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The Rise of Star Firms: Intangible Capital and Competition

Meghana Ayyagari
School of Business, George Washington University, USA

Asli Demirgüç-Kunt
Center for Global Development, USA

Vojislav Maksimovic
Robert H. Smith School of Business at the University of Maryland, USA

The large divergence in the returns of top-performing star firms and the rest of the economy is substantially reduced when we account for the mismeasurement of intangible capital. Star firms produce and invest more per dollar in invested capital, have more valuable innovations as measured by the market value of patents, and are as exposed to competitive shocks as nonstars. Star firms have higher markups that are predicted early in their life cycle at a time when they are small. Overall, after we correct for the mismeasurement of intangibles, the evidence points to the superior ability of star firms. (*JEL* E22, L1)

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Recent academic literature in finance and economics has pointed to the growing importance of superstar firms in the U.S. economy (see Autor et al. 2020; Hall 2018; Van Reenen 2018; De Loecker, Eeckhout, and Unger 2020) and worldwide (see Andrews, Criscuolo, and Gal 2015; Freund and Pierola 2015).

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The rise of star firms in the United States has been largely linked to an increase in the concentration of product markets over time and firms' ability to exploit market power (e.g., Grullon, Larkin, and Michaely 2019; Barkai 2020; Gutiérrez and Philippon 2017).

However, we have little systematic evidence on the characteristics of star firms and whether they exploit their market power in traditional ways by cutting output and investment compared to other firms. Importantly, we also know little about whether the rise of star firms is associated with another dominant trend in the economy, namely, the introduction of new technologies and a fundamental structural change toward a more intangible, intensive economy (Corrado and Hulten 2010).[1] While other papers have alluded to productivity differences between firms and sectors (e.g., Autor et al. 2020; Crouzet and Eberly 2019), our aim in this paper is to understand the extent to which the high returns on capital of star firms are due to unmeasured differences in intangible invested capital and how, once these are corrected, star firms differ in their output and investment strategies from other firms.

We first identify star firms (defined as firms in the top 10% of Return on Invested Capital (ROIC), pretax, in a particular year)[2] and their industries using a data set of publicly listed firms from the Compustat database. Next, we will outline a model of heterogeneous firms facing monopolistic competition to generate predictions on how star status (or more generally, ROIC) is related to firm markups and intangible capital. In doing so, we account for one of the key concerns with the measurement of intangible capital, that conventional return metrics do not capitalize research and development, brand capital, or other forms of organizational capital with far-reaching consequences for earnings and estimates of pricing power.[3]

Finally, we examine whether star firms are generating their high profits by cutting output and investment relative to nonstar firms. This concern arises because higher markups might predict star status. Market power as traditionally defined (e.g., Stigler 1983) and as considered illegal by the U.S. Department of Justice (e.g., Krattenmaker, Lande, and Salop 1987) is the firm's ability to profitably increase the market price of a product or service over marginal cost (so $markups > 1$) by using anticompetitive practices, such as restricting output,

[1] Several papers have explored the implications of the rise in intangible assets and knowledge capital on corporate investment (e.g., Peters and Taylor 2017; Falato et al. 2022) and other macroeconomic variables (e.g., Atkeson and Kehoe 2005; McGrattan and Prescott 2010; Eisfeldt and Papanikolaou 2014).

[2] 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; Furman and Orszag 2015) and by practitioners (e.g., Koller 1994; Koller, Goedhart, and Wessels 2017). For instance, the Chief Financial Officer of General Motors, Chuck Stevens stated "ROIC provides the clearest picture of how we are managing our capital and our business" in Benoit (2016). In a parallel treatment we also obtain similar results when we use Tobin's q to define star firms.

[3] The measurement error in intangible capital affects measures of firms' earnings, the identification of variable costs, capital investment, and estimates of pricing power, all of which are outcomes that are subject to controversy. This measurement error is greatest in industries that heavily rely on intellectual and organizational capital, neither of which is measured by ROIC prepared according to generally accepted accounting principles.

or colluding. On the contrary, high markups may also occur due to superior entrepreneurship. The argument is stated in Demsetz (1973): "Superior ability also may be interpreted as a competitive basis for acquiring a measure of monopoly power. In a world in which information is costly and the future is uncertain, a firm that seizes an opportunity to better serve customers does so because it expects to enjoy some protection from rivals because of their ignorance of this opportunity or because of their inability to imitate quickly. One possible source of some monopoly power is superior entrepreneurship." Below, we will investigate whether the output and investment decisions of star firms are consistent with superior entrepreneurship.

Our analysis yields the following main findings. First, the current accounting standards lead to a misclassification of star firms. We find that recomputing ROIC to factor in estimates of intangible capital from the finance literature (see Eisfeldt and Papanikolaou 2013; Peters and Taylor 2017 and the references therein) has consequences for both the identification of star firms and the measurement of markups: the run-up in ROIC over time for the top decile of U.S. publicly traded firms compared to the median firm shown in the previous literature (e.g., Furman and Orszag 2015) is substantially reduced after the intangible capital correction. By the end of our sample period in 2015, 53% of the divergence in ROIC between the $90th$ percentile and median firm in high intangible capital industries is explained by the mismeasurement of intangible capital. Similarly, once we adjust the markups based on operating expenses for intangible capital, we find only a modest rise in markups over time, unlike what De Loecker and Eeckhout (2017) suggest, and most of this increase is in the top 10% of firms in high intangible capital industries. The intangible capital correction reduces the number of firms classified as stars in the Healthcare sector (12.94% in the adjusted case vs. 21.63% in the unadjusted case), while increasing the number of stars in Manufacturing (18.80% in the adjusted case vs. 13.98% in the unadjusted case).

Second, consistent with the model predictions, we find that markups are positively related to high profits and greater probability of being a star. However, the implications of this finding for star firms are not straightforward. On the one hand, there is a clear textbook cost of markups due to static deviations from marginal cost pricing. On the other hand, we also see that not all star firms have high markups, with 72.2% of star firms having markups outside the top 10%. More importantly, for star firms these markups or pricing power may arise because of their success in a larger competitive process that benefits buyers.[4]

[4] Policy makers recognize this view by noting "It is important to note that it is not illegal for a company to have a monopoly, to charge high prices, or to try to achieve a monopoly position by aggressive methods. A company violates the law only if it tries to maintain or acquire a monopoly through unreasonable methods." See https://www.ftc.gov/enforcement/anticompetitive-practices, accessed May 26, 2022. See also Carlton and Heyer (2008).

Third, we find that firms' markups in the early years of the firm are highly persistent and predict subsequent star status in both high and low intangible intensity industries. Young firms are small and unlikely to have accumulated much market power by actions considered unreasonable and predatory by antitrust authorities.[5] If early markups predict future star status, it is more likely that future star firms were founded to exploit products that are priced high because they are more highly valued by customers, have discovered new markets or have unique managerial talent that is contributing to their high initial pricing power and their future star status. This is consistent with the Demsetz view of superior entrepreneurship cited above.

Fourth, we investigate the concern that star firms are generating high profits by following an allocatively inefficient strategy of low output and low investment. Empirically, we show that at every level of intangible capital intensity, star firms have higher output and investment (Capex, R&D, and SG&A) per unit of invested capital than nonstar firms.[6] These results are also robust to identifying stars as q-adjusted star firms. Thus, there is no evidence that star firms produce less than similar nonstar firms. Consistent with this, we find that star firms have more economically important patents than nonstars. Specifically, the Kogan et al. (2017) measure of the economic value of new innovations based on stock market reactions to patent grants is positively associated with star status. Our findings suggest that star firms have higher innovation output than nonstars. Relatedly, we also find that higher total factor productivity is positively associated with star status.

Fifth, we examine whether star firms are differentially affected compared to other firms by exogenous shocks to their market power. If star status is acquired by exercising market power and product differentiation, star firms should be protected from foreign competitive shocks compared to nonstar firms. We measure increased competition in U.S. manufacturing by the penetration of Chinese imports into the United States, instrumented by Chinese imports into eight other developed economies following Autor, Dorn, and Hanson (2013). While the exogenous shock to competition (increase in Chinese imports to the United States) affects return on invested capital, output, and markups of all firms negatively, we find no evidence that star firms are differentially affected by import competition compared to other firms in the economy, suggesting that monopoly power is not the key driver of star status.[7]

[5] This is in line with models of predatory behavior (e.g., Fudenberg and Tirole 1986; Bolton and Scharfstein 1990; Poitevin 1989) that posit predatory behavior by well-established incumbents toward new entrants.

[6] We assume heterogeneous firm organizational competencies and compare star firms to other firms in their industries, and not to a hypothetical industry structure.

[7] As an alternative measure of competitive shocks, following Fresard (2010), we also exploit large exogenous reductions in industry-level import tariffs as a quasi-natural experiment. Difference-in-differences regressions once again confirm that star firms are not differentially affected by increases in competition compared to other firms in the economy.

Finally, we see that once we correct for the mismeasurement of intangible capital, intangible intensity is nonmonotonically related to star status and explains far less of the variation in star status (and ROIC) compared to markups. In exploring the nonmonotonic relation between intangible intensity and ROIC, our results highlight the importance of product life cycle factors (see Hoberg and Maksimovic 2022). In particular, we show that firms with very high intangible intensity and which are also doing a great deal in product development (i.e., firms in Life1 stage of product life cycle as in Hoberg and Maksimovic 2022) have very low revenues and a low realized return on invested capital. As the product goes to market, the firm lowers intangible intensity, and revenues increase.

Taken together, our results suggest that the inherent characteristics of the firm, which are reflected in high markups in the firm's initial life and can predict higher future markups, act as an important driver of high ROIC and star status. Moreover, while star firms and nonstar firms with the same level of markups face similar incentives to increase prices and reduce output and investment, star firms have higher output than do nonstar firms. If anything, rather than restricting output, at the margin star firms are producing more by following more growth focused strategies, as in the discussion of Amazon below. Moreover, the conventional focus on markups as evidence of market power that does not take into account intangible capital has the potential of penalizing highly skilled and productive firms, with adverse effects on the economy.

Our findings however come with the proviso that we are focused on exploring specific firm strategies rather than a complete welfare analysis of whether consumers are better off or not with star firms.[8]

Our results are robust to a number of checks and alternative specifications. First, our results hold using 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 also find all our conclusions above to hold even when we tighten the requirement for star status down to the top-100 or top-150 firms (when ranked by ROIC) each year. There is no run-up over time of the top-100 or top-150 firms once we correct for intangible capital. Moreover, we do find that the effects of star status are persistent. Five years later, star firms have higher ROIC, sales growth, and Tobin's q, suggesting that our results are not driven by firms that have randomly realized high returns in specific years.

One of the concerns with our analyses might be that we are picking up mechanical relations since ROIC, Markups, and Sales/Invested Capital are revenue based. This concern is alleviated since we find similar results using

[8] In particular, our findings are consistent with star firms producing less than what a perfectly competitive pricing criterion would suggest. However, this does not imply that consumers are necessarily better off with fewer star firms as splitting up star firms is likely to affect cost structures.

Tobin's q to define star status. Furthermore, we also examine several investment variables, including Capex, R&D investment and SG&A investment, not subject to the same concern.

Finally, to account for the fact that cash holdings at some of the technology companies are substantial, we use yet another definition of star status, one in which we consider only noncash working capital in our definition of ROIC.[9] 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. We follow Peters and Taylor (2017) in constructing our measure of intangible capital to include knowledge capital (R&D expenses) and organization capital (SG&A expenses), and we obtain similar results when we include only knowledge capital in our definition of intangible capital.

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, some of their markups, such as that of Apple and Amazon, are not necessarily much larger than those of the $90th$ percentile firm over the sample period. As discussed in Section 4.1 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.

1. Related Literature

Our paper is related to the growing literature exploring the rise in concentration (see Grullon, Larkin, and Michaely 2019, Baker and Salop 2015; Kurz 2017), decline in labor share (see Barkai 2020; Autor et al. 2020), and hollowing out of investment in physical capital (Gutiérrez and Philippon 2017; Alexander and Eberly 2018). One interpretation of these related literatures is that the divergence in the performance of star firms from other firms reflects increased market power and reduced competitiveness and economic efficiency (De Loecker and Eeckhout 2017).

An alternative interpretation is that it reflects productivity differences between firms. By investing in intangible capital, firms could become

[9] 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, excess cash retained by the firm's managers and should not be used in evaluating the economic value of the firm's business.

more efficient, deliver higher-quality products at lower prices and thus gain market share. Crouzet and Eberly (2019) highlight the heterogeneity across sectors, finding that in the manufacturing and consumer sectors, labor productivity increases but markups do not, suggesting efficiency-enhancing mechanisms. In healthcare and high-tech, on the other hand, both markups and labor productivity increase, suggesting both market power and efficiency mechanisms are at work. Autor et al. (2020) and Bessen (2016) also look within industries and point to efficiency considerations. Autor et al. (2020) find that industries with greater increases in concentration also have faster growth in patent rates, capital intensity, and productivity, whereas Bessen (2016) shows IT-intensive firms are larger, are more productive, and have higher operating margins.

While our paper is related to the Crouzet and Eberly papers in emphasizing the role of intangible capital, it differs from them along the following aspects: First, our paper emphasizes the heterogeneity among firms in terms of markups and returns. In contrast, Crouzet and Eberly (2022) are focused on decomposing the gap between observable Tobin's q and marginal q into components reflecting the effects of rents (rising market power) and the effects of omitted capital. They use this decomposition to show that the investment gap is driven by fast-growing industries but that these industries' investment gaps are mostly explained by intangibles. Thus, even though they use data at the firm level, their focus is on explaining sectoral differences in investment gap. Our analysis uses industry fixed effects and looks within industries to understand how star firms differ not only in their investment but also along output, productivity, and patenting activities compared to nonstars. Second, we also examine whether star firms are differentially affected compared to other firms by exogenous shocks to their market power as measured by the penetration of Chinese imports into the United States. Crouzet and Eberly (2019, 2022) do not have a concept of star firms in their paper and do not examine shocks to market power.

The firm-level focus in our paper is shared by Andrews, Criscuolo, and Gal (2015), who document an increasing productivity gap between the global frontier and laggard firms. They argue that the labor productivity gap between global frontier and laggard firms reflects not only the increasing market power of frontier firms but also their success in combining various intangibles in the production processes and their innovation. However, Andrews, Criscuolo, and Gal (2015) do not focus on the measurement issues related to intangible capital as we do so that their claim is difficult to evaluate. Our paper differs from theirs in its focus on U.S. firms (compared to firms across the world) and returns to shareholders (compared to productivity differences).

A number of finance studies have studied the role of competitive shocks on firm financing (e.g., Zingales 1998; Khanna and Tice 2000; Campello 2003; Fresard 2010) and stock returns (e.g., Hou and Robinson 2006;

Hoberg and Phillips 2010; Bustamante and Donangelo 2017). In particular, Hou and Robinson (2006) find that firms in more competitive markets tend to earn higher stock returns whereas Bustamante and Donangelo (2017) find that competition erodes markups and firms in competitive markets earn lower returns.

Our contribution to this literature and the broader literature on competition and market power is twofold: First, we show measurement issues related to intangible capital affect both firm-level measures of competition (market power) and returns. Correcting for the measurement error in intangible capital affects which firms are identified as star firms and the point estimates of markups and their relation to star status. In this aspect, our paper is related to Traina (2018), who argues that if we used only cost of goods sold (COGS) as a measure of variable inputs as in De Loecker and Eeckhout (2017), we would be misestimating markups since Selling, General, and Administrative expenses (XSGA) have been an increasing share of firm's expenses over time. We show that Traina (2018) overadjusts markups for intangible capital (details are in Section 2.3) and that our adjustment is more conceptually consistent with the literature (e.g., Peters and Taylor 2017). We differ from Traina (2018) in arguing that part of XSGA is actually capital expenses, which build the capital stock of a firm and not operating expenses at all. Specifically, following Peters and Taylor (2017), we treat R&D expenditures as an intangible investment and 30% of the Selling, General, and Administrative expenses as an organizational investment. Hence, we again compute operating expenses without these two components, which we treat instead as additions to capital stock of the firm. Second, in contrast to these papers, the focus in our paper is not on explaining the rise in concentration or markups in an industry, but on establishing that the star firms' comparatively higher industry-adjusted returns are consistent with higher ability. In this, our paper is also related to the Demsetz (1973) critique, which argues that successful firms are more likely to be efficient than other firms, and that their success is due to this efficiency rather than market power. Our results are consistent with this critique, in that we argue that star firms have higher output, controlling for their markups.[10]

More generally, our paper points to the importance of adjusting for intangible capital in corporate finance research. Differences in intangible capital across firms and over time not only affect ROIC and our evaluation of investment and market power but also most likely will affect optimal capital structures, governance, and firms' cash policies.

10 As noted above, Demsetz (1973) also argues that firms' markups also may be the result of their superior choice of markets to enter and ability to set up superior organizations. The predictive power of early markups for future star status, reported below, is consistent with that view.

2. Star Firms, Intangible Capital, and Markups

In this section, we present a model deriving simple testable hypotheses relating markups and the role of measurement error in the financial accounting treatment of intangible capital and profitability.[11] Consider a firm that is a monopolist in its variety and faces the following demand function:

$$Y_{i,t} = P_{i,t}^{-\frac{\mu_{i,t}}{\mu_{i,t}-1}} D_t, \tag{1}$$

where $P_{i,t}$ is the price for its product; $Y_{i,t}$ is the gross output; D_t is an index of aggregate demand; and $\mu_{i,t}$ is the markup of marginal cost over price charged by the firm.[12]

The firm's production function is

$$Y_{i,t} = Z_{i,t} L_{i,t}^{1-\alpha} K_{1,i,t}^{(1-\eta_{i,t})\alpha} K_{2,i,t}^{\eta_{i,t},\alpha}, \tag{2}$$

where the firm's inputs of production are labor L, physical capital K_1, and intangible capital K_2; Z is Hick's neutral efficiency (TFPQ). We assume Z is heterogeneous across firms (Melitz 2003; Hopenhayn 1992) and productive, higher Z firms have higher levels of factor inputs and greater sales; $1-\alpha$ is labor share; and η is intangible intensity. So both intangible intensity, $\eta_{i,t}$ and markups, $\mu_{i,t}$ vary over firm and time.

We assume that factor markets are competitive but allow for imperfect competition in the product market. So W is wage rate associated with labor L, and R_1 and R_2 are the two user costs of capital associated with K_1 and K_2, respectively. The firm solves the following optimization problem (we will drop the subscripts i and t for simplicity going forward):

$$\Pi = \max_{L,K_1,K_2} DP^{-\frac{1}{\mu-1}} - WL - R_1 K_1 - R_2 K_2, \tag{3}$$

subject to the production constraint

$$ZL^{1-\alpha} K_1^{(1-\eta)\alpha} K_2^{\eta\alpha} \geq DP^{-\frac{\mu}{\mu-1}}. \tag{4}$$

Note that the firm's optimization problem is a dual profit maximization problem and a cost minimization problem where the firm chooses factor inputs L, K_1, K_2 to produce Y at minimum cost.[13] Solving this gives us the following marginal cost:

$$\lambda = \frac{1}{Z}\left(\frac{R_1}{\alpha(1-\eta)}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_2(1-\eta)}{R_1\eta}\right)^{\alpha\eta} \equiv MC. \tag{5}$$

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11 We thank an anonymous referee for suggestions on the model structure.

12 Empirically, we measure markups using the cost-share approach used in Foster, Haltiwanger, and Syverson (2008) and De Loecker, Eeckhout, and Unger (2020).

