0.070	0.069	0.069	0.069	0.069	0.069	0.069	0.069
Fixed Effects	Industry, Year				Industry, Year				Industry, Year			

Table 8: **Human Capital and Star Status Robustness: Measurement of Excess Cash (Continued...)**
Panel B: $ROIC^{TOT}$ computed using 10% of sales as excess cash

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star	$ROIC^{TOT}$ Star
Skill	RMAN				CPS				NRCOG			
Log(Assets)	0.021***	0.018***	0.018***	0.017***	0.015***	0.018***	0.017***	0.017***	0.018***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Age)	-0.069***	-0.069***	-0.069***	-0.070***	-0.070***	-0.070***	-0.070***	-0.070***	-0.070***	-0.070***	-0.070***	-0.070***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HHI	0.067	0.069	0.481**	0.065	0.068	0.071	0.054	0.069	0.072	0.068	-0.025	0.069
	(0.082)	(0.083)	(0.211)	(0.082)	(0.083)	(0.083)	(0.085)	(0.085)	(0.083)	(0.082)	(0.152)	(0.084)
Market Share	-0.091	-0.162	-0.169	0.076	-0.077	-0.147	-0.148	-0.149	-0.119	-0.142	-0.144	-0.133
	(0.113)	(0.108)	(0.107)	(0.229)	(0.110)	(0.108)	(0.108)	(0.109)	(0.109)	(0.109)	(0.109)	(0.210)
Markups	0.131***	0.138***	0.132***	0.134***	0.132***	0.125***	0.134***	0.134***	0.131***	0.135***	0.135***	0.134***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)
Log(Assets) x Skill	-0.010***				0.008***				0.005			
	(0.003)				(0.003)				(0.003)			
Markups x Skill		-0.026*				0.018				-0.013		
		(0.014)				(0.012)				(0.017)		
HHI x Skill			-0.588**				-0.091				-0.154	
			(0.239)				(0.193)				(0.225)	
Market Share x Skill				-0.375				0.035				0.034
				(0.275)				(0.384)				(0.415)
N	39659	39659	39659	39659	39659	39659	39659	39659	39659	39659	39659	39659
Adj. R-sq	0.072	0.070	0.071	0.070	0.071	0.070	0.070	0.070	0.070	0.070	0.070	0.070
Fixed Effects	Industry, Year				Industry, Year				Industry, Year			

Table 8: **Human Capital and Star Status Robustness: Measurement of Excess Cash (Continued...)**

Panel C: ROICTOT computed using no excess cash

	1	2	3	4	5	6	7	8	9	10	11	12
	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star	Cash ROIC^{TOT} Star
Skill	RMAN				CPS				NRCOG			
Log(Assets)	0.021***	0.018***	0.018***	0.017***	0.015***	0.018***	0.018***	0.017***	0.018***	0.017***	0.018***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Age)	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.067***	-0.066***	-0.066***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HHI	0.079	0.082	0.497**	0.075	0.081	0.082	0.065	0.078	0.084	0.079	0.005	0.079
	(0.087)	(0.087)	(0.208)	(0.086)	(0.088)	(0.087)	(0.090)	(0.090)	(0.087)	(0.087)	(0.152)	(0.089)
Market Share	0.036	-0.027	-0.037	0.282	0.049	-0.017	-0.017	-0.022	0.007	-0.008	-0.014	0.077
	(0.127)	(0.122)	(0.121)	(0.260)	(0.123)	(0.122)	(0.122)	(0.125)	(0.122)	(0.123)	(0.123)	(0.214)
Markups	0.070***	0.076***	0.071***	0.073***	0.071***	0.067***	0.073***	0.073***	0.071***	0.075***	0.074***	0.073***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log(Assets) x Skill	-0.009***				0.007***				0.004			
	(0.002)				(0.003)				(0.003)			
Markups x Skill		-0.019				0.012				-0.020		
		(0.012)				(0.010)				(0.015)		
HHI x Skill			-0.593**				-0.101				-0.127	
			(0.234)				(0.189)				(0.229)	
Market Share x Skill				-0.499*				0.205				0.216
				(0.294)				(0.381)				(0.411)
N	42384	42384	42384	42384	42384	42384	42384	42384	42384	42384	42384	42384
Adj. R-sq	0.051	0.050	0.051	0.050	0.051	0.050	0.049	0.049	0.050	0.050	0.049	0.049
Fixed Effects	Industry, Year				Industry, Year				Industry, Year			