13 See the Internet Appendix for a derivation of the expression for the Lagrangian multiplier, λ

Solving the first-order conditions (FOC) from the firm's profit maximization problem gives us the following:

$$P=\mu\lambda=\mu MC, \tag{6}$$

$$WL=\frac{(1-\alpha)PY}{\mu}, \tag{7}$$

$$R_1K_1=\frac{\alpha(1-\eta)}{\mu}PY, \tag{8}$$

$$R_2K_2=\frac{\alpha\eta}{\mu}PY. \tag{9}$$

2.1 Mapping the production model to ROIC

The underestimation of intangible capital (and thus an overestimation of ROIC and biased regression estimates) could arise from two situations: First, given the difficulty in measuring intangible capital accurately, assume that we are only measuring a portion of the intangible capital, that is, νK_2, where $0\leq \nu\leq 1$. Thus, total *Invested capital* in the firm's reported financial statements is given by

$$\textit{Invested capital}=K_1+\nu K_2. \tag{10}$$

Second, the treatment of intangible investment from the perspective of standard accounting rules is not uniform. Some intangibles like marketing are expensed so that a portion γR_2K_2, (where $0\leq\gamma\leq 1$), are treated as operating expenses instead of being treated as investment or capital costs; and other types of intangibles like the creation of in-house software are capitalized (so that $\gamma=0$) and are not treated as operating expenses. These latter intangibles are treated correctly from an economic standpoint.

Earnings is given by:[14]

$$\textit{Earnings}=PY-WL-\gamma R_2K_2. \tag{11}$$

Combining Equations (10) and (11), we have

$$ROIC=\frac{PY-WL-\gamma R_2K_2}{K_1+\nu K_2}. \tag{12}$$

To relate to the model, we substitute the FOC from (7), (8), and (9) into the above equation to get

$$ROIC=\left(\frac{\mu-(1-\alpha)}{\alpha}-\gamma\eta\right)\left(\frac{1-\eta}{R_1}+\frac{\nu\eta}{R_2}\right)^{-1}. \tag{13}$$

Using the above definition, we can now highlight how ROIC varies with markups μ and intangible intensity η and the impact of the adjustments to

[14] Note that we have assumed no depreciation for simplicity.

intangible capital. Of special interest are the instances when $\nu=1-\gamma$ and $\nu\neq 1-\gamma$. When $\nu=1-\gamma$, the intangibles that are capitalized (i.e., ν) are also the same intangibles that are exempt from being expensed. In addition, if $\nu=1$ and $\gamma=0$, the accounting treatment will accurately reflect the underlying economics of the model.

When $\nu\neq 1-\gamma$, the accounting system is not consistent at the firm level.[15] Suppose that $\gamma>0$ of an investment in an intangible asset is expensed, but none of it is capitalized (say, in the case of marketing expenses), then $0=\nu<1-\gamma$, or $\nu+\gamma<1$, which will result in a *higher* ROIC (because of a lower denominator in Equation (13) above) than if $\nu=1-\gamma$. On the other hand, if $\nu>1-\gamma$, or $\nu+\gamma>1$, the reverse will happen, with a *lower ROIC* than the case when $\nu=1-\gamma$.

Below, we start with a couple of specialized cases to highlight the economic forces that explain the variation in *ROIC* before analyzing the general case.

2.1.1 Case 1: No intangible capital $\eta=0$. When firms do not use any intangible capital in production, the expression for *ROIC* is given by

$$ROIC_1=\left(\frac{\mu-(1-\alpha)}{\alpha}\right)R_1. \tag{14}$$

Thus, the cross-section variation in ROIC is driven by markups, and we should expect high markup firms to have high ROIC in all instances.

2.1.2 Case 2: Perfectly competitive markets $\mu=1$. Assume perfectly competitive markets and all firms have same markup, that is, $\mu=1$ that makes it straightforward to analyze how ROIC varies with intangible intensity. The expression for *ROIC* for $\mu=1$ is given by

$$ROIC=(1-\gamma\eta)\left(\frac{1-\eta}{R_1}+\frac{\nu\eta}{R_2}\right)^{-1}. \tag{15}$$

A special case is when intangible capital is not included at all in the measurement of overall capital, so $\nu=0$. The expression for ROIC is then given by

$$ROIC_2=\left(\frac{1-\gamma\eta}{1-\eta}\right)R_1. \tag{16}$$

In this scenario, all the variation in $ROIC_2$ is driven by intangible intensity and we should expect high-intangible-intensity firms to have high ROIC. More

[15] For example, when $\nu=1$ and $\gamma=1$, the same asset would be both fully capitalized and fully expensed. Similarly, if $\nu=0$ and $\gamma=0$, the asset would neither be capitalized nor expensed. For any given level of γ, $\nu+\gamma<1$ implies that some intangible assets are neither expensed nor capitalized. For $\nu+\gamma>1$, some intangible assets are both expensed and capitalized.

generally for $\nu \neq 0$, differentiating wrt intangible intensity, we see that $ROIC_2$ is increasing in η if

$$R_2 > R_1 \frac{\nu}{1-\gamma}. \tag{17}$$

Under consistent accounting, that is when $\nu = 1-\gamma$, ROIC is increasing in intensity under the plausible condition $R_2 > R_1$. So also when intangible capital is overcapitalized and $\nu+\gamma > 1$. However, when $\nu+\gamma < 1$, ROIC is increasing in intensity when $R_2 < R_1$; that is, the user cost of intangible capital is less than that of tangible capital, which is unlikely given recent estimates of intangible capital in the literature (e.g., Crouzet and Eberly 2022).

2.1.3 Case 3: General case $\mu > 1$ and $\eta > 0$. Coming back to the general case in Equation (13):

$$ROIC = \left(\frac{\mu-(1-\alpha)}{\alpha} - \gamma\eta\right)\left(\frac{1-\eta}{R_1} + \frac{\nu\eta}{R_2}\right)^{-1}.$$

Here, *ROIC* is increasing in markups μ, and decreasing in the proportion of intangibles capitalized ν and the proportion of intangibles expensed γ as shown in the Appendix Section C.

To see how *ROIC* varies with intensity, differentiating wrt η, we get

$$\frac{\partial ROIC}{\partial \eta} = -\left(\frac{R_1 R_2}{\alpha(\eta\nu R_1 + (1-\eta)R_2)^2}\right)(R_1\nu(\mu+\alpha-1) + R_2(1+\alpha(\gamma-1)-\mu)). \tag{18}$$

Rearranging the second term, we see that *ROIC* is increasing in intangible intensity, η if

$$R_2 > R_1\nu \frac{\mu+\alpha-1}{\mu+\alpha(1-\gamma)-1} = R_1\nu\kappa, \tag{19}$$

where $\kappa \geq 1$.

In the important special case we examine empirically below, when intangible capital is not erroneously expensed (so $\gamma = 0$) then *ROIC* is increasing in intensity for $R_2 > R_1\nu$, a very plausible condition given that $0 \leq \nu \leq 1$. Also, when intangible capital is not measured as capital (so $\nu = 0$), thenA ROIC is always increasing in intensity, η. The condition (19) also becomes less stringent (i.e., κ decreases) as μ increases.

In more general cases, additional assumptions are required to understand how changing γ affects the condition. To allow for inconsistent accounting treatment of expenses and capitalization so that $\gamma+\nu \neq 1$, let us define $\rho = \nu+\gamma-1$. To explore the impact of expensing too much or too little of intangible capital, we substitute for ν into the condition above, and differentiate with respect to γ, to obtain

$$\left(\frac{(\mu-(1-\alpha))(1-\mu+\alpha\rho)}{(1-\mu-\alpha(1-\gamma))^2}\right).$$

Thus, as more intangible capital is expensed (γ increases), the condition (19) that *ROIC* increases in intangible intensity holds at higher values of R_1 relative to R_2 if $\gamma+\nu\leq 1$. If $\gamma+\nu>1$, $\rho>0$, the condition that *ROIC* increases in intangible intensity holds at higher values of R_1 relative to R_2 only for $\rho<\frac{\mu-1}{\alpha}$ and reverses for $\rho>\frac{\mu-1}{\alpha}$. Thus, we expect reported *ROIC* to increase with intangible capital intensity if the accounting reporting is consistent or if it undercapitalizes intangibles relative to how much it expenses them. However, *ROIC* may decrease with intangible capital intensity if the accounting reporting is inconsistent and overcapitalizes relative to expensing intangibles, especially if the market is competitive so that μ is close to one.[16]

Below, we adjust firms' reported financials to be consistent and to approximate $\nu=1$ and $\gamma=0$. We will then test the relations between ROIC, markups, sales, and intangible intensity in Section 3. For the most part of the empirical tests, we assume that our adjustments to intangible capital are consistent, accurate, and complete. However, in a robustness section (Section 6.4) we will also allow for an incomplete adjustment for intangible capital (i.e., $\nu\neq 1$) and show that our results relating markups, intangible intensity, and ROIC remain.

Overall, the simple model outlined in this section provides guidance on how to adequately interpret ROIC in the presence of mismeasured intangibles and the relationship between ROIC and markups. However, as we show in the sections below, the model is not equipped to rationalize all the empirical findings in the data.

2.2 Measures of ROIC, and intangible capital

To derive measures of the Return on Invested Capital (ROIC), we use data from Compustat that provides detailed financial information on publicly traded firms in the United States over an extended period of time. We drop cross-listed American depositary receipts (ADRs) and restrict the sample to firms incorporated in the United States. We also drop firms in Utilities (SIC code 49), Finance, Insurance and Real estate (SIC codes 60-69), and Public Administration (SIC codes 90-99), observations with missing SIC codes,

[16] Given the ranges for observed labor share α (0.5-0.8, the average labor share in the United States from 1990 to 2015 is 0.61 from FRED), markups μ (1-4, as seen in our data), and $0\leq\nu\leq 1$, we see $1\leq\kappa\leq 2$ and $0\leq\nu\kappa\leq 1$. Thus, we expect for most firms, ROIC to be increasing in intensity η for $R_2>R_1$. Note that there are edge cases, where γ and μ are close to one, when this may fail if the accounting system inconsistently overcapitalizes intangible investment, given how much it expenses them.

negative values for employees, sales, total assets, current assets and current liabilities, fixed assets, cash, and goodwill and missing total assets or sales.[17]

We begin by using a standard definition of ROIC as our measure of returns, where ROIC for firm i in year t is defined as

$$ROIC_{it}^{unadj} = \frac{EBIT_{it} + AM_{it}}{Invested\ Capital_{it-1}^{unadj}}, \tag{20}$$

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, Graham, and Harvey (2013), among many others, computes the earnings that a corporation realizes over a period, as a fraction of capital that investors have invested into the corporation. The advantage of ROIC is that it measures investment capital as more than physical capital (fixed asset investment), which Doidge et al. (2018) show to be a declining portion of total assets over time in the United States.

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

$$\begin{aligned} Invested\ Capital_{it}^{unadj} = & PPENT_{it} + ACT_{it} + INTAN_{it} - LCT_{it} - GDWL_{it} \\ & - max(CHE_{it} - 0.02 \times SALE_{it}, 0), \end{aligned} \tag{21}$$

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.[18]

The intangible assets as registered in Compustat, *INTAN*, include externally purchased assets like blueprints, copyrights, patents, or licenses, and goodwill

[17] The advantage of using Compustat is that we have detailed balance sheet information that allows us to compute intangible capital. The caveat, however, is firm selection issues. First, listed firms, as a class, might not consistently represent star firms. Doidge et al. (2018) and Kahle and Stulz (2017) show that there are fewer U.S.-listed corporations today than 40 years ago. However, Grullon, Larkin, and Michaely (2019) argue that the void left by listed firms has not been filled by an increase in the number of private unlisted businesses. Using U.S. Census data that include 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 U.S. employment (Davis et al. 2006) and about 41% sales (Asker, Farre-Mensa, and Ljungqvist 2014). Also using U.S. Census data, Maksimovic, Phillips, and Yang (2019) show that high initial firm quality at birth predicts subsequent listing decision. These findings suggest that while our sample will not be picking up small and young potential star firms in their private stages, we are targeting the sample of firms among which economically significant stars are highly likely to arise. The second, and potentially more important issue, as pointed out by Doidge et al. (2018), is that small, young, high-technology firms may benefit from private status where specific financial institutions, such as venture capital partnerships and private equity firms, better meet their financing needs than do 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.

[18] We replace missing values of AM and GDWL with zero.

but do not include internal intangible assets like R&D and SG&A. Following Furman and Orszag (2015), in the computation of invested capital in Equation (21), we exclude Goodwill, which are the intangible assets arising out of M&A transactions when one company acquires another for a premium over fair market value. Thus, our measure is not distorted by price premiums paid for in acquisitions, allowing for an even comparison of operating performance across companies. As a result, ROIC measures the return that an investment generates for the providers of capital and reflects management's ability to turn capital into profits.[19] We also subtract cash stocks in excess of those required for transactions purposes in calculating *Invested capital*. Following Koller, Goedhart, and Wessels (2017), we treat cash above 2% of sales as excess cash and subtract it from the firm's invested capital. In Section 6.3 we undertake robustness tests allowing for varying percentages. Our estimates are not affected by firms' decisions on whether to stockpile cash in low-tax jurisdictions in order to manage their tax liabilities, as is the case of many large U.S. multinationals.

We define star firms as firms that realize high returns for their investors. Thus, $ROIC^{unadj}$ *star* is a dummy variable that takes the value of one if the firm's ROIC is above the $90th$ percentile of ROIC across all firms in the U.S. economy in a particular year and zero otherwise. One of the concerns with the above definition of star firms is that financial statements do not measure intangible assets accurately and the consequent underestimation of intangible capital is likely to be more important in high-skilled industries. This would lead to overestimation of ROIC and biased regression estimates.

The concern that conventional measures of invested capital do not properly capitalize the value of intangibles is a long standing one. Earlier attempts to address it include Peles (1971), Hirschey (1982), and Falato et al. (2022). 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 alternative definition of invested capital, we replace the $INTAN_{it}$ in Equation (21), with the new definition of intangible capital from Peters and Taylor (2017), $ICAP_{it}$.

$$Invested\ Capital^{adj}_{it} = PPENT_{it} + ACT_{it} + ICAP_{it} - LCT_{it} - GDWL_{it} - max(CHE_{it} - 0.02 \times SALE_{it}, 0), \tag{22}$$

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

where $ICAP_{it}$, is defined as the sum of externally purchased intangible capital (Compustat item *INTAN*) and internally purchased intangible capital. Internally purchased intangible capital is measured at replacement cost and is 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.[20] The estimates of *ICAP*, *K_int_know*, and *K_int_org* have been made publicly available by Peters and Taylor (2017). We follow a large literature, including Hulten and Hao (2008), Eisfeldt and Papanikolaou (2014), Xiaolan (2014), and Peters and Taylor (2017), in counting only 30% of SG&A spending as an investment in intangible capital (and the remaining 70% as operating costs); however, the uncertainty in this fraction across industries is considerable. We provide several robustness regressions to ensure that our results are not entirely dependent on the proportion of SG&A treated as intangible capital.

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

$$ROIC^{adj}_{it} = \frac{ADJPR_{it}}{Invested\ Capital^{adj}_{it-1}}, \tag{23}$$

where

$$\begin{aligned} ADJPR_{it} = {} & EBIT_{it} + AM_{it} + XRD_{it} + 0.3 \times SGA_{it} \\ & - \delta_{RD} \times K\_int\_know_{it} - \delta_{SGA} \times K\_int\_org_{it}. \end{aligned} \tag{24}$$

where δ_{RD} is the depreciation rate associated with knowledge capital and is set to 15% following Peters and Taylor (2017)[21] and δ_{SGA} is the depreciation rate associated with organization capital and is set to 20% following Falato et al. (2022). Going forward, we just use *ROIC* to refer to the adjusted value, $ROIC^{adj}$.

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 SG&A expenditure, which would have been previously expensed, are now treated as additions to capital

[20] 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 zero.

[21] In robustness tests, we find our results to be materially similar if we were to vary the R&D depreciation rates by industry sector as in Ewens, Peters, and Wang (2019) or if we were to use their average R&D depreciation rate of 32%.

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*)[22] and top and bottom 1% outliers in *ROIC*, we define *ROIC star* as a dummy variable that takes the value of one if the firm's *ROIC* is above the 90th percentile of *ROIC* across all firms in the U.S. economy in a particular year and zero otherwise.

As a proxy for the variable η in our theoretical model, we also define *Intangible intensity* as the ratio of intangible capital to the sum of intangible and tangible capital:

$$Intangible\ intensity = \frac{ICAP - GDWL}{ICAP - GDWL + PPENT}. \tag{25}$$

Remember the above results rely on defining star firms based on returns to invested capital. As an alternative definition, we will define stars in terms of Tobin's q. Again following Peters and Taylor (2017), we define q as the ratio of firm value to *TOTCAP*, which is the sum of physical (*PPENT*) and intangible capital (*ICAP*):

$$q_{it} = \frac{V_{it}}{TOTCAP_{it}}, \tag{26}$$

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 the top and bottom 1% of outliers in q, we define *q star* as a dummy variable that takes the value of one if the firm's q is above the 90th percentile of q across all firms in the U.S. economy in a particular year and zero otherwise.

While q has the advantage of using a market valuation of the firm's prospects, a large literature has shown that the measure is prospective in that it captures the value of the firm's investment opportunities given the market's view of its investment plans (e.g., Tobin 1956; Brainard and Tobin 1968; Abel 1981; Lindenberg and Ross 1981; Hayashi 1982; Erickson and Whited 2000).

22 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.

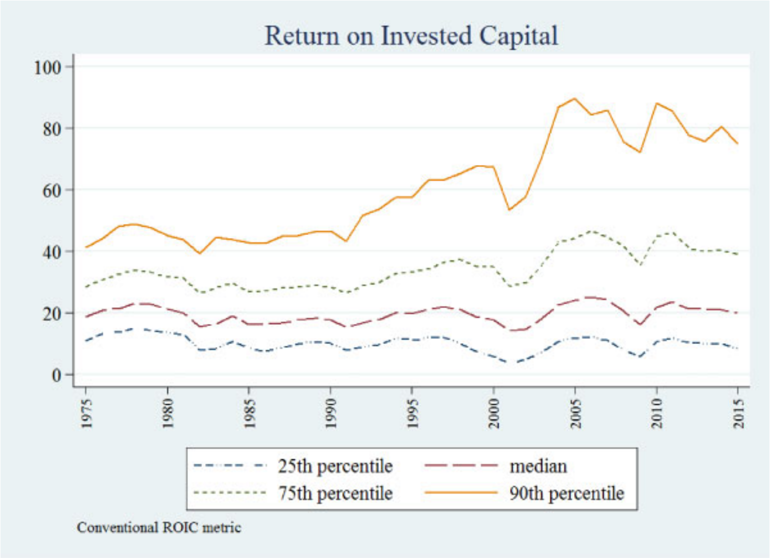


Figure 1
Rise in star firms: Conventional ROIC Metric
This figure plots the 25th, 50th, 75th, and 90th percentiles of Return on invested capital, the conventional metric unadjusted for intangible capital, $ROIC^{unadj}$ in each year across all large public firms (defined as firms with assets more than US$(2009)200 million, adjusted for inflation) in the U.S. economy. Appendix Table A9 defines the variables in detail.

2.3 Identification of star firms

We first explore patterns in the conventional ROIC metric, unadjusted for intangible capital, across time and across industries. Figure 1 plots the 25th, 50th, 75th, and 90th percentiles of $ROIC^{Unadj}$ in each year across all large public firms in the United States. To replicate the figure in previous studies, such as Furman and Orszag (2015) and Koller, Goedhart, and Wessels (2017), we restrict our sample to large firms (defined as firms with assets more than US$(2009)200 million, adjusted for inflation) and drop firms with negative invested capital. The figure shows a large rise in $ROIC^{Unadj}$ over the past three decades where the ratio of the 90th percentile firm to the median firm has increased by over 69%.[23]

Next, we explore whether there is heterogeneity in the presence of star firms across industry sectors. We split industries by their *Intangible intensity* into Low (*Intangible intensity* < *Median*) and High (*Intangible intensity* ≥ *Median*) intangible intensity industries. In Figure 2, we identify star firms in each of

[23] Similar evidence is presented in Council of Economic Advisors (2016), Furman and Orszag (2015), and Koller, Goedhart, and Wessels (2017) based on a proprietary data set of U.S. 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 return on invested capital for the top decile of firms.

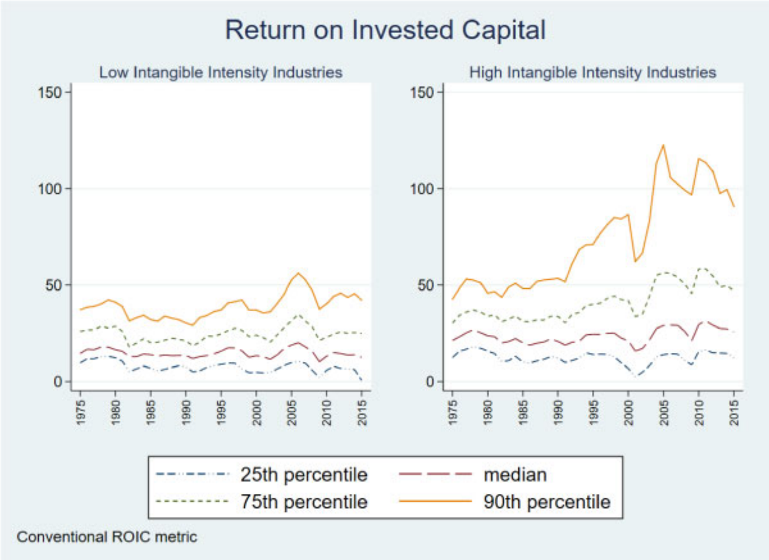


Figure 2
Differences in intangible intensity: Conventional ROIC metric
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Return on invested capital, the conventional metric unadjusted for intangible capital, $ROIC^{unadj}$ in each year in industries with Low ($<$ median) and High ($\geq$ median) intangible intensity. Intangible intensity includes the Peters and Taylor (2017) adjustment for intangible capital. Appendix Table A9 defines the variables in detail.

these subsamples as firms in the top 10% of $ROIC^{Unadj}$ 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 $ROIC^{Unadj}$ and the run-up for star firms is higher in industries with high intangible intensity.

Next, we investigate how correcting the mismeasurement in intangible capital changes the above figures. We focus on the years 1990-2015 for all the figures and tables henceforth since the high run-up in ROIC in Figures 1 and 2 starts around 1990.

When we correct invested capital to include intangible capital, we see no run-up in *ROIC* for the top 10% of firms in Figure 3. In Figure 4, we present estimates for High versus Low intangible intensity industries. The run-up we saw in Figure 2 in high intangible intensity industries disappears once we adjust for intangible capital. These differences are also statistically significant.

For simplicity, if we define divergence as the difference in ROIC between the $90th$ percentile and median firm each year, the divergence in unadjusted ROIC is always significantly larger than the divergence in adjusted ROIC. For instance, the mean difference in divergence in unadjusted ROIC and adjusted ROIC is 7 percentage points in low intangible intensity industries and 25 percentage points in high intangible intensity industries. Figure 5 plots the (Divergence in Unadjusted ROIC-Divergence in ROIC adjusted for intangible

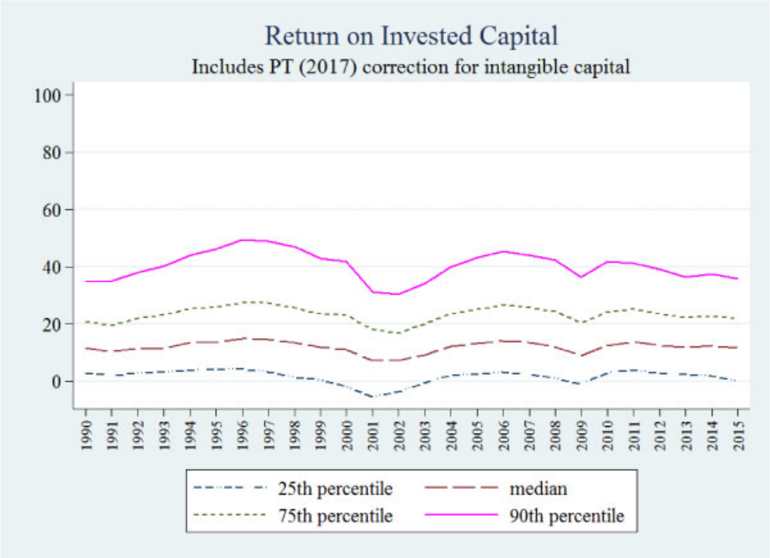


Figure 3
Rise in star firms: ROIC adjusted for intangible capital
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Return on invested capital, adjusted for intangible capital (*ROIC*) in each year across all public firms in the U.S. economy. *ROIC* includes the Peters and Taylor (2017) adjustment for intangible capital. Appendix Table A9 defines the variables in detail.

capital)/Divergence in Unadjusted ROIC to show the percentage of Divergence that is explained by our adjustment to intangible capital. The figure shows that a greater percentage of the divergence between the $90th$ percentile firm and median firm is explained over time. By the end of the sample period in 2015, 53% of the divergence between the $90th$ percentile and median firm in high intangible intensity industries is explained by the mismeasurement of intangible capital. In addition, our correction for intangible capital explains a statistically significant greater percentage of the divergence in high-skilled industries than low-skilled industries. The statistically significant difference in explained portion between high and low intangible intensity industries is 21% (p-value = .000).

In Table 1, we examine a clustering of industries among the ROIC star firms and how this clustering may change with the intangible capital correction. Following Crouzet and Eberly (2019), we split the sample into five broad sectors: Consumer sector (primarily retail and wholesale trade), High-tech sector (primarily software and IT), Healthcare sector (producers of medical devices, drug companies, and healthcare service companies), Manufacturing sector, and Other sector (Service industries, Real Estate, Warehousing and storage, Transit and ground transportation, Performing Arts, Social Assistance, etc.). Table 1 shows significant differences within and across industries. Columns 1 and 2 show the percentage of star firms within each of these

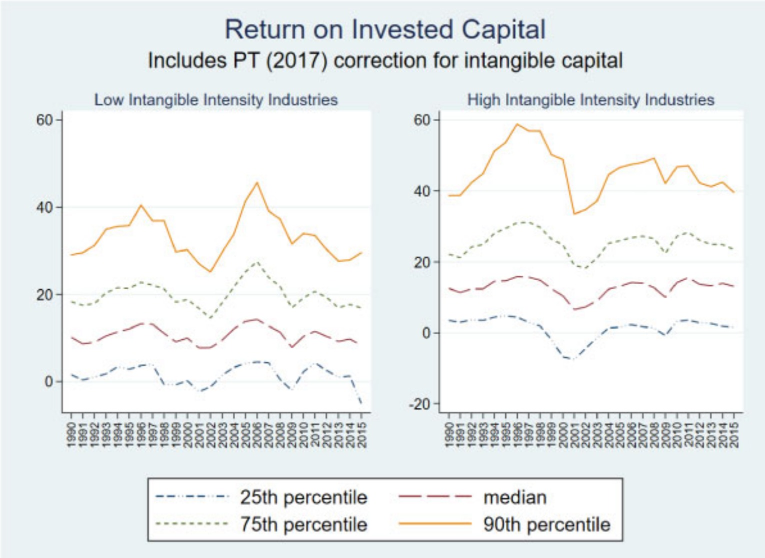


Figure 4
Differences in intangible intensity: ROIC adjusted for intangible capital
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Return on Invested Capital, adjusted for intangible capital (*ROIC*) in each year in industries with Low (< median) and High (≥ median) intangible intensity. Intangible intensity includes the Peters and Taylor (2017) adjustment for intangible capital. Appendix Table A9 defines the variables in detail.

industry groups for the adjusted and unadjusted cases, respectively. When we don't adjust for intangible capital, we find a higher percentage of stars in the healthcare sector compared to the adjusted case (14.68% compared to 8.35%) and a lower percentage of stars in all other sectors, except for high-tech, where the difference is marginal (15.85% in the unadjusted case vs. 15.30% in the adjusted case). As an alternative cut, in columns 3 and 4, we look across industries and examine the percentage of stars in the whole economy that belong to each of these sectors. The intangible capital correction reduces the number of firms classified as stars in the Healthcare sector (12.94% in the adjusted case vs. 21.63% in the unadjusted case), while increasing the number of stars in Manufacturing (18.80% in the adjusted case vs. 13.98% in the unadjusted case). Thus, by not adjusting for intangible capital correctly, the current financial reporting system is inaccurately classifying firms as stars and nonstars.

In summary, this section shows that correcting for the mismeasurement of intangible capital has the following implications for the analysis of star firms: First, our intangible capital correction eliminates the run-up in *ROIC* over time and explains more than half of the divergence between the $90th$ percentile firm and the median firm in high intangible capital industries, where the correction presumably matters the most. Second, it allows for a more

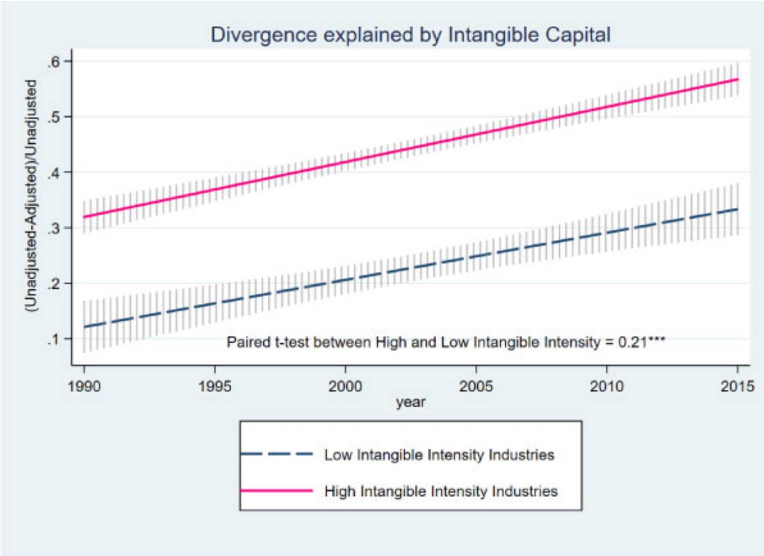


Figure 5
Divergence between the $90th$ **percentile and median firm explained by Intangible capital**
This figure plots (Divergence in Unadjusted ROIC($ROIC^{unadj}$)-Divergence in adjusted ROIC ($ROIC$))/Divergence in Unadjusted ROIC($ROIC^{unadj}$), where Divergence is defined as the difference between the $90th$ percentile and median firm. *Intangible intensity* includes the Peters and Taylor (2017) adjustment for intangible capital and Low- and High-Intangible-intensity industries are defined based on the median value each year. Appendix Table A9 defines the variables in detail.

Table 1
Industry distribution of star firms

	1	2	3	4
	Within industries		Across industries	
Industry groups	ROIC stars	$ROIC^{Unadj}$ stars	ROIC stars	$ROIC^{Unadj}$ stars
Consumer	7.02%	5.59%	6.09%	4.90%
Healthcare	8.35%	14.68%	12.94%	21.63%
High-tech	15.30%	15.85%	41.38%	42.47%
Manufacturing	6.06%	4.41%	18.80%	13.98%
Other	11.70%	9.48%	20.80%	17.03%
Total	10.00%	10.00%		

This table shows the distribution of ROIC stars within and across industry sectors. Columns 1 and 2 show the percentage of firms in each industry that are stars, with and without adjustment for intangible capital, respectively. Columns 3 and 4 show the percentage of stars in the whole economy that belong to each of these sectors, again with and without adjustment for intangible capital, respectively.

accurate identification of star firms, for example, reducing the number of stars in the Healthcare sector and increasing the number of stars in Manufacturing. Below, we will also discuss how our correction affects the measurement of markups and the point estimate of the relationship between markups and star status.

2.4 Markups and intangible capital measurement

Following Foster, Haltiwanger, and Syverson (2008) we use cost shares, that is, firms' markup of price over marginal cost, *Markups*, as our measure of market power. There has been a recent debate in the literature on the right measure of marginal costs. De Loecker and Eeckhout (2017) use Cost of Goods Sold, *COGS* as a measure of variable costs and show that average markups have increased from 18% in 1980 to 67% by 2014. Traina (2018) however argues that COGS has been a declining share of variable costs for U.S. firms (see Figure IA1 of the Internet Appendix) and other expenses, such as Selling, General, and Administrative Expenses, are increasingly a lion's share of variable costs. Traina shows that once we use Operating expenses (OPEX), which include Cost of Goods Sold (COGS), Selling, General, and Administrative Expenses (XSGA), and Other Operating Expenses, as a measure of variable inputs, there is no increase in markups of public firms.

While we agree with Traina (2018), our argument is that part of XSGA is actually capital expenses, which build the capital stock of a firm rather than operating expenses. Specifically, following Peters and Taylor (2017), we treat R&D expenditures as an intangible investment and 30% of the Selling, General, and Administrative expenses as an organizational investment. Hence, we recompute operating expenses without these two components and instead treat them as additions to capital stock of the firm. To operationalize this, we first note that the Compustat item XSGA includes Research and Development expenses (Compustat item XRD) and in-process R&D expenses (Compustat item RDIP). We first isolate the portion of XSGA that does not include R&D expenses and call it SGA:

$$SGA = XSGA - RDIP - XRD.$$

Next, we define the variable inputs to only be the portion of OPEX that does not include R&D expenses (intangible knowledge capital) and 30% of SG&A expenses (organizational capital). Thus, our measure of variable costs is OPEX*:

$$OPEX^* = OPEX - XRD - RDIP - 0.3 \times SGA. \tag{27}$$

Once we define the variable inputs, markups are simply given by

$$Markups = \mu = \frac{SALES}{OPEX^*}. \tag{28}$$

To examine the effects of R&D versus SGA independently, we also define Markups using two other variables for variable costs, one excluding just R&D expenses and one excluding just SG&A expenses:

$$OPEX^*_{RD} = OPEX - XRD - RDIP, \tag{29}$$

$$OPEX^*_{SGA} = OPEX - 0.3 * SGA. \tag{30}$$

The above definition of markups is transparent and not subject to econometric and optimization challenges faced by alternative methods that rely on explicit estimates of productivity using the control function approach (Rovigatti and Mollisi 2018). Furthermore, this is close to the Lerner Index (measured by the difference between the output price of a firm and the marginal cost divided by the output price) that is widely used in the literature as a measure of market power (see, e.g., Grullon, Larkin, and Michaely 2019; Gutiérrez and Philippon 2017). An alternative measure of markups is one following the production framework by De Loecker and Warzynski (2012) and De Loecker and Eeckhout (2017). For consistency with the preceding literature, we also detail our estimation of markups using the production function approach in the Internet Appendix.

2.5 Rise in markups

As discussed above, using marginal costs measured by COGS, De Loecker and Eeckhout (2017) document a stunning rise in markups in the United States over the past three decades. However, Traina (2018) argues that COGS are a declining share of firm costs, and once we use operating expenses that include COGS and SGA, firm markups do not rise. This is an important policy question that also speaks to the discussion on the rise in industrial concentration and decline in labor share (see Grullon, Larkin, and Michaely 2019; Autor et al. 2020; Hartman-Glaser, Lustig, and Xiaolan; Kehrig and Vincent 2018). Once we take into account intangible capital, how have markups evolved over this period?

In Figure 6, we estimate the evolution of *Markups*, that is markups using intangible capital adjustment, over our sample period. We see an upward trend only for the $90th$ percentile firms.[24] To determine whether there is dispersion in markups by industry, we look at industries that have high versus low intangible intensity in Figure 7. We find that for the top 10% of firms, markups are higher in high-intangible-intensity industries than in low-intangible-intensity industries.

To explore whether there is convergence in markups over time, we follow the portfolio approach in Lemmon, Roberts, and Zender (2008). First, each calendar year, we sort firms into quartiles according to their current year markup, denoted as Highest, High, Medium, and Low. The portfolio formation year is denoted event year zero. Second, the average markup for each portfolio is calculated in each of the subsequent 14 years, holding the portfolio composition constant unless a firm exits the sample. Third, we repeat the sorting and averaging for every calendar year in the sample period. This process generates 26 sets of event time averages, one for each calendar year in the

[24] Figure IA2 in the Internet Appendix shows the evolution of markups using the COGS measure in Traina (2018), the OPEX measure in De Loecker and Eeckhout (2017) and our measure of markups (OPEX*). When we don't adjust for industry, the COGS measure is the highest but on adjusting for industry, the OPEX measure is the highest. Either way, we see that the OPEX* measure used in this paper lies between the COGS and OPEX measures.

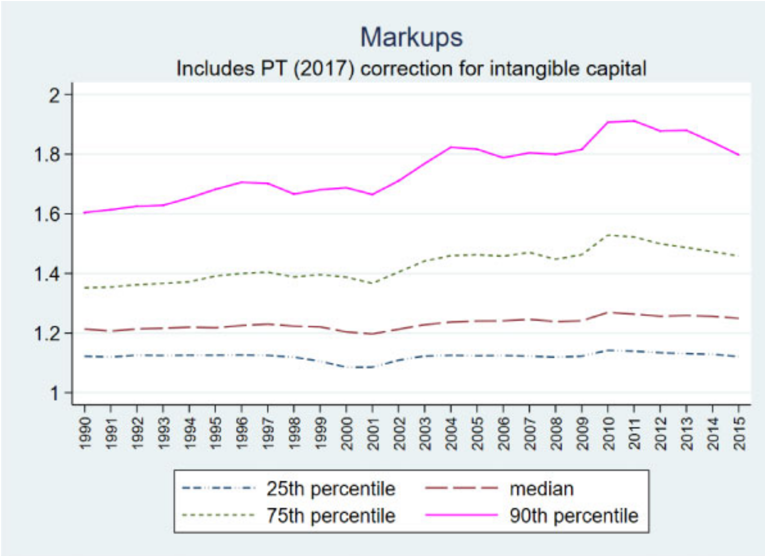


Figure 6
Markups in the U.S. economy
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Markups in each year across all public firms in the U.S. economy. Markups are defined as Sales/Variable Cost, where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost. Appendix Table A9 defines the variables in detail.

sample. Fourth, the average markup of each portfolio across the 26 sets is computed and plotted by event year. Figure 8 shows that the markups are highly persistent. We see very little convergence over time across markup portfolios and the top portfolio of markups is persistently higher than all other portfolios even 14 years after portfolio formation.

In an alternative formulation shown in Figure 9, we look at the persistence of initial markups where initial markups are measured 5 years after an initial public offering (IPO; i.e., 5 years after the firm appears in Compustat). We form five portfolios in the fifth year after IPO including four portfolios corresponding to the four quartiles and a top 10% portfolio. We then plot the average markup in each of these portfolios for the next 15 years. We see that the initial markups at the time of IPO of the firm are highly persistent. Firms whose markups were in the top 10% of markups in year 5 after IPO continue to have high markups in the top 10% fifteen years hence.

Overall, we do indeed see a rise in markups once we adjust operating expenses for investment in intangible capital. While there is just a modest divergence between the top 10% of firms with the highest markups and the rest of the economy, we see these differences amplified in industries that use more intangible capital. We also see that markups are highly persistent over time.