Figure A1: **Rise in Star Firms - Large Firm Sample**

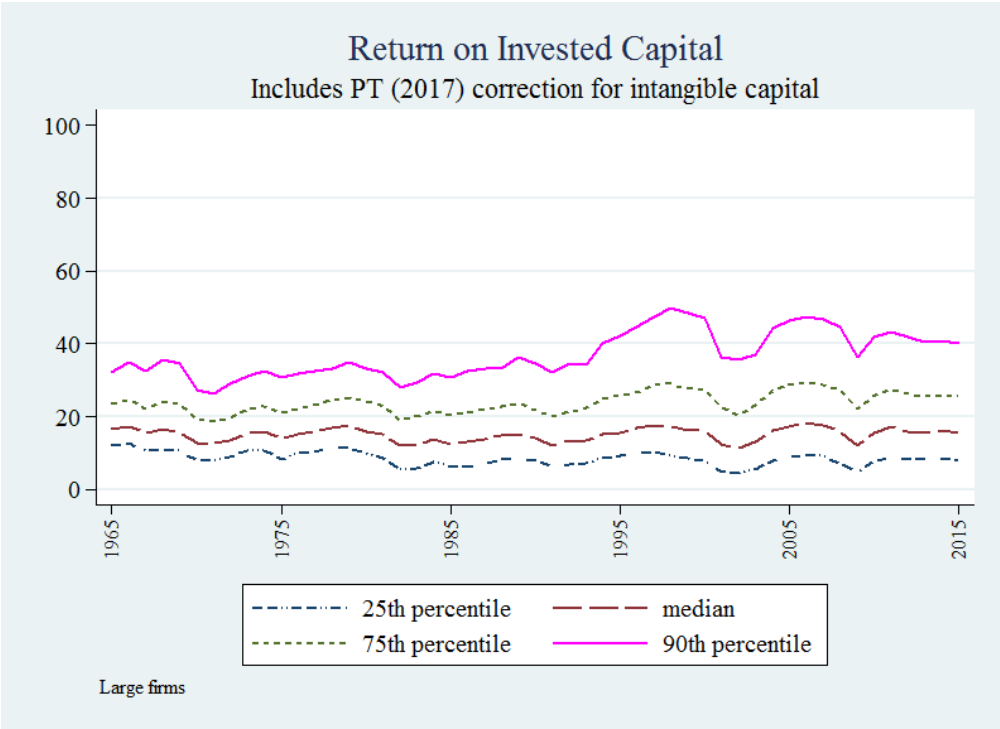

Figure A2: **COGS are a declining share of firm variable costs**

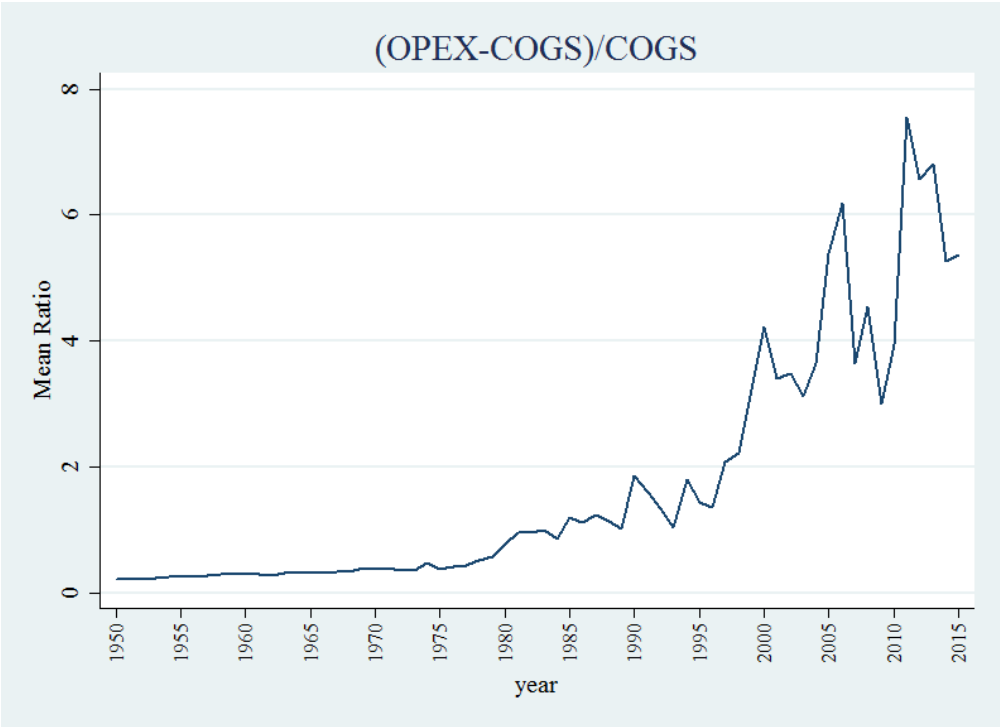

Figure A3: $ROIC^{TOT}$ **of Top 100 and Top 150 firms**

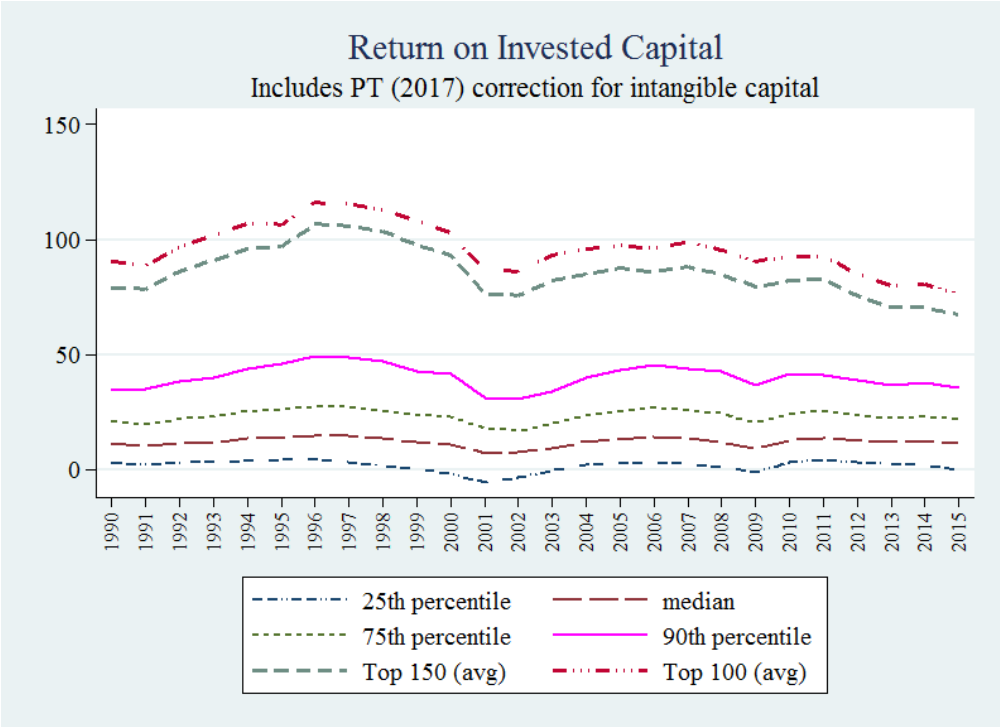

Table A1: **Variable Definitions**

Variables	***Definition***
Invested Capital	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 (excluding Goodwill), 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	(EBITt+AMt)/Invested Capitalt-1 where EBIT is Earnings before Interest and Taxes and AM is Amortization of Intangibles
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.
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
Invested Capital^{TOT}	Invested Capital^{TOT} = 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^{TOT}	ROIC^{TOT} = (EBIT + AM + XRD + 0.3 x SGA - δ_{RD} x K_int_know - δ_{SGA} x K_int_org)/Lagged value of Invested Capital^{TOT} where EBIT is Earnings before Interest and Taxes, AM is Amortization of Intangibles, XRD is Research and Development Expense, 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)
ROIC^{TOT} Star	Dummy variable that takes the value 1 if the firms ROICTOT is above the 90th percentile of ROIC^{TOT} across all firms in the US economy in a particular year and 0 otherwise
Markups	Markups following the estimation in De Loecker and Eeckhout (2017) using Operating Expenses (OPEX) as a variable input
Markups^{TOT}	Markups following the estimation in De Loecker and Eeckhout (2017) using Operating Expenses* (OPEX*) as a variable input where $OPEX^* = OPEX - XRD - RDIP - 0.3 \times XSGA$ where OPEX is Total Operating Expenses, XRD is Research and Development Expense, RDIP is in-process R&D expense, XSGA is Selling, General, and Administrative Expense
COGS Markups	Markups following the estimation in De Loecker and Eeckhout (2017) using Cost of Goods Sold (COGS) as a variable input
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

Table A1: **Variable Definitions**

Variables	***Definition***
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
Sales/IC	Sales/Invested Capital^{TOT}
Capex/IC	Capital Expenditures/Invested Capital^{TOT}
Tobin's Q^{TOT}	Q^{TOT} = 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).
CPS	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.Source: O*NET
NRCOG	Mathematical Reasoning + Inductive Reasoning + Developing Objectives and Strategies + Making Decisions and Solving Problems. Source: O*NET
RMAN	Spend time making repetitive motions + Pace Determined by Speed of Equipment + Manual Dexterity + Finger Dexterity. Source: O*NET