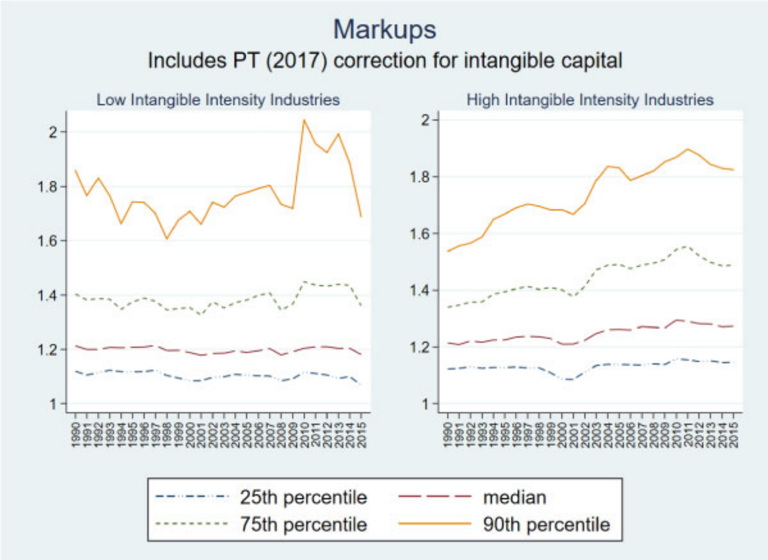


Figure 7
Markups in the U.S. economy: Differences in intangible intensity
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Markups in each year in low (< median) and high (≥ median) intangible intensity industries. Markups are defined as Sales/Variable Cost, where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Appendix Table A9 defines the variables in detail.

Table A1 of the Appendix presents summary statistics of the main variables in our analysis. We drop the top and bottom 1% of outliers when constructing all our firm-level variables. In addition to the variables discussed above, we also use a proxy for firm age that is defined as the number of years since the firm first appears in Compustat following Giroud and Mueller (2010). The mean *ROIC* in our sample once we adjust for intangible capital is 13%. By definition, 10% of our sample is classified as star firms. Once we take into account intangible capital, the average markup is 1.313 using the cost shares approach (*Markups*) and 1.221 using the production function approach ($Markups\_prodfn$). The latter has fewer observations because they are first estimated within each industry necessitating a minimum number of firms in that industry.

3. Markups and Star Status

In this section, we empirically test the predictions generated by our model of star firms in Section 2. To test the prediction that markups are associated with high ROIC, we estimate the following regression for firm i in industry j in year t:

$$ROIC\ or\ ROIC\ star_{ijt} = a + \beta_1 \times log(Invested\ capital)_{ijt-1} + \beta_2 \times log(Age)_{ijt-1} + \beta_3 \times Markups_{ijt-1} + \phi_j \times \gamma_t + \epsilon_{ijt}, \quad (31)$$

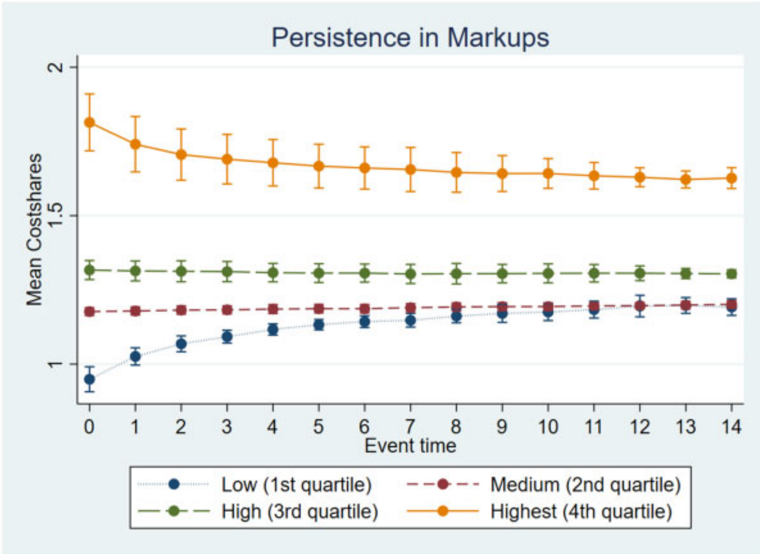


Figure 8
Persistence in markups
This figure plots the persistence in markups using the portfolio approach in Lemmon, Roberts, and Zender (2008).

where *ROIC* is the return on invested capital and *ROIC star* is a dummy variable that takes the value of one if the firm is a star firm (top 10% of ROIC) and zero otherwise. Our measures of *ROIC*, *ROIC star* and *Markups* incorporate intangible capital. *log(Invested capital)* and *log(Age)* serve as measures of firm size and age, respectively. The main coefficient of interest is β_3, which shows the sensitivity of star status to firm markups. All the regressions are estimated using ordinary least squares (linear probability models) but we get similar results using a logit estimation when *ROIC star* is the dependent variable. We cluster the standard errors at the firm level to capture the lack of independence among the residuals for a given firm across years (Petersen 2009) and control for time varying industry heterogeneity with $\phi_j \times \gamma_t$ fixed effects. In relation to the model in Section 2, under the assumption of constant variable input share $1-\alpha$, our measured markups are proportional to the true markup. Since we use industry x year fixed effects in all our empirical tests, we find this to be a reasonable assumption.

In column 1 of panel A of Table 2, we find that in line with the prediction from our theoretical model, correcting for intangible capital, high markups predict ROIC. Column 2 of panel A of Table 2 shows that high markups predict star status. The effects are also economically significant. There is a 6.2-percentage-point increase in the probability of being a star firm when markups go up by one standard deviation. In column 3, we repeat the full

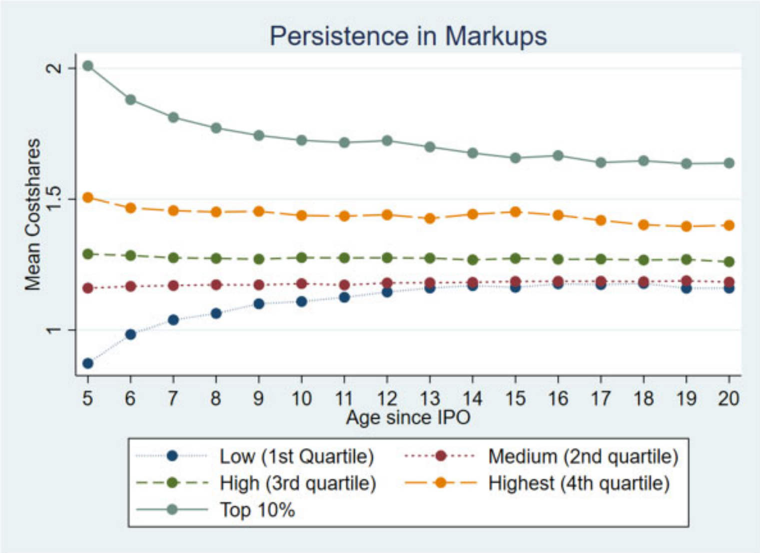


Figure 9
Persistence in early markups
This figure plots the persistence in initial markups using the portfolio approach in Lemmon, Roberts, and Zender (2008). The initial markups are measured 5 years after IPO.

sample specification in column 1 using an alternative performance measure, Tobin's q and once again find markups to be positively associated with Tobin's q. Column 4 shows that markups are also associated with star status when we define star firms on the basis of Tobin's q, alleviating concerns about a mechanical correlation between revenue-based measures of markups and star status.

Thus, panel A of Table 2 provides evidence consistent with our theoretical model that star firms are associated with market power as measured by the elasticity of demand. However, empirically we find that 72.2% of star firms have markups outside the top 10% of markups. In Internet Appendix Figure IA3, we present a histogram of markups for firms that were classified as ROIC stars and for all other firms. For each of those subsamples, we also present a nonparametric smoothed scatter plot of *ROIC* against markups using kernel-weighted local polynomial smoothing. The figure shows that while firms are distributed across the range of markups even when we look at just the star firms, the tails are thin, so there are few firms with very low markups and very high markups for both star firms and all other firms.

Demsetz (1973) argued that while profitable firms may have market power, a substantial portion of their market positioning may be due to their provision of superior products that cannot be emulated by competitors and by greater productivity. To assess this claim, we analyze whether firm markups just

Table 2
Who are America's stars? Correcting for intangible capital

A: Markups and Star Status

	1	2	3	4
	ROIC	ROIC star	Tobin's q	q star
L.Log(Invested capital)	1.625***	−0.006***	0.010	−0.008***
	(0.109)	(0.001)	(0.007)	(0.001)
L.Log(Age)	−2.941***	−0.052***	−0.367***	−0.050***
	(0.237)	(0.003)	(0.016)	(0.003)
L.Markups	25.624***	0.161***	0.696***	0.102***
	(0.643)	(0.007)	(0.041)	(0.008)
Fixed effects	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	81,525	81,525	78,632	78,632
Adj. R-sq	.262	.110	.130	.068

B: Initial Markups and Star Status

	(1)	(2)	(3)	(4)
	ROIC star	ROIC star	ROIC star	ROIC star
L.Log(Invested capital)	0.004***	0.003**	0.002	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
L.Log(Age)	−0.056***	−0.057***	−0.030***	−0.029***
	(0.003)	(0.003)	(0.004)	(0.007)
Initial markups (t0)	0.010***			
	(0.003)			
Initial markups (t5)		0.008**		
		(0.003)		
L5.Markups			0.083***	
			(0.009)	
L10.Markups				0.049***
				(0.011)
Fixed effects	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	70,231	80,554	50,552	27,522
Adj. R-sq	.068	.071	.068	.054

This table reports estimates from the following regression model in panel A:

$$Y_{ijt}=\alpha_0+\beta_1\times log(Invested\ capital_{ijt-1})+\beta_2\times log(Age_{ijt-1})+\beta_3\times Markups_{ijt-1}+\phi_j\times\gamma_t+\varepsilon_{ijt}.$$

The dependent variable in panel A is one of the following variables: *ROIC*, $Tobin's\ q$, *ROIC* $star$ or $q\ star$. *ROIC* $star$($q\ star$) is a dummy variable that takes the value of one if firm i's *ROIC* ($Tobin's\ q$) is above the 90th percentile of *ROIC* ($Tobin's\ q$) across all firms in a particular year and zero otherwise; log(Invested capital) is used as a proxy for firm size and log(Age) is logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. In panel B, in column 1, markups are measured at t0 (the first year the firm appears in Compustat), in column 2, markups are measured at t5 (5 years after the firm appears in Compustat) and in columns 3 and 4, we use markups lagged 5 years ago and 10 years ago to contemporaneous ROIC. All regressions are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

after an IPO predict future star status. Substantial evidence suggests that the firm's characteristics in early life predict future productivity and growth.[25] However, young, small firms are unlikely to be exercising market power through predatory behavior. Thus, if markups within 5 years of an IPO predict star status later, it is strongly supportive of the hypothesis that high-quality productive firms become star firms rather than the hypothesis that star firm

25 See Guzman and Stern (2020), Maksimovic, Phillips, and Yang (2019), and Bonelli, Liebersohn, and Lyonnet (2021).

status is acquired by firms of average productivity that are able to acquire market power.

In panel B of Table 2, we repeat our analyses using more exogenous measures of markups, such as markups measured in the initial life of the firm, when the firm presumably has not accumulated the ability to dominate markets yet. In column 1 we use markups measure at t_0 (the first year the firm appears in Compustat), and in column 2, we use markups measured at t_5 (5 years after the firm appears in Compustat). In columns 3 and 4, we use markups lagged 5 years ago and 10 years ago, respectively, to ROIC. These lagged specifications also provide a test for the stability relation between markups and future star status. In all instances, we see that initial markups predict future star status. In unreported tests, we also find that the relation between markups in the first 5 years and future star status holds in both subsamples of firms that use high and low levels of intangible capital, suggesting that the differences in the legal protection of tangible and intangible capital are not the drivers of this result.

Overall, our findings in Figures 8 and Figure 9 and Table 2 show that markups are highly persistent and markups measured in the initial life of the firm (when the firm presumably is not exercising market power by adverse actions considered predatory) predict whether the firm is going to be a star firm in the future.

Our results are robust to a number of tests. First, in unreported robustness, we find that these results on markups hold in different subsamples, including manufacturing, large firms (defined as firms with more than $200 million in assets in real terms obtained by deflating total assets by a GDP deflator), and young firms (defined as firms younger than 5 years old).[26]

Second, in Appendix Table A2, we examine the sensitivity of our estimates to the portion of intangible investment adjusted for by varying the portion of SGA used in computing ROIC from 10% to 60%. Column 3 is the same as our main specification (column 2 in panel A of Table 2) but is repeated here for comparison. The table shows that high markups are always associated with high markups, though the point estimates are different. A one-SD increase in markups increases probability of being a ROIC star from 5.4% (for 0.6*SGA) to 6.5% (for 0.1*SGA).

In Appendix Table A3, we present a comparison of our estimates to the measure of markups in De Loecker and Eeckhout (2017) based on OPEX and the one in Traina (2018) based on COGS. As seen in the table, a unit increase in COGS markups increases the probability of being a star firm by 3.4% (column 1), a unit increase in OPEX markups increases the probability of being a star firms by 27.2% (column 2), where as a unit increase in the markups adjusted for intangible capital (OPEX*) increases the probability of being a star firms

[26] A growing literature (e.g., Decker et al. 2014; Pugsley and Sahin 2019) points to declining entrepreneurship in the U.S. economy, even in the intangible intensive high-tech sector (e.g., Pugsley and Sahin 2019). Hence, we think it is unlikely that new firm entry drives the findings in our paper.

by 16.1% (column 3). Thus, the Traina (2018) measure of markups provides an upper bound and that of De Loecker and Eeckhout (2017) provides a lower bound for the relationship between markups and star status, respectively.[27]

Finally, in Appendix Table A4, we perform two additional robustness tests. First using firm fixed effects in place of industry x year fixed effects in columns 1–4, we find markups to be associated with star status (both ROIC stars and q stars), ROIC, and Tobin's q. In columns 5–8, we use the production function approach to estimate Markups, $Markups\_prodfn$ and find similar association between these markups and star status, ROIC, and Tobin's q. The use of industry fixed effects makes the cost share approach similar to the production function approach. The effect of market power indicators likely vary across levels of *ROIC*. Hence, in unreported tests, we reestimate the full model using quantile regressions. We use the generalized quantile regression estimator developed in Powell (2020) that allows us to estimate unconditional quantile effects in the presence of additional covariates. The results show that the profitability of firms at the top of the distribution of *ROIC* appears to be more sensitive to markups than that at the bottom.

Overall, the above results show that high markups are associated with star status. Markups—even in the early life of the firm—are predictive of future star status and future markups. In the next section, we will build on this argument to show that the markups of star firms reflect higher efficiency and, to some extent, greater intangible investment.

3.1 Role of intangible intensity

In this section, we focus on the association between intangible intensity, markups, and star status. We begin by estimating the equation below looking at the first-order effects of markups versus intangible intensity on star status.

$$\begin{aligned} ROIC\ star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ Capital)_{ijt-1} \\ + \beta_2 \times log(Age)_{ijt-1} + \beta_3 \times Markups_{ijt-1} \\ + \beta_4 \times Intangible\ intensity_{ijt-1} + \phi_j \times \gamma_t + \epsilon_{ijt}. \end{aligned} \tag{32}$$

We explore the association between intangible intensity and star status in panel A of Table 3. In column 1 when we don't use any industry fixed effects, we see a positive association between intangible intensity and ROIC star status. However, in column 2 we see that when we look within industries, the relationship between intangible intensity and ROIC star status is negative. To investigate the relation between intensity and ROIC (not just star status), we plot the relation between the two in the first panel in Figure 10. At an intensity of around 0.75, the relation between ROIC and intangible intensity

[27] See Section 6.2 for additional details on why our markups seem to be a lower estimate than those in Traina (2018).

Table 3
Intangible capital, markups, and star status

A: Intensity and star status - Role of the product life cycle

	1	2	3	4	5
	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star
Sample	Full	Full	$Intensity \geq 0.75$	$Intensity < 0.75$	Full
L.Log(Invested capital)	−0.007***	−0.007***	−0.006**	−0.008***	−0.006***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
L.Log(Age)	−0.056***	−0.051***	−0.068***	−0.045***	−0.041***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
L.Markups	0.150***	0.165***	0.195***	0.139***	0.161***
	(0.007)	(0.008)	(0.010)	(0.010)	(0.008)
L.Intangible intensity	0.042***	−0.038***	−0.312***	0.048***	-0.017
	(0.007)	(0.011)	(0.034)	(0.014)	(0.023)
L.Life1					0.223***
					(0.049)
L.Intangible intensity x L.Life1					−0.211***
					(0.069)
Fixed effects	Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	80,739	80,639	32,235	47,647	53,527
Adj. R-sq	.073	.114	.136	.114	.110

B: Markups versus intangible intensity - Variance decomposition

	1	2	3	4	5	6	7	8	9
	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star
	Full sample			$Intensity \geq 0.75$			$Intensity < 0.75$		
L.Log(Invested capital)	0.003**	−0.006***	−0.007***	0.013***	−0.003	−0.006**	−0.002*	−0.008***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
L.Log(Age)	−0.057***	−0.052***	−0.051***	−0.075***	−0.068***	−0.068***	−0.047***	−0.043***	−0.045***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
L.Markups		0.165***	0.165***		0.193***	0.195***		0.138***	0.139***
		(0.008)	(0.008)		(0.010)	(0.010)		(0.010)	(0.010)
L.Intangible intensity			−0.038***			−0.312***			0.048***
			(0.011)			(0.034)			(0.014)
FE	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	80,639	80,639	80,639	32,235	32,235	32,235	47,647	47,647	47,647
Adj. R-sq	.071	.113	.114	.067	.130	.136	.087	.113	.114
Change in R-sq		*.042*	*.001*		*.063*	*.006*		*.026*	*.001*

This table reports estimates from the following panel regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Markups_{ijt-1} +$$
$$\beta_4 \times Intangible\ intensity_{ijt-1} + \beta_5 \times Intangible\ intensity_{ijt-1} \times Life1_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

The dependent variable is *ROIC* or *ROIC star* which is a dummy variable that takes the value of one if firm i's ROIC is above the $90th$ percentile of ROIC, respectively, across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is the logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. *Intangible intensity* is defined as the ratio of intangible capital to the sum of intangible and tangible capital. Life1 is a firm product life cycle variable that measures the intensity of product innovation from Hoberg and Maksimovic (2022). All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. In panel B, we do a variance decomposition to compare the explanatory power of Markups versus Intangible intensity. Appendix Table A9 defines the variables in detail. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

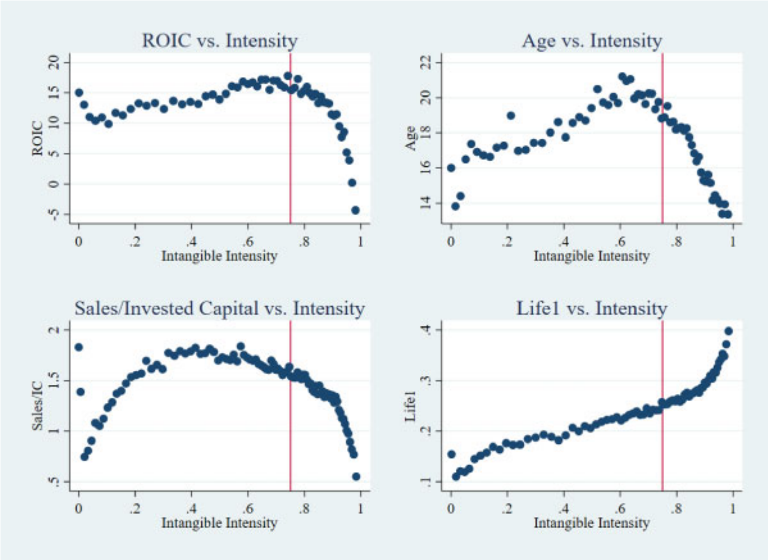


Figure 10
Product life cycle and intangible intensity
This figure plots the binscatter plots of Return on invested capital (*ROIC*), Age, Sales/Invested capital, and Life1 across *Intangible intensity*. *ROIC*, *Sales/Invested capital*, and *Intangible intensity* include the Peters and Taylor (2017) adjustment for intangible capital. Life1 is a firm product life cycle variable that measures the intensity of product innovation from Hoberg and Maksimovic (2022). Appendix Table A9 defines the variables in detail.

reverses. Hence, in columns 3 and 4 of Table 3, we estimate the above equations for subsamples of firms with very high (*Intangible intensity* ≥ 0.75) and low (*Intangible intensity* < 0.75), respectively. We see that the negative association between intensity and star status is driven by the sample of very-high-intensity firms rather than the whole distribution.[28]

The above patterns are not explained by our model in Section 2.1, which is a one-period model in which firms use labor and two forms of capital to obtain revenue. Thus, the model does not account for the nonmonotonic relationship between high-ROIC status and intangible intensity. Hence, as an exploratory exercise, we look at factors outside the model parameters to understand the above patterns.

28 A closer inspection of these high-intangible-intensity firms (say *Intangible intensity* ≥ 0.75) reveals that these firms tend to be largely in the high-tech (44.5%) and healthcare (19.21%) sectors and are typically small firms (median assets without adjusting for intangible capital is \$134 million and median sales is \$135 million). They have lower Sales/Invested Capital ratio (1.48) compared to firms with *Intangible intensity* < 0.75, which have Sales/Invested capital ratio of 1.85. Even firms in the immediate vicinity with Intangible intensity = [0.65, 0.75) have higher Sales/Invested capital ratios (1.81) compared to very-high-intensity firms. For instance, very-high-intensity firms include Novavax, Inc., a biotechnology company incorporated in 1987 with mean sales of just \$13.35 million and negative earnings (EBIT) over our sample period. By comparison, the average firm that is not a high-intensity firm in the same NAICS code (325) as Novavax, has positive earnings, a higher ratio of sales to invested capital (1.066 compared to Novavax's 0.096), and a lower intangible intensity (0.50 compared to Novavax's 0.91).

Recent research in corporate finance suggests a richer dynamic at play where firms use different mixtures of processes at different stages of the product life cycle. For example, Hoberg and Maksimovic (2022) model the product cycle for an output as going through four different stages: research and development of the product (Life1); development of efficient products (Life2); exploitation of market (Life3); and the wind down (Life4). These stages require different mixes of inputs and vary by industry. In particular, firms that focus on the first R&D stage (Life1) in technically intensive industries require a great deal of intangible capital, unlike say the market exploitation stage (Life3) that requires more physical capital. This has important consequences since young firms in the development stage are more likely to be heavily invested in intangible capital, but not yet at the exploitation stage that generates profits.

The relation between intensity and life cycle is evident in the second panel of Figure 10, where age declines for highly intangible intense firms and in the third panel in the relationship between Sales/Invested Capital and intensity. More directly, in the fourth panel we indeed see the firms at very high intangible intensity levels are focused on development activities (Life1). We test the relation directly in column 5 of panel A of Table 3. The interaction of intangible intensity and Life1 is negative and significant suggesting that firms doing a great deal of development in Life1 and that have high intangible intensity are less likely to be profitable. We see similar results if we replace the star dummy with ROIC as the dependent variable in Appendix Table A5.

Thus, the very-high-intensity firms include a greater proportion of companies that have not (yet?) been able to leverage their intangible investment into successful products. Moreover, technology-based firms that are successful in designing high value products may require additional tangible investments to generate revenues, whereas firms that are not at that stage are still focusing on intangible capital.[29]

To examine whether the variation in ROIC star status primarily reflects markups or intangible intensity, we do a simple variance decomposition in panel B of Table 3. In columns 2 and 3, after accounting for size, age, and industry-time effects, adding markups explains 4.2% of the remaining variation in ROIC star status, whereas intangible intensity explains only an additional 0.1% of the variation. In Appendix Table A6, we find similar results if we were to enter intangible intensity first and then markups. In columns 4–9 in panel B of Table 3, we again see that markups explain a lot more of the variation in star status than intangible intensity when we look at samples

[29] This outcome is also consistent with the argument in Haskel and Westlake (2018) that intangible investment leads to divergent outcomes depending on scalability, synergies, and spillovers generating winners and losers. Winning firms realize high profits whereas other firms, including failed start-ups, those have not yet been able to market their products, and older firms whose business models give way to creative destruction, see very low returns. When we look at the patenting activity of these high-intensity firms, we see that while high-intensity firms have higher mean market value of patents (the ratio of *Patent market value* to Total assets from Kogan et al. (2017) is 0.17 for high-intensity firms compared to 0.11 for low-intensity firms), there is also a lot of variation. High intensity star firms have much higher market value of patents to asset ratios (0.22) than the nonstars.

of just high-intensity ($Intangible\ intensity \geq 0.75$) and low-intensity firms ($Intangible\ intensity < 0.75$). Thus, differences in intangible intensity, *once we correct for the mismeasurement of intangibles*, do not explain much of the variation in ROIC. In unreported tests, we find similar results for a variance decomposition on ROIC rather than on ROIC star status. After accounting for size, age, and industry-time effects, we find that adding markups explain 13.9% of the remaining variation in ROIC, whereas intangible intensity explains only an additional 0.6% of the variation.[30]

4. Star Firms, Productivity, Investment, and Output

An important policy concern surrounding star firms is the extent to which they affect consumer welfare by their output decisions. There are several viewpoints on this. On the one hand, star firms could attain their high profits by producing higher volumes, given their efficiency. This is the implication in the original theoretical work on market power and profitability by Demsetz (1973) and more recently in the empirical analysis of Autor et al. (2020). On the other hand, Gutiérrez and Philippon (2017) and Grullon, Larkin, and Michaely (2019), among other studies, argue that high profits come from restrictions in market output and investment, and we would not expect higher output of star firms, controlling for their markups.[31]

To fully address these issues we have to step out of the context of our stylized model.[32] To examine the relationship between star status and output, we use nonparametric regressions in Figure 11 showing the relation between Productivity[33] and Intangible intensity for stars and nonstars, controlling for Markups, log(Invested capital), log(Age), and Industry x year fixed effects.

Following Cattaneo et al. (2019), we present least squares binned scatter regression plots with robust confidence intervals and uniform confidence bands over the period 1990 to 2015 for ROIC stars and rest of the firms in the economy. The nonparametric regressions characterize the relation between star status and total factor productivity (TFP) at all levels of intangible capital without a priori imposing a parametric form, which might hide breaks in the

30 In unreported tests we see that the interaction of intangible intensity and Life1 variable also explains much less of the variation in ROIC and star status than markups.

31 This is consistent with the earlier literature (e.g., Bresnahan 1989; Schmalensee 1989) that argued a concentrated market structure will generally lead to higher price-cost margins, higher profitability of firms, less output, and lower welfare and allocative efficiency.

32 In the stylized model of Section 2, productivity Z does not directly determine *ROIC* (see Equation (13)). Such relations can be derived assuming a more complex demand structure (e.g., Autor et al. 2020) or multiple products.

33 As detailed in the Internet Appendix, we have a measure of total factor productivity from the production function estimations used to derive markups, $Markups\_prodfn$, that measures the productivity of firms relative to other firms in its industry. Note that a firm with high pricing power (high markups) may have high or low total factor productivity, depending on how much tangible and intangible capital it uses in production. Conversely, a firm with high productivity may or may not have pricing power, depending on whether or not it can maintain prices above marginal cost.

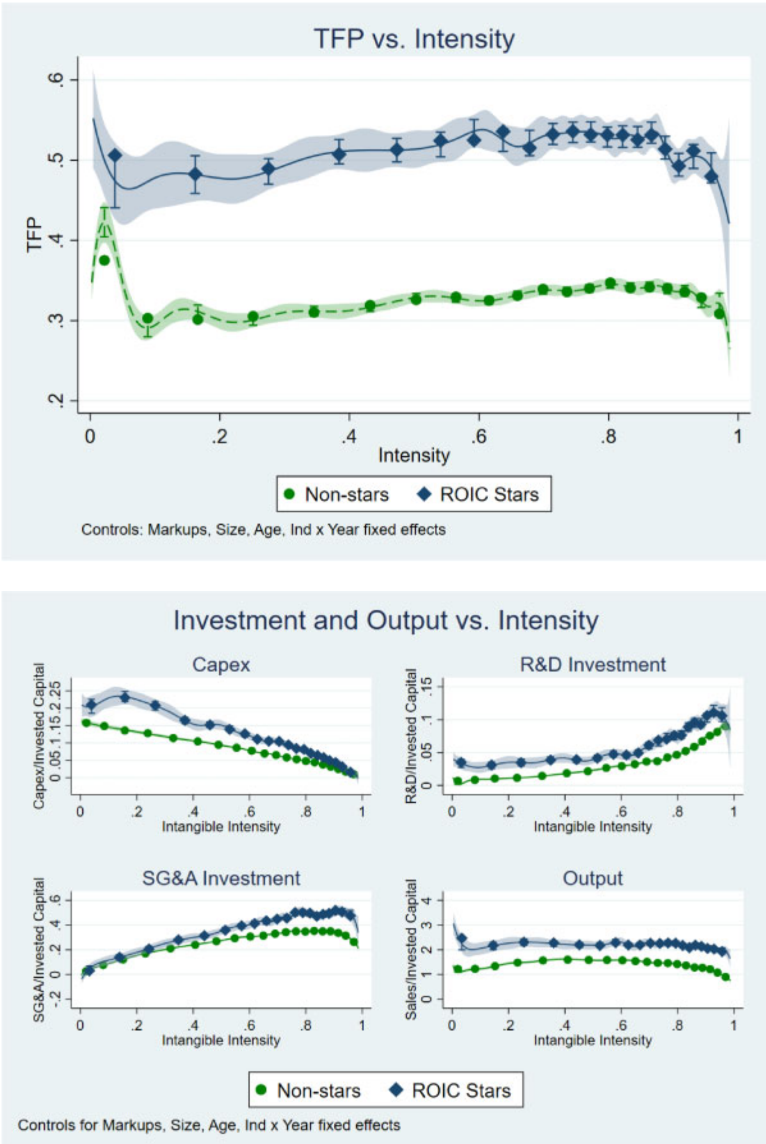


Figure 11
TFP, investment, and output
This figure plots the binned scatterplots with robust pointwise confidence intervals and uniform confidence bands of Productivity, Capex/Invested Capital, R&D Investment/Invested Capital, SG&A Investment/Invested Capital, and Sales/Invested Capital on *Intangible intensity* for *ROIC* stars and all other firms, controlling for Markups, Size, Age, and industry x year fixed effects. *ROIC* stars are firms that are in the top 10% of *ROIC* in a particular year. *Markups* are defined as Sales/Variable Cost, where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. *Markups*, and *Intangible intensity* include the Peters and Taylor (2017) adjustment for intangible capital. Appendix Table A9 defines the variables in detail.

relation between TFP and intangible intensity at different levels of intensity. In the top panel, where we present the binscatter regressions for TFP, we control for markups since we are running the regressions separately for stars and nonstars. The figure shows that conditioning on markups (and other control variables), star firms have statistically significant higher productivity than nonstar firms at every level of intangible intensity. Note that these findings are outside that predicted by the model because the model does not have a role for productivity or efficiency, and all the effects of higher productivity of star firms are already captured through higher markups, μ.

Next, we examine how the association between markups and star status varies with firms' past innovation output as proxied by the market value of the patents issued to them. This measure has the advantage of partially controlling for the net present value in the heterogeneity in the economic value of the knowledge stock created (see, e.g., Hall, Jaffe, and Trajtenberg 2005; Kortum and Lerner 1998; Kortum 1993.)[34] Specifically, we use the *Patent market value* (scaled by assets) measure from Kogan et al. (2017), who use event studies to estimate the excess market return realized by the grant date of U.S. patents assigned to publicly traded firms. On aggregating the values of patents granted to a firm, the *Patent market value* is essentially the total dollar value of innovation produced by a firm in a year scaled by the book value of assets. Kogan et al. (2017) show that this measure is strongly positively associated with the scientific value of innovation as measured by forward patent citations, and also predicts firm growth and reallocation of resources across firms. Since their measure is at the security (PERMNO)-year level, we first use the CCM (CRSP/Compustat Merged Database) link table to link the PERMNO to firm IDs (GVKEY) in Compustat and then take the highest market value of innovation associated with each firm in a year across all its securities. We then estimate the following equation:

$$
\begin{aligned}
Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ Capital)_{ijt-1} \\
+ \beta_2 \times log(Age)_{ijt-1} + \beta_3 \times Markups_{ijt-1} \\
+ \beta_4 \times Patent\ Market\ Value_{ijt-1} + \phi_j \times \gamma_t + \epsilon_{ijt}.
\end{aligned} \tag{33}
$$

Table 4 presents the results of the above estimation. Columns 1–3 show that firms with higher economic value of patents are more likely to be star firms in the full sample as well as for high intensity (*Intangible intensity* ≥ 0.75) and low intensity (*Intangible intensity* < 0.75) firms. A one standard deviation increase in innovation is associated with a 2.16%[35] probability of being a ROIC star in column 1. In columns 4–6, we repeat the above estimations

[34] The measure has the disadvantage in that the patenting rates differ across industries and that firms are not able to patent all forms of intangible capital that creates value to the firm.

[35] Standard deviation of patent market value in our sample is 0.245.

Table 4
Star firms, innovation output, and productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star
Sample	Full	*Intensity* ≥ 0.75	*Intensity* < 0.75	Full	*Intensity* ≥ 0.75	*Intensity* < 0.75
L.Log(Invested capital)	0.001	0.007	−0.008**	−0.008***	−0.009***	−0.008***
	(.003)	(.004)	(.004)	(.001)	(.003)	(.001)
L.Log(Age)	−0.046***	−0.060***	−0.036***	−0.043***	−0.056***	−0.035***
	(.006)	(.008)	(.008)	(.003)	(.005)	(.003)
L.Markups	0.141***	0.128***	0.195***	0.120***	0.128***	0.106***
	(.011)	(.011)	(.027)	(.007)	(.010)	(.010)
L.Patent market value	0.088***	0.078***	0.115***			
	(.020)	(.022)	(.036)			
L.Productivity				0.133***	0.207***	0.082***
				(.010)	(.017)	(.012)
Fixed effects	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	18,508	9,116	8,928	73,428	29,799	42,482
Adj. R-sq	.111	.124	.118	.113	.144	.109

This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{it-1}) + \beta_3 \times Markups_{ijt-1}$$
$$+ \beta_3 \times Patent\ market\ value_{ijt-1}\ or\ Productivity_{ijt-1} + +\phi_j \times \gamma_t + \varepsilon_{ijt}.$$

ROIC star is a dummy variable that takes the value of one if the firm i's ROIC is above the $90th$ percentile of ROIC, respectively, across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. Patent market value is from Kogan et al. (2017) and measures the value of granted patents using excess market returns. Productivity is the Total Factor Productivity derived from the production function estimations of markups. All regressions are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

replacing *Patent Market Value* with *Productivity*. We see that both markups and productivity are positive and significant in predicting star status. A one-standard-deviation increase in productivity increases the probability of being a ROIC star by 5.61%, whereas a one standard deviation in markups increases the probability of being a ROIC star by 4.52% in column 4.

As robustness we also look at investment. If star firms also invest more than nonstar firms controlling for firm characteristics, then it provides plausible evidence that star status is derived from stars' better capability. Looking at investment also addresses the concern that sales may be artificially inflated due to monopoly power. For investment, we use physical investment *Capex/Invested capital* and the two components of intangible investments (*XRD/Invested capital* and *SGA/Invested capital*). The first three figures in the lower panel of Figure 11 present the binscatter regressions for the investment variables Capex/Invested Capital, R&D Investment/Invested Capital, and SG&A Investment/Invested Capital. Once again, we see that star firms have higher investment than nonstar firms at all levels of intangible intensity. The difference between stars and nonstars in Capex Investment is greatest at lower levels of intangible intensity whereas the difference between stars and nonstars in SG&A investment is greatest at higher levels of intangible intensity. In robustness tests, we find that dropping all the control variables, except the fixed effects gives the same results.

Table 5
Do star firms cut investment and output?

	1	2	3	4	5	6	7	8
	Capex/IC	Capex/IC	R&D/IC	R&D/IC	SG&A/IC	SG&A/IC	Sales/IC	Sales/IC
L.Log(Invested capital)	0.002***	0.002***	0.001***	0.002***	−0.017***	−0.013***	−0.021***	−0.018**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	(0.007)
L.Log(Age)	−0.011***	−0.006***	−0.016***	−0.016***	−0.009***	-0.000	0.046***	0.073***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.014)	(0.021)
L.ROIC star	0.033***		0.008***		0.073***		0.661***	
	(0.002)		(0.002)		(0.005)		(0.026)	
L5.ROIC star		0.014***		0.006***		0.051***		0.333***
		(0.002)		(0.002)		(0.005)		(0.029)
FE	Ind x Yr	Ind x Yr	Ind x Yr	Ind x Yr	Ind x Yr	Ind x Yr	Ind x Yr	Ind x Yr
N	80,618	49,961	81,929	50,678	81,537	50,430	80,805	49,984
Adj. *R*-sq	.340	.383	.417	.421	.345	.366	.305	.300

This table reports estimates from the following panel regression model:

$$Y_{ijt}=\alpha_0+\beta_1\times log(Invested\ capital_{ijt-1})+\beta_2\times log(Age_{ijt-1})+\beta_3\times Star_{ijt-1}(/Star_{ijt-5})+\phi_j\times\gamma_t+\varepsilon_{ijt}.$$

The dependent variable is Capex/Invested Capital, R&D Investment/Invested Capital, SG&A Investment/Invested Capital, or Sales/Invested Capital. Star is a dummy variable that takes the value of one if the firm i's ROIC is above the $90th$ percentile of ROIC across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is the logarithm of firm age. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

We examine the relation between star status and investment in a regression setting controlling for *log(Invested capital)*, *log(Age)* and industry x year fixed effects in the following regression:

$$Y_{ijt}=\alpha_0+\beta_1\times log(Invested\ capital)_{ijt-1}+\beta_2\times log(Age)_{ijt-1}+$$
$$\beta_3\times Star_{ijt-1}+\phi_j\times,\gamma_t+\varepsilon_{ijt}, \tag{34}$$

where the dependent variable, Y is different measures of investment (*Capex/Invested capital, R&D/Invested capital, and SG&A/Invested capital*). All the independent variables are lagged by one period. Our main coefficient of interest is β_3, which provides an estimate of whether star firms in an industry-year have higher Y_{ijt} than nonstar firms in the same industry-year controlling for firm-level characteristics. In columns 1 to 6 of Table 5, we note that star firms have greater investment, both CAPEX and Intangible investment (R&D and SG&A) compared to other firms. This also holds when we used lagged star status.

Finally, we focus on Sales/Invested capital as a proxy for output.[36] and repeat the investment analysis using Sales/Invested capital instead. Following the firm

[36] The Sales/IC measure standardizes sales by firm size. It can be rationalized as both an empirical standardization, given our limited understanding of distributions of firm size, and as a metric of greater efficiency in utilization of firm assets (e.g., Ang, Cole, and Lin 2000; Duong et al. 2022; Soliman 2008). In an alternative conceptualization in Appendix Section I.1, we show that one way of rationalizing star firms having higher returns and output is by assuming that they have high user costs. While this characterization precludes the role of efficiency, it does provide an alternative hypothesis to market power being the primary driver of returns of star firms.

value optimization in Section 2, the expression for Sales/Invested capital is

$$Sales/IC = \frac{PY}{K_1 + \nu K_2}. \tag{35}$$

This statistic gives the revenues of the firm per unit of invested capital. In the Appendix Section B we establish that given a markup, Sales/IC, and output comove in our model. Thus, our conclusions on Sales/IC should also apply to output, which is of direct interest to consumers and regulators.

In the last figure in the lower panel of Figure 11 we present the binscatter regressions for Sales/Invested Capital, controlling for markups since we are running the regressions separately for stars and nonstars. The figure shows that conditioning on markups (and other control variables), star firms have statistically significant higher output than nonstar firms at every level of intangible intensity. Columns 7 and 8 of Table 5 also confirm that ROIC stars have higher Sales/Invested Capital ratios than nonstars, plausibly because of higher productivity.

Taken together, the results in this section suggest that the high markups of star firms are reflective of greater ability of the star firms including higher productivity and innovation.

4.1 Superstar firms

The above finding that the exercise of market power by star firms is relatively modest contrasts with the popular public policy debate in the United States that has been dominated by anecdotal evidence of a few star firms, namely, Facebook (FB), Amazon.com (AMZN), Apple (AAPL), Microsoft(MSFT), and Alphabet (GOOGL). These firms are often accused of wielding monopoly power through the use of proprietary technology and increasing returns to scale. To explore this, we examine the returns to capital and markups of these firms in relation to the rest of the economy. Figure 12 shows that these firms (especially Apple) have abnormally high returns to capital that exceed even the top 10% of *ROIC* firms. Their markups in Figure 13 however show that for some of these firms like Apple and Amazon, the markups are below the $90th$ percentile of markups in our sample for most of the sample period.[37]

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. Consider the example of Amazon, where Jeff Bezos, the founder and CEO of Amazon in his letter to shareholders in 1997, stated that Amazon makes decisions and weighs tradeoffs differently than most other firms:

[37] Figure IA8 in the Internet Appendix reproduces this figure using Markups estimated by the production function approach and finds similar results.

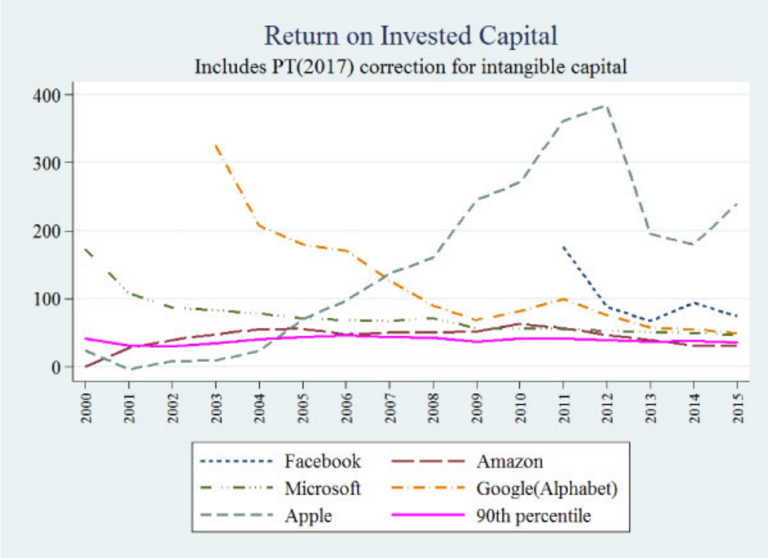


Figure 12
ROIC of elite firms (Apple, Facebook, Amazon, Microsoft, Google)
This figure plots the $90th$ percentile of Return on Invested Capital (*ROIC*) in each year across all public firms in the U.S. economy as well as the *ROIC* for five firms referred to as superstars anecdotally. *ROIC* includes the Peters and Taylor (2017) adjustment for intangible capital. Appendix Table A9 defines the variables in detail.

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)[38]

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

38 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

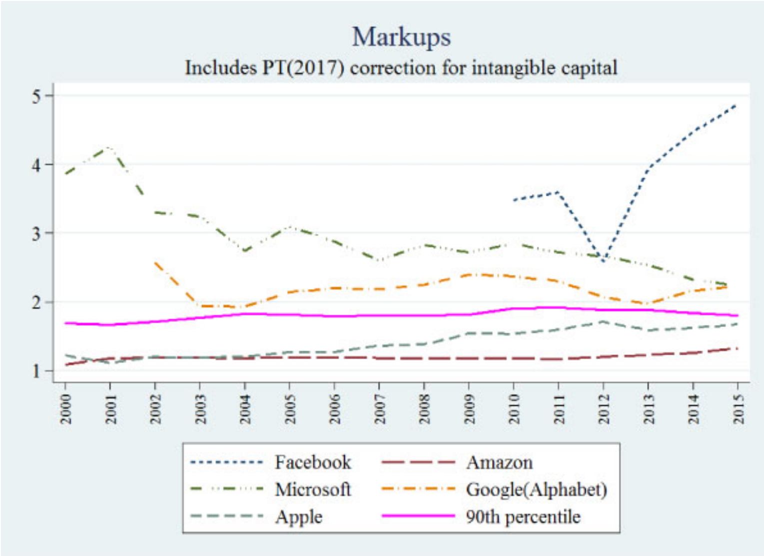


Figure 13
Markups of elite firms (Apple, Facebook, Amazon, Microsoft, Google)
This figure plots the 90*th* percentile of *Markups* in each year across all public firms in the U.S. economy as well as the *Markups* for five firms referred to as superstars anecdotally. *Markups* are defined as Sales/Variable Cost, where we use operating expenses with intangible capital adjustments, OPEX*, as a measure of variable cost in estimation of markups. Appendix Table A9 defines the variables in detail.

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 antitrust laws and their focus on short-run consumer welfare are just not equipped to recognize the anticompetitive 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 U.S. 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 also 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, Ederer, and Ma (2021) for a discussion of mergers and the subsequent liquidation of new technologies by incumbent firms in order to maintain market dominance.

5. Import Competition and Star Firms

We would expect that an increase in competitive pressure would cause a decline in ROIC, Markups, and Output. However, those firms that have market power, are going be less affected than firms without such advantages.[39] Thus, if star firms rely on market power to generate profits more than other firms, then we would expect that an exogenous increase in competitive pressure in their industry would affect them less than nonstar firms. We test this in Table 6.

We investigate the effect of market competition on firm star status directly by examining the effect of increased market competition on markups, ROIC, Sales/IC, and investment of both star and nonstar firms below. We measure increases in market competition by the penetration of Chinese imports at the four-digit NAICS level, *Imports*, defined as the value of Chinese imports into the United States in each four-digit industry each year scaled by the initial industry absorption over the years 2005 to 2015. Initial industry absorption is measured in the year 2000 and is computed as Shipments + Imports - Exports. The mean value of *Imports* in our sample is 0.049 with a standard deviation of 0.088. To address endogeneity issues, we instrument *Imports*, by Chinese imports into eight other developed economies, $Imports^{\mathrm{OTH}}$, constructed similarly. Our identification strategy is derived from Autor, Dorn, and Hanson (2013) and identifies the component of U.S. import growth that is due to Chinese productivity and trade costs. Autor et al. identify the supply-driven component of Chinese imports by instrumenting the growth in Chinese imports to the United States using contemporaneous composition and growth of Chinese imports in eight other developed countries. The identifying assumption underlying this strategy is that the surge of Chinese exports across the world is primarily driven by China-specific events: China's transition to a market-oriented economy and its accession to the World Trade Organization (WTO) and the accompanying rise in its comparative advantage and falling trade costs explain the common within-industry component of rising Chinese imports to the United States and other high-income countries. Specifically, we estimate the following difference-in-differences specification for firm i, in industry j, at time t:

$$\begin{aligned} Y_{ijt} = {} & \alpha_0 + \beta_1 \times log(Invested\ capital)_{ijt-1} + \beta_2 \\ & \times log(Age)_{ijt-1} + \beta_3 \times Imports_{jt-1} \\ & + \beta_4 \times Star_{ijt-2} + \beta_5 \times Star_{ijt-2} \times Imports_{jt-1} + \gamma_j + \delta_t + \varepsilon_{ijt}, \end{aligned} \tag{36}$$

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

Table 6
Who are America's stars? Role of import competition

A: Without interaction terms

	(1)	(2)	(3)	(4)	(5)	(6)
	Markups	ROIC	Sales/IC	Capex/IC	R&D/IC	SG&A/IC
L.Log(Invested capital)	0.075***	3.361***	0.011	0.001	0.003**	−0.010***
	(0.020)	(0.332)	(0.016)	(0.001)	(0.001)	(0.002)
L.Log(Age)	−0.006	−1.394	−0.003	−0.011***	−0.020***	−0.018*
	(0.014)	(1.056)	(0.033)	(0.002)	(0.006)	(0.011)
L.Imports	−0.838**	−71.283**	−1.550*	0.068	0.039	−0.247*
	(0.332)	(32.704)	(0.802)	(0.067)	(0.093)	(0.139)
Fixed effects	Ind, year	Ind, year	Ind, year	Ind, year	Ind, year	Ind, year
N	12,576	12,805	12,666	12,758	12,777	12,824
First-stage F-statistic	57.32	56.68	56.98	56.38	56.97	56.83

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
	Markups	ROIC	Sales/IC	Capex/IC	R&D/IC	SG&A/IC
L.Log(Invested capital)	0.071***	2.957***	0.002	0.001*	0.003**	−0.009***
	(0.020)	(0.256)	(0.014)	(0.001)	(0.001)	(0.002)
L.Log(Age)	0.014	1.318	0.044	−0.008***	−0.019***	−0.010
	(0.019)	(0.965)	(0.035)	(0.002)	(0.006)	(0.011)
L.Imports	−0.513*	−75.548**	−1.222	0.098*	0.023	−0.203
	(0.260)	(36.755)	(0.931)	(0.053)	(0.068)	(0.124)
L.Imports x L2.ROIC star	0.044	−2.250	−0.722	−0.006	0.011	−0.065
	(0.329)	(22.358)	(0.669)	(0.044)	(0.054)	(0.139)
L2.ROIC star	0.253***	26.597***	0.494***	0.023***	0.002	0.060**
	(0.059)	(2.515)	(0.094)	(0.005)	(0.011)	(0.024)
Fixed effects	Ind, year	Ind, year	Ind, year	Ind, year	Ind, year	Ind, year
N	10,403	10,595	10,486	10,540	10,570	10,590
Weak instruments test	22.22	21.99	22.08	22.07	22.04	22.01

This table reports estimates from the following instrumental variable regression model:

$$Y_{ijt}=\alpha_0+\beta_1\times log(Invested\ capital_{ijt-1})+\beta_2\times log(Age_{ijt-1})+\beta_3\times Imports_{jt-1}+$$

$$\beta_4\times Star_{ijt-2}+\beta_5\times Star_{ijt-2}\times Imports_{jt-1}+\gamma_j+\delta_t+\varepsilon_{ijt}.$$

Y is one of the following variables: Markups, ROIC, Sales/Invested Capital or Investment (CAPEX/Invested Capital or R&D Expenses/Invested Capital or SG&A Expenses/Invested Capital). Star is a dummy variable that takes the value of one if firm i's ROIC is above the $90th$ percentile of ROIC, respectively, across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. Imports is the value of Chinese Imports in each industry in the United States scaled by initial absorption in that industry in 2000, instrumented by the value of Chinese imports in each industry in eight other developed countries scaled by initial absorption in that industry in 2000. Initial Industry Absorption is defined as $Shipments+Imports-Exports$. Panel A shows results without interaction terms, and panel B reports results including the interaction of Imports and past ROIC star status. Both the main effect of Imports and the interaction terms are instrumented in panel B. In panel A, we report the first-stage F-statistic and in panel B we report the weak instrument test (Kleibergen-Paap rk Wald F-statistic), which is the Stock-Yogo weak identification test with critical values: 10% maximal IV size=7.03, 15%=4.58, 20%=3.95, 25%=3.63. All regressions are estimated using industry and year fixed effects and standard errors clustered at the industry level. Appendix Table A9 defines the variables in detail. $*p<.1$; $**p<.05$; $***p<.01$.

where Y_{ijt} is Markups, ROIC, Sales/Invested Capital, Capex Investment/Invested Capital, R&D Investment/Invested Capital, and SG&A Investment/Invested Capital; *Imports* are the instrumented value of imports into the United States; and γ_j and δ_t are industry and year fixed effects. All regressions are estimated with standard errors clustered at the industry level.

In panel A of Table 6, we first present estimates without the interaction effect with past star status. As expected, imports reduce markups, ROIC, and Sales/IC in general. Using the industry standard deviation for imports, we see that a one standard deviation increase in imports decreases markups by 11.6%, ROIC by 9.84% and Sales/IC by 21.4%. We see very little evidence of the effect of import competition on Capex or R&D and only a weak negative relation with SG&A investment potentially because firms are investing to meet the competitive challenge. In panel B, we examine whether star firms are differentially affected by import competition by interacting import competition with star status. To mitigate reverse causality, we measure star status as of the 2 years prior. We instrument *Imports* and *Imports* x $ROICstar_{ijt-2}$ with $Imports^{\mathrm{OTH}}$ and $Imports^{\mathrm{OTH}}$ x $ROICstar_{ijt-2}$.[40] All the interaction terms are insignificant. In particular, interactions in the markups and ROIC regressions are insignificant, suggesting that star firms do not have differentially smaller declines in markups, output, ROIC, or investment when faced with import competition in their industry compared to other firms in their industry. In panel B, the Cragg-Donald F-statistic test (Stock and Yogo 2005), which is a weak identification test for the excluded exogenous variables, is highly significant. This test is essential when the number of endogenous variables is more than one and the standard F-test may not truly reflect the relevance of instruments (for details, see Baum, Schaffer, and Stillman 2007).

In unreported robustness tests, as an alternative measure of competitive shocks, we identify large reductions in industry-level import tariffs as a quasi-natural experiment following Fresard (2010). In particular, using difference-in-differences, we look at how star firms and nonstars have differential responses following exogenous increase in competition triggered by the tariff reductions. We once again find that star firms do not have a differential response to exogenous competitive shocks compared to other firms in the economy. These results are robust to restricting the sample to just manufacturing industries, restricting the period to 2001, when most of the tariff reductions occurred and also to the period 1972 to 2001 as in Fresard (2010).

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

40 The results are unaffected when we measure star status in the current year or 3 years prior. In this Table, we are exploring if exogenous import shocks affect star firms differentially and hence we lag star status by one period (t-2) relative to imports (t-1). The results are unaffected when we measure star status in the same year as the imports (t-1) or 2 years prior to imports (t-3). All the interaction terms of Imports with past and current star status are insignificant suggesting that star firms are not differentially affected by exogenous competitive shocks.

6. Additional Tests and Robustness

In this section, we subject our findings to a series of robustness tests. At the outset, we look for churning in the top 10% of firms each year with different sets of firms randomly realizing high returns each year. Or examine whether these high returns are persistent and ask whether being a superstar is associated with superior performance. Next, we conduct robustness tests of our main results using alternative measures of ROIC, excess cash, and intangible capital.

6.1 Persistence in star status

To explore persistence in star status, we construct five nonoverlapping panels: 1990–1995, 1995–2000, 2000–2005, 2005–2010, and 2010–2015 and examine whether being a star is associated with higher average performance in the subsequent 5-year period. Specifically, for firm i in industry j in year t, the regression we estimate is as follows:

$$Performance_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital)_{ijt-5} + \beta_2 \times log(Age)_{ijt-5} + \beta_3 \times Star_{ijt-5} (or ROIC_{ijt-5}) + \phi_j \times \gamma_t + \epsilon_{ijt}. \quad (37)$$

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

Columns 1 and 2 of Table 7 shows that both star status and high *ROIC* are on average positively associated with higher average *ROIC* in the subsequent 5-year period. The predicted value of average 5-year *ROIC* for firms that were superstars 5 years ago is 44.01 compared to 7.48 for firms that were not superstars 5 years ago. Columns 3–8 show that prior star status is also associated with higher sales growth, employment growth, and labor productivity. Replacing *ROIC* star by *ROIC* yields very similar results, except for sales growth where it is not significant.

In Internet Appendix Table IA1, we find that q stars are also associated with higher Tobin's q, sales growth, employment growth, and labor productivity in the subsequent 5-year period. We find similar results replacing q star by q.

As further evidence of persistence, for the star firms each year, we explore what percentage remain stars in the 2–5 consecutive years going forward. Figure 14 shows that, on average, 56% of stars remain a star firm for each of 2 consecutive years, 35% for each of 3 consecutive years ahead, 23% for

Table 7
Are star firms persistent performers?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROIC	ROIC	Sales growth	Sales growth	Empl. growth	Empl. growth	Labor productivity	Labor productivity
L5.Log(Invested capital)	3.074***	0.801***	−0.007***	−0.007***	−0.007***	−0.009***	36.037***	29.955***
	(0.103)	(0.063)	(0.001)	(0.001)	(0.001)	(0.001)	(2.156)	(2.178)
L5.Log(Age)	0.159	0.578***	−0.030***	−0.032***	−0.021***	−0.021***	−36.207***	−35.293***
	(0.231)	(0.141)	(0.002)	(0.002)	(0.002)	(0.002)	(4.534)	(4.489)
L5.ROIC star	35.807***		0.031***		0.052***		104.147***	
	(0.636)		(0.005)		(0.005)		(8.889)	
L5.ROIC		0.643***		0.000		0.001***		1.787***
		(0.007)		(0.000)		(0.000)		(0.106)
Fixed Effects	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	18,085	18,085	11,831	11,831	11,389	11,389	17,638	17,638
Adj. R-sq	.382	.729	.086	.082	.079	.088	.403	.413

This table reports estimates from the following panel regression model:

$$Performance_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-5}) + \beta_2 \times log(Age)_{ijt-5} + \beta_3 \times ROIC_{ijt-5} + \beta_4 \times Star_{ijt-5} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Performance is Sales growth/Employment growth (each defined as the 5-year log difference in sales or employment, respectively, divided by five), Labor Productivity, or *ROIC* averaged over 5 years. log(Invested capital) is the 5-year-lagged value of Invested Capital as a proxy for firm size. log(Age) is the 5-year-lagged value of the firm age. *Markups* is the 5-year-lagged value of Markups computed using operating expenses as a variable input of production and includes correction for intangible capital. Star is a dummy variable that takes the value of one if firm i's 5-year-lagged *ROIC* was above the 90th percentile of *ROIC*, respectively, across all firms 5 years back and zero otherwise. The regressions are 5-year stacked panel regressions: 1990–1995, 1995–2000, 2000–2005, 2005–2010, and 2010–2015 and include industry x year fixed effects with standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

4 consecutive years ahead, and 16% of stars remain stars for each of the 5 consecutive years ahead. We also see an increase in persistence over time.

To explore whether there is convergence in ROIC over time, we follow the portfolio approach in Lemmon, Roberts, and Zender (2008). First, each calendar year, we sort firms into quartiles according to their current year ROIC, denoted as Highest, High, Medium, or Low. The portfolio formation year is denoted event year zero. Second, the average ROIC for each portfolio is calculated in each of the subsequent 14 years, holding the portfolio composition constant unless a firm exits the sample. Third, we repeat the sorting and averaging for every calendar year in the sample period. This process generates 26 sets of event time averages, one for each calendar year in the sample. Fourth, the average ROIC of each portfolio across the 26 sets is computed and plotted by event year. The second figure in Figure 14 shows noticeable convergence across the four portfolio averages over time, but the top ROIC portfolio has persistently higher ROIC than the other portfolios. For instance, after 14 years, the Highest ROIC portfolio remains significantly different, both statistically and economically, from the other portfolios.

6.2 Alternative measures of adjusted ROIC and markups

In this subsection, we first subject our adjustments to ROIC to a number of checks. To begin, we find similar results if we were to adjust for just R&D capital or just SG&A capital. Figure 15 shows figures with adjustments for just

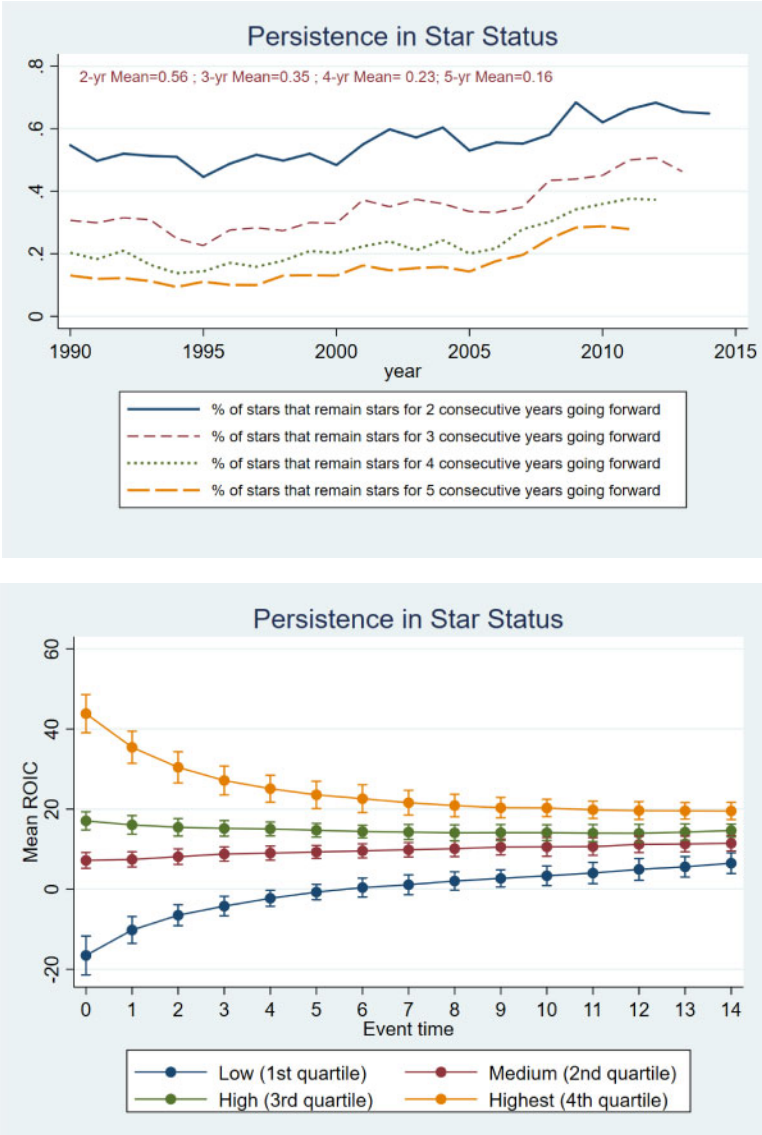
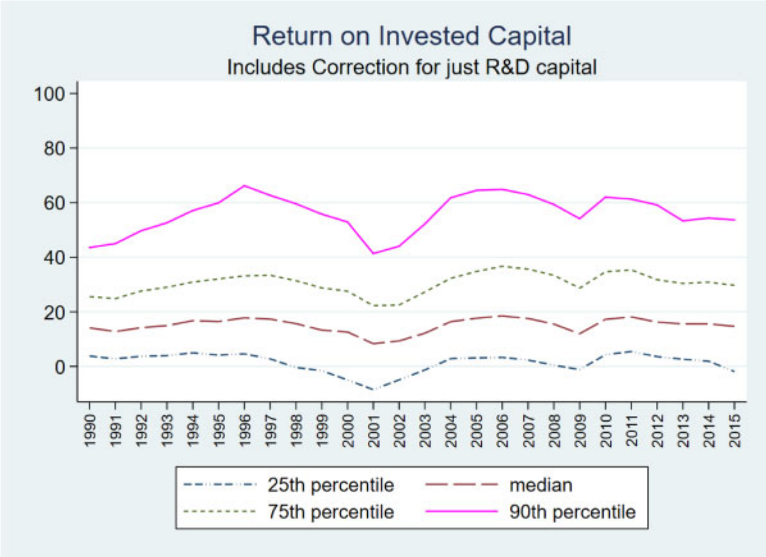


Figure 14
Persistence in Star Status
The top figure plots the percentage of firms that remain stars in the 2 to 5 consecutive years going forward. The figure below plots the persistence in star status using the portfolio approach in Lemmon, Roberts, and Zender (2008).



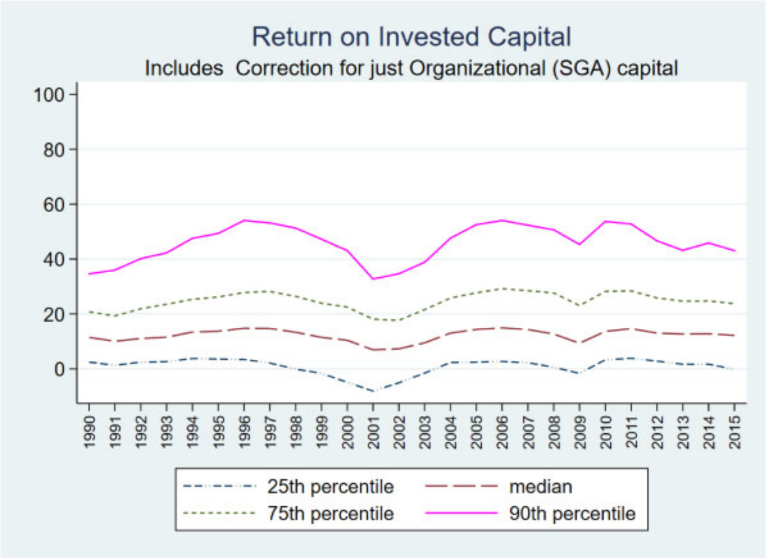


Figure 15
Rise in star firms: Correcting for R&D capital versus SG&A capital
This figure plots the $25th$, $50th$, $75th$, and $90th$ percentiles of Return on Invested Capital (*ROIC*) in each year. In the first figure, the *ROIC* measure only includes correction for knowledge (R&D) capital and in the second figure, the *ROIC* measure only includes correction for organization (SG&A) capital. Appendix Table A9 defines the variables in detail.

R&D capital and for just SG&A capital. If we only corrected for R&D capital, the average ROIC numbers are higher and the gap between the 90th percentile and median firm is wider. Overall however, both the figures are consistent with each other and with Figure 3, which includes correction for both R&D and SG&A capital

Next, as shown in Figure IA4 of the Internet Appendix, we obtain a similar picture when we restrict the sample to large firms, and extend the time period to 1975 to be consistent with the sample in Figure 1. In Figure IA5 of the Internet Appendix, we obtain a similar picture if we were to NOT subtract goodwill from our estimates of invested capital. Finally, in Figure IA6 of the Internet Appendix, we narrow our definition of star firms and plot the mean ROIC for the top-100 and top-150 firms each year. Once again, we find no run-up in ROIC over time for even the top-100 or top-150 firms.

Next, we try to further explore our findings in Section 3, where our estimates of markups appear to be lower than those estimated by Traina (2018). We see that this is once again driven by firms with very high intangible intensity that do a lot of R&D. These firms do not report many sales and, as a result, do not make a profit (low ROIC firms). While Traina would treat their entire operating expenditure (OPEX) as variable costs thus giving rise to very low markups, we apply a correction removing R&D expenses and a fraction of SG&A expenses (i.e., OPEX-XRD-RDIP-0.3*SGA) and instead capitalizing them. Thus, our markups would be higher for these loss-making firms than Traina's markups. This, in turn, drives down the correlation between our markups and those of Traina's. To see this, in Appendix Figure A.1, we plot the difference between our Markups (OPEX*) and Traina's Markups (OPEX) against deciles of Intangible intensity and Age. The figure shows that the difference between our markups and Traina's markups are the biggest for very-high-intangible-intensity firms (deciles, I9, I10) and young firms (lowest age deciles, a1, a2, a3). To see this in a regression setting, in Appendix Table A7, we see that for low-intensity firms, the difference in explanatory power between OPEX markups (Traina) and OPEX* markups (Ours) is negligible. Note that the coefficients in columns 1 and 2 are different from the ones reported in Table A3 because here we are restricting the observations to be the same in both columns to allow for a cleaner comparison.

6.3 Measurement of excess cash

A great deal of controversy surrounds how to treat a firm's cash holdings in the computation of a firm's invested capital. Standard financial reporting practice dictates the inclusion of 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, Goedhart, and Wessels 2017). The rationale for doing this is that the excess cash is unnecessary to support operations and confounds valuations of product market opportunities. A large body of academic work (e.g., Jensen 1986; Harford, Mansi, and Maxwell 2008; Dittmar and Mahrt-Smith 2007) also supports this view and argues that large cash holdings reflect 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, Hankins, and Petersen 2019). Against that, numerous findings point to high cash positions typically occurring in R&D-intensive firms, and these cash holdings may be economically rational (see Boyle and Guthrie 2003; Bates, Kahle, and Stulz 2009; Harford, Klasa, and Maxwell 2014). In particular, to the extent that R&D-intensive firms face higher operational risks and that intellectual capital cannot be easily used as collateral for bank loans, high cash positions are economically motivated. Moreover, from the perspective of the firms' owners, the relevant returns should be calculated as a function of all the capital committed, not just the portion that would have been committed under an alternative corporate governance regime. Moreover, Damodaran (2005) notes analysts have used the 2% ratio as a rule of thumb; however, it 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's cash holdings.

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

$$Invested\ Capital_{it}^{CASH} = PPENT_{it} + ACT_{it} + ICAP_{it} - LCTit - GDWL_{it}. \tag{38}$$

Analogously, we define ROIC with this new adjustment as

$$ROIC_{it}^{CASH} = \frac{ADJPR_{it}}{Invested\ Capital_{it}^{CASH}}. \tag{39}$$

In Figure IA7 of the Internet Appendix, we present four *ROIC* graphs, where *ROIC* is recomputed 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 no run-up in *ROIC* for the top 10% of firms as in Figure 3.

In Table 8, we repeat estimations in Table 3 but re-estimate *ROIC* using different treatments of cash. In columns 1 and 2, we use the firm's total cash holdings in computing ROIC, $ROIC^{\text{CASH}}$, in columns 3 and 4, we consider excess cash to be any cash over 1% of sales, $ROIC^{\text{1per}}$, and in columns 5 and 6 we consider excess cash to be any cash over 10% of sales, $ROIC^{\text{10per}}$. Across the columns, we obtain similar results wherein intangible intensity is negatively associated with star status and this seems to be driven by product life cycle effects where firms that have high intensity and doing a lot of Life1 are losing money.

Table 8
Intangible capital, markups, and star status: Measurement of excess cash

	1	2	3	4	5	6
	$ROIC^{Cash}$ star	$ROIC^{Cash}$ star	$ROIC^{1Per}$ star	$ROIC^{1Per}$ star	$ROIC^{10Per}$ star	$ROIC^{10Per}$ star
L.Log(Invested capital)	−0.002	−0.001	−0.008***	−0.006***	−0.008***	−0.007***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
L.Log(Age)	−0.048***	−0.034***	−0.060***	−0.043***	−0.062***	−0.043***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
L.Markups	0.125***	0.118***	0.160***	0.152***	0.165***	0.158***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
L.Intangible intensity	−0.062***	-0.018	−0.040***	−0.015	−0.046***	−0.017
	(0.011)	(0.022)	(0.011)	(0.023)	(0.011)	(0.021)
L.Life1		0.234***		0.248***		0.248***
		(0.048)		(0.050)		(0.047)
L.Intangible intensity x L.Life1		−0.291***		−0.238***		−0.242***
		(0.066)		(0.070)		(0.066)
FE	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	80,908	53,733	84,218	54,048	84,353	54,145
Adj. R-sq	.088	.084	.118	.107	.119	.108

This table reports estimates from the following panel regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt}) + \beta_3 \times Life1_{ijt-1} + \beta_4 \times Intangible\ intensity_{ijt-1}$$
$$+ \beta_5 \times Life1_{ijt-1} \times Intangible\ intensity_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Star is a dummy variable that takes the value of one if the firm i's ROIC is above the $90th$ percentile of ROIC, respectively, across all firms in a particular year and zero otherwise. In columns 1–3, we use the firm's total cash holdings in computing ROIC, $ROIC^{CASH}$, in columns 4–6, we consider excess cash to be any cash over 1% of sales in computing ROIC, $ROIC^{1per}$ and in columns 7–9 we consider excess cash to be any cash over 10% of sales in computing ROIC, $ROIC^{10per}$. log(Invested capital) is used as a proxy for firm size, and log(Age) is the logarithm of firm age. Markups are estimated using operating expenses as a variable input of production and includes correction for intangible capital. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

6.4 Alternate definitions of intangible capital

In this section, we examine whether our main results are robust to varying the amount of knowledge capital being used to define intangible capital. In the empirical implementation of the optimization model of Section 2, we assumed that we are able to completely adjust for intangible capital and thus take $\nu = 1$, while defining invested capital ($= K_1 + \nu K_2$) where K_2 is referred to as *ICAP* in Equation (22) and is measured by the sum of externally purchased intangible capital (*INTAN*), knowledge capital (*K_int_know*), and organization capital (*K_int_org*).

Suppose our intangible capital correction is less than perfect. Below, we will examine what happens to the relationship between markups, intensity, and ROIC for different values of ν (= 0.9, 0.7, and 0.5). Correspondingly, we alter the definitions of ROIC, Invested capital, and Intangible intensity in each of these cases. Appendix Table A8 presents these robustness tests. Across the columns, we see that both markups and initial markups (defined 5 years after the firm's IPO) are always positively associated with star status across alternate definitions of intangible capital. Intangible intensity is negatively associated with star status except in columns 3 and 6 where it is not significant. Note that in these two columns we are greatly discounting the knowledge capital of the firm and thus discounting most of the Life1 firms.

7. Conclusion

A large academic and public policy debate considers whether the observed macro trends on concentration and markups reflect a rise in market power or an increase in firm productivity. In this paper, we assess the performance and strategies of publicly listed star firms in the United States to examine evidence that these firms are generating high returns by cutting output and investment compared to firms with similar markups.

We first find that measurement of intangible capital is key to understanding the profits and market power of star firms. When we use financial statement data as conventionally presented, star firms, especially in industries with high levels of intangible capital are pulling away over time from other firms in the economy in terms of their return on capital. 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 little evidence that the most profitable 10% of firms are pulling away from the rest of the economy, and the differences in firm returns in industries with high levels of intangible capital and other industries shrink dramatically. By the end of our sample period in 2015, more than half of the divergence between the $90th$ percentile and median firm in high intangible capital industries is explained by the mismeasurement of intangible capital. Furthermore, once we adjust markups based on operating expenses for investment in intangible capital, we only find a modest increase in markups, especially in industries with high levels of intangible capital.

We present a simple theoretical model to explain how to adequately interpret firms' returns to capital in the presence of mismeasured intangibles, and to motivate the positive association between markups and star status as seen in the data. However, the stylized model cannot account for at least two patterns observed in the data: the nonmonotonic relationship between high-ROIC status and intangible intensity; and the fact that firms with the same intangible intensity and the same markups may have different output. More complex models are needed to explain all the patterns in the data. For instance, we find that while star firms may have higher markups than other firms, these are predicted early in their life cycle and firms' early markups are highly persistent and predict subsequent start status. Furthermore, at each level of intensity star firms tend to produce more and invest more than other firms. Importantly, we find that star firms are more innovative as measured by the stock market value of the patents granted to them as in Kogan et al. (2017). We also find no evidence that star firms are differentially affected by exogenous competitive shocks compared to other firms in the economy.

Overall, we see little evidence that these star firms are using their market power to reduce output to achieve supernormal returns more than other comparable firms. The evidence is consistent with star firms being more productive than other firms and maximizing value by increasing output, investment, and R&D but at the margin following different long-term strategies, trading off some additional profits for a stronger long-term franchise through higher revenues.

However, there may be reason for concern about a smaller subset of elite publicly listed firms. The usual suspects for membership in such an elite group are Apple, Facebook, Google, Amazon, and Microsoft. When we examine these firms individually, the ROIC and markups of most of these elite firms do not seem extraordinary initially and then explode but again only for a couple of firms that have built up a large enough market. Even for these firms, the critical policy concern may be not only the regulation of their use of market power today but also the need to maintain contestable markets that allow the creation of independent technologies in the future.

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

Appendix A. Role of User Costs

The model in Section 2 of the paper is intended as a tool for explaining how to adequately interpret returns on invested capital (ROIC) in the presence of mismeasured intangibles, and for the positive relationship between markups and ROIC as seen in the data. However, we have to look beyond the stylized model to explain some of the patterns in the data including the finding that star firms have higher Sales/Invested Capital ratio than nonstars. While we attribute this to greater productivity of star firms in the main paper, in this section, we derive a more generalized form of the model showing high user costs of star firms to be an alternative consideration to market power being the primary driver of high returns and output of star firms.

From Equation (2) in Section 2, we have the firm's production function to be

$$Y = ZL^{1-\alpha}(K_1)^{(1-\eta)\alpha}(K_2)^{\eta\alpha},$$

where

- the firm's inputs of production are labor L, physical capital K_1, and intangible capital zK_2;
- Z is Hick's neutral efficiency (TFPQ);
- $1-\alpha$ is labor share;
- η is intangible intensity.

Suppose star firms have higher user costs captured by z. The new optimization problem for the firm is given by

$$\Pi = \max_{L,K_1,K_2} DP^{\frac{-1}{\mu-1}} - WL - zR_1K_1 - zR_2K_2, \tag{A1}$$

subject to the production constraint

$$ZL^{1-\alpha}(K_1)^{(1-\eta)\alpha}(K_2)^{\eta\alpha} \geq DP^{-\frac{\mu}{\mu-1}}. \tag{A2}$$

Table A1
Summary statistics

Variable	Obs	Mean	SD	Min	Max
ROIC star	81,525	0.100	0.285	0	1
ROIC	81,525	13.162	24.643	−129.511	150.069
log(Invested capital)	81,145	5.435	1.861	−3.498	12.559
log(Age)	81,525	2.752	0.700	1.386	4.205
Markups	81,009	1.313	0.384	0.006	3.628
Markups_prodfn	78,225	1.221	0.278	0.204	2.627
Intangible intensity	80,495	0.601	0.291	0.000	0.988
Industry-level variables					
ImportsUSA	808	0.071	0.138	5.88E-05	0.928
ImportsOTH	808	0.060	0.103	0.000208	0.809

This table reports the summary statistics of the key variables used in our analysis. Appendix Table A9 defines the variables in detail.

Table A2
Markups and star status: Varying proportions of SGA in ROIC

	1	2	3	4	5
	ROIC* star	ROIC* star	ROIC* star	ROIC* star	ROIC* star
Use of SGA in ROIC definition	0.1*SGA	0.2*SGA	0.3*SGA	0.5*SGA	0.6*SGA
L.Log(Invested capital)	−0.004***	−0.005***	−0.006***	−0.007***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Log(Age)	−0.045***	−0.048***	−0.052***	−0.055***	−0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.Markups	0.171***	0.166***	0.161***	0.147***	0.140***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Fixed effects			Industry x Year		
N	81,521	81,530	81,525	81,524	81,530
Adj. R-sq	.103	.106	.110	.116	.119

This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Markups_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Star is a dummy variable that takes the value of one if firm i's *ROIC* is above the 90th percentile of *ROIC* across all firms in a particular year and zero otherwise. *Markups* are defined as Sales/OPEX* where OPEX* is operating expenses adjusted for intangible capital. While 30% of Selling, General, and Administrative Expenses (SGA) are typically used in measuring ROIC (column 3), the percentage of SGA expenses used in measuring ROIC varies between 10% (column 1) to 60% (column 5). All regressions in all panels are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. * p <.1; ** p <.05; *** p <.01.

Setting up the Lagrangian, we get

$$\Pi = \max_{L,K_1,K_2} DP^{-\frac{1}{\mu-1}} - WL - zR_1K_1 - zR_2K_2 + \lambda\left[ZL^{1-\alpha}(K_1)^{(1-\eta)\alpha}(K_2)^{\eta\alpha} - DP^{-\frac{\mu}{\mu-1}}\right]. \tag{A3}$$

The FOC yield

$$\lambda = \frac{P}{\mu}, \tag{A4}$$

$$WL = \frac{(1-\alpha)PY}{\mu}, \tag{A5}$$

$$zR_1K_1 = \frac{\alpha(1-\eta)}{\mu}PY, \tag{A6}$$

Table A3
Markups and star status: Alternative definitions of markups

	(1)	(2)	(3)
	ROIC star	ROIC star	ROIC star
L.Log(Invested capital)	0.001	−0.009***	−0.006***
	(0.001)	(0.001)	(0.001)
L.Log(Age)	−0.052***	−0.061***	−0.052***
	(0.003)	(0.003)	(0.003)
L.Markups (COGS)	0.034***		
	(0.003)		
L.Markups (OPEX)		0.272***	
		(0.010)	
L.Markups (OPEX*)			0.161***
			(0.007)
Fixed effects	|————	Industry x Year	——|
N	81,078	81,536	81,525
Adj. R-sq	.080	.127	.110

This table reports estimates from the following regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Markups_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Star is a dummy variable that takes the value of one if firm i's *ROIC* is above the $90th$ percentile of *ROIC* across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is logarithm of firm age. We use three different definitions of markups in this table. *Markups* is Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. $Markups(COGS)$ is Sales/Cost of Goods sold and $Markups(OPEX)$ is Sales/Operating expenses. All regressions in all panels are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. $^*p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

Table A4
Markups and star status: Additional robustness

	1	2	3	4	5	6	7	8
	ROIC star	ROIC	Q star	Tobin's q	ROIC star	ROIC	q Star	Tobin's q
L.Log(Invested capital)	−0.098***	−5.762***	−0.073***	−0.425***	−0.002	2.169***	−0.007***	0.021***
	(0.004)	(0.307)	(0.003)	(0.019)	(0.001)	(0.117)	(0.001)	(0.007)
L.Log(Age)	−0.073***	−6.293***	−0.088***	−0.685***	−0.045***	−2.447***	−0.044***	−0.320***
	(0.008)	(0.604)	(0.008)	(0.041)	(0.003)	(0.268)	(0.003)	(0.016)
L.Markups	0.123***	19.040***	0.062***	0.472***				
	(0.007)	(0.717)	(0.007)	(0.036)				
L.Markups_prodfn					0.183***	24.039***	0.171***	1.117***
					(0.012)	(1.030)	(0.012)	(0.064)
Fixed effects	Firm, year	Firm, year	Firm, year	Firm, year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	80,673	80,673	77,750	77,750	74,166	74,166	71,803	71,803
Adj. R-sq	.408	.587	.368	.511	.090	.185	.067	.131

This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Markups_{ijt-1} + \delta_i (or \phi_j \times \gamma_t) + \varepsilon_{ijt}.$$

Star is a dummy variable that takes the value of one if firm i's *ROIC* (or Tobin's q) is above the $90th$ percentile of *ROIC* (or $Tobin's\ q$) across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is logarithm of firm age. In columns 1 and 2, *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. In column 3, $Markups\_prodfn$ is estimated using the production function approach. All regressions are estimated using ordinary least squares with firm fixed effects in column 1 and industry x year fixed effects in columns 2 and 3. Standard errors are clustered at the firm level. Appendix Table A9 defines the variables in detail. $^*p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

Table A5
Intangible capital, markups, and star status: Robustness

	1	2	3	4	5
	ROIC	ROIC	ROIC	ROIC	ROIC
Sample	Full	Full	High intensity	Low intensity	Full
L.Log(Invested capital)	1.518***	1.425***	1.410***	1.318***	1.438***
	(0.109)	(0.111)	(0.184)	(0.128)	(0.132)
L.Log(Age)	−2.657***	−2.745***	−3.144***	−2.993***	−1.789***
	(0.247)	(0.237)	(0.385)	(0.280)	(0.295)
L.Markups	21.643***	25.887***	28.406***	23.864***	25.309***
	(0.691)	(0.655)	(0.862)	(0.910)	(0.720)
L.Intangible intensity	0.760	-10.132***	-35.788***	2.799**	2.605
	(0.685)	(0.941)	(2.952)	(1.194)	(1.724)
L.Life1					28.271***
					(3.884)
L.Intangible intensity x L.Life1					-56.170***
					(5.472)
Fixed effects	Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	80,739	80,639	32,235	47,647	53,527
Adj. R-sq	.158	.269	.329	.251	.288

This table reports estimates from the following panel regression model:

$$ROIC_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Intangible\ intensity_{ijt-1} +$$

$$\beta_4 \times Markups_{ijt-1} + \beta_5 \times Intangible\ intensity_{ijt-1} \times Life1_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

The dependent variable is *ROIC*. log(Invested capital) is used as a proxy for firm size, and log(Age) is the logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. *Intangible intensity* is defined as the ratio of intangible capital to the sum of intangible and tangible capital. Life1 is a firm product life cycle variable that measures the intensity of product innovation from Hoberg and Maksimovic (2022). All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. $*p<.1$; $**p<.05$; $***p<.01$.

$$zR_2K_2 = \frac{\alpha\eta}{\mu}PY. \tag{A7}$$

Mapping the above generalized production model to ROIC:

$$Invested\ Capital = K_1 + \nu K_2, \tag{A8}$$

$$Earnings = PY - WL - \gamma R_2 K_2, \tag{A9}$$

$$ROIC = \frac{PY - WL - \gamma R_2 K_2}{K_1 + \nu K_2}, \tag{A10}$$

$$Sales/IC = \frac{PY}{K_1 + \nu K_2}. \tag{A11}$$

Substituting the FOC into the above expressions for ROIC and Sales/IC, we get

$$ROIC = \frac{z}{\alpha}\left[\mu - (1-\alpha) - \frac{\gamma\alpha\eta}{z}\right]\left[\frac{1-\eta}{R_1} + \frac{\nu\eta}{R_2}\right]^{-1}, \tag{A12}$$

$$Sales/IC = \frac{z\mu}{\alpha}\left[\frac{1-\eta}{R_1} + \frac{\nu\eta}{R_2}\right]^{-1}. \tag{A13}$$

Thus, firms with higher user costs of capital have higher ROIC and higher ratios of sales to invested capital.

Table A6
Intangible capital, markups, and star status: Variance decomposition robustness

	1	2	3	4	5	6	7	8	9
	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star
		Full sample			$Intensity \geq 0.75$			$Intensity < 0.75$	
L.Log(Invested capital)	0.003**	0.003**	−0.007***	0.013***	0.011***	−0.006**	−0.002*	−0.002	−0.008***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
L.Log(Age)	−0.057***	−0.056***	−0.051***	−0.075***	−0.076***	−0.068***	−0.047***	−0.048***	−0.045***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
L.Intangible intensity		−0.038***	−0.038***		−0.285***	−0.312***		0.038***	0.048***
		(0.011)	(0.011)		(0.036)	(0.034)		(0.014)	(0.014)
L.Markups			0.165***			0.195***			0.139***
			(0.008)			(0.010)			(0.010)
FE	Ind x year	Ind x year	Ind x year	Ind x year	Ind x year	Ind x year	Ind x year	Ind x year	Ind x year
N	80639	80639	80639	32235	32235	32235	47647	47647	47647
Adj. R-sq	.071	.072	.114	.067	.072	.136	.087	.088	.114
Change in R-sq		*.001*	*.042*		*.005*	*.064*		*.001*	*.026*

This table reports estimates from the following panel regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age_{ijt-1}) + \beta_3 \times Markups_{ijt-1} + \beta_4 \times Intangible\ intensity_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt},$$

This table is a robustness of panel B of Table 3 in the paper where we do a variance decomposition to compare the explanatory power of Markups versus Intangible intensity by entering Intangible intensity first in the regression followed by Markups. The dependent variable is *ROIC star* which is a dummy variable that takes the value of one if firm *i*'s ROIC is above the $90th$ percentile of ROIC, respectively, across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is the logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. *Intangible intensity* is defined as the ratio of intangible capital to the sum of intangible and tangible capital. All regressions include industry x year fixed effects and are estimated using ordinary least squares with standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. $*p<.1$; $**p<.05$; $***p<.01$.

Table A7
Traina markups (OPEX) versus our markups (OPEX*)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star	ROIC star
Sample	Full sample		High intensity		Low intensity	
L.Log(Invested capital)	−0.009***	−0.006***	−0.009***	-0.004	−0.010***	−0.009***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
L.Log(Age)	−0.060***	−0.050***	−0.091***	−0.064***	−0.045***	−0.042***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
L.Markups (OPEX)	0.285***		0.403***		0.218***	
	(0.011)		(0.016)		(0.014)	
L.Markups (OPEX*)		0.186***		0.206***		0.175***
		(0.009)		(0.011)		(0.012)
FE	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year	Ind x Year
N	79,828	79,828	31,389	31,389	47,198	47,198
Adj. *R*-sq	.124	0.11	.158	.122	.12	.118
R-sq		*-0.014*		*-0.036*		*-0.002*

This table reports estimates from the following regression model in panel A:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{ijt-1}) + \beta_2 \times log(Age)_{ijt-1} + \beta_3 \times Markups_{ijt-1} + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Star is a dummy variable that takes the value of one if firm i's *ROIC* is above the $90th$ percentile of *ROIC* across all firms in a particular year and zero otherwise. log(Invested capital) is used as a proxy for firm size, and log(Age) is logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. $Markups(OPEX)$ are defined as Sales/Operating expenses. All regressions in all panels are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. $^{*}p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

Table A8
Alternative definitions of intangible capital

	(1)	(2)	(3)	(4)	(5)	(6)
	$ROIC_{IC1}$ star	$ROIC_{IC2}$ star	$ROIC_{IC3}$ star	$ROIC_{IC1}$ star	$ROIC_{IC2}$ star	$ROIC_{IC3}$ star
L.Log(Age)	−0.054***	−0.053***	−0.052***	−0.059***	−0.059***	−0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.Markups	0.159***	0.176***	0.188***			
	(0.008)	(0.008)	(0.008)			
Initial markups (t5)				0.008**	0.009**	0.012***
				(0.003)	(0.004)	(0.004)
L.Log($Invested\ capital_1$)	−0.006***			0.002		
	(0.001)			(0.001)		
L.Log($Invested\ capital_2$)		−0.007***			0.002	
		(0.001)			(0.001)	
L.Log($Invested\ capital_3$)			−0.008***			0.002
			(0.001)			(0.001)
L.$Intangible\ intensity_1$	−0.059***			−0.059***		
	(0.011)			(0.012)		
L.$Intangible\ intensity_2$		−0.029***			−0.028**	
		(0.011)			(0.011)	
L.$Intangible\ intensity_3$			-0.003			0.001
			(0.011)			(0.011)
N	80,120	80,026	79,823	79,048	78,960	78,778
Adj. R-sq	.106	.117	.132	.072	.076	.086

This table reports estimates from the following regression model:

$$Star_{ijt} = \alpha_0 + \beta_1 \times log(Invested\ capital_{it-1}) + \beta_2 \times log(Age_{it-1}) + \beta_3 \times Intensity_{it-1} + \beta_4 \times Markups_{it-1}\ or\ InitialMarkups + \phi_j \times \gamma_t + \varepsilon_{ijt}.$$

Invested capital in the model in Section 2 is defined as $(=K_1 + \nu K_2)$. In most of the tables we assume we are able to completely adjust for intangible capital and thus take $\nu = 1$, while defining invested capital. In this table we explore what happens when the intangible capital correction is less than perfect for different values of ν (=0.9, 0.7, and 0.5). Correspondingly we alter the definitions of ROIC, Invested Capital, and Intangible intensity in each of these cases. Thus the dependent variable is $ROIC_{IC1}$ *Star*, $ROIC_{IC2}$ *Star*, or $ROIC_{IC3}$ *Star*, corresponding to the three different values of ν in defining invested capital. In each case, *Star* is a dummy variable that takes the value of one if firm *i*'s *ROIC* is above the 90*th* percentile of *ROIC* across all firms in a particular year and zero otherwise; log(Invested capital) is used as a proxy for firm size and again we have three versions of Invested capital corresponding to ν (=0.9, 0.7, and 0.5), respectively. Similarly for Intangible intensity. log(Age) is logarithm of firm age. *Markups* are defined as Sales/OPEX*, where OPEX* is operating expenses adjusted for intangible capital. In columns 3–6, markups are measured at t5 (5 years after the firm appears in Compustat). All regressions are estimated using ordinary least squares with industry x year fixed effects and standard errors clustered at the firm level. Appendix Table A9 defines the variables in detail. *p <.1; **p <.05; ***p <.01.

Table A9
Variable definitions

Variables	***Definition***
Invested capital^{unadj}	Invested Capital = PPENT + ACT + INTAN - LCT - GDWL - max(CHE-0.02 x SALE, 0) where PPENT is Net Property, Plant, and Equipment, ACT is Current Assets, INTAN is Total Intangible Assets, LCT is Current Liabilities, GDWL is Goodwill that represents the excess cost over equity of an acquired company, CHE is Cash and Short-term Investments, and SALE is net sales/turnover. This definition does not include the Peters and Taylor (2017) correction for intangible capital.
ROIC^{unadj}	$(EBIT_t + AM_t)$/Invested capital$^{unadj}_{t-1}$, where EBIT is Earnings before Interest and Taxes and AM is Amortization of Intangibles. This definition does not include the Peters and Taylor (2017) correction for intangible capital

(*Continued*)

Table A9
(Continued)

Variables	*Definition*
ROIC star^{unadj}	Dummy variable that takes the value one if the firm's ROIC^{unadj} is above the 90th percentile of ROIC^{unadj} across all firms in the U.S. economy in a particular year and zero otherwise. This definition does not include the Peters and Taylor (2017) correction for intangible capital
Invested capital	Invested Capital = PPENT + ACT + ICAP - LCT - GDWL - max(CHE-0.02 x SALE, 0) where PPENT is Net Property, Plant, and Equipment, ACT is Current Assets. ICAP is defined as the sum of externally purchased intangible capital (INTAN) and internally purchased intangible capital, the latter measured at replacement cost. Internally purchased intangible capital is in turn measured as the sum of knowledge capital (K_int_know) and organization capital (K_int_org). LCT is Current Liabilities, GDWL is Goodwill that represents the excess cost over equity of an acquired company, CHE is Cash and Short-term Investments, and SALE is net sales/turnover
ROIC	ROIC = (EBIT + AM + XRD + 0.3 x SGA - δ_{RD} x K_int_know - δ_{SGA} x K_int_org)/Invested Capital$_{t-1}$ where EBIT is Earnings before Interest and Taxes, AM is Amortization of Intangibles, XRD is Research and Development Expense, SGA is Selling, General, and Administrative Expense defined below, δ_{RD} is the depreciation rate associated with knowledge capital and is set to 15% following Peters and Taylor (2017) and δ_{SGA} is the depreciation rate associated with organization capital and is set to 20% following Falato et al. (2022) and Peters and Taylor (2017). K_int_know and K_int_org are the firm's intangible capital replacement cost and organization capital replacement cost respectively from Peters and Taylor (2017)
SGA	SGA= XSGA-XRD-RDIP where XRD is Research and Development Expense, RDIP is in-process R&D expense, XSGA is Selling, General, and Administrative Expense. This definition of SGA follows Peters and Taylor (2017)
ROIC star	Dummy variable that takes the value one if the firm's ROIC is above the 90th percentile of ROIC across all firms in the U.S. economy in a particular year and zero otherwise
Intangible intensity	Intangible intensity is defined as the ratio of intangible capital (ICAP-GDWL) to the sum of intangible capital (ICAP-GDWL) and tangible capital (PPENT)
OPEX*	Operating expenses adjusted for intangible capital given by $OPEX^{*} = OPEX - XRD - RDIP - 0.3 \times SGA$ where OPEX is Total Operating Expenses, XRD is Research and Development Expense, RDIP is in-process R&D expense, SGA is Selling, General, and Administrative Expense
Markups	Markups following the cost share approach = Sales/Variable Input, where Operating Expenses* (OPEX*) is used as a variable input
Markups_prodfn	Markups following the estimation in De Loecker and Eeckhout (2017) using Operating Expenses* (OPEX*) as a variable input
Markups(COGS)	Markups following the cost share approach = Sales/Variable Input, where Cost of Goods Sold (COGS) is used as a variable input
Markups(OPEX)	Markups following the cost share approach = Sales/Variable Input, where Operating Expenses (OPEX) is used as a variable input
log(Age)	log(1+Firm Age), where Firm Age is the number of years the firm has appeared in Compustat
Output	Sales/Invested Capital
Investment	Capital Expenditures/Invested Capital
R&D	R&D Expenses/Invested Capital.

(*Continued*)

Table A9
(Continued)

Variables	*Definition*
Tobin's q	q = V/TOTCAP where V is the market value of the firm defined as the market value of equity (=total number of common shares outstanding (Compustat item CSHO) times closing stock price at the end of the fiscal year (Compustat item PRCC_F) plus the book value of debt (Compustat items DLTT + DLC) minus the firm's 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 (the latter being measured at replacement cost). Internally purchased intangible capital is in turn measured as the sum of knowledge capital (K_int_know) and organization capital (K_int_org). q is provided by Peters and Taylor (2017).
Skill(CPS)	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions. *Source:* O*NET
Skill(NRCOG)	Mathematical Reasoning + Inductive Reasoning + Developing Objectives and Strategies + Making Decisions and Solving Problems. *Source:* O*NET
ImportsUSA	Total value of Chinese imports into the United States in each four-digit NAICS industry j scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ minus total exports, $E_{j,2005}$ in that industry in 2005. *Source:* U.S. Census Bureau
ImportsOTH	Total value of Chinese imports into eight other developed economies in each four-digit NAICS industry j scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ minus total exports, $E_{j,2005}$ in that industry in 2005. *Source:* UN Comtrade Database

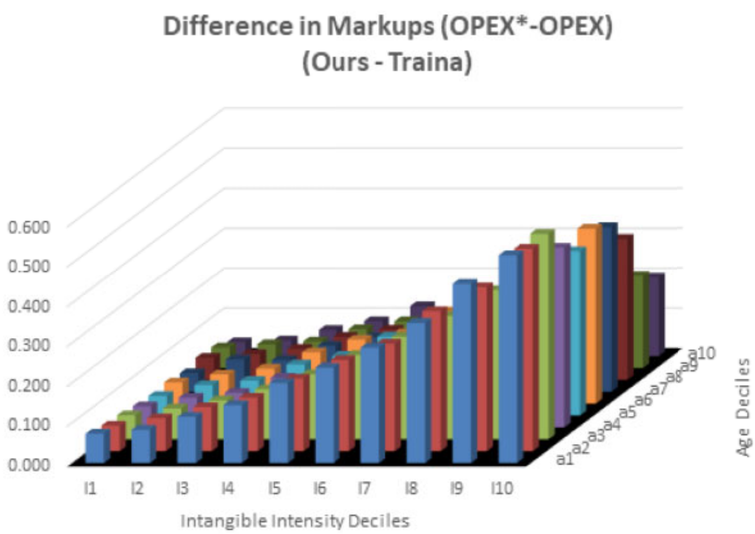


Figure A.1
Difference between our markups and Traina (2018) markups

Appendix B. Comovement in Revenues and Output

To motivate our use of sales revenues (PY) in place of output (Y) in Section 4, we first derive the expression for price, P . As a recap, the production function is given by

$$Y = ZL^{1-\alpha}(K_1)^{(1-\eta)\alpha}(K_2)^{\eta\alpha}.$$

From Equation (35) we know,

$$\frac{PY}{Y} = P = \mu * \lambda. \tag{A14}$$

From cost minimization, we know the expression for λ (see Internet Appendix for a derivation of λ):

$$\lambda = \frac{1}{Z}\left(\frac{R_1}{\alpha(1-\eta)}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_2(1-\eta)}{R_1\eta}\right)^{\alpha\eta} \equiv c. \tag{A15}$$

Therefore, price is given by

$$P = \frac{\mu}{Z}\left(\frac{R_1}{\alpha(1-\eta)}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_2(1-\eta)}{R_1\eta}\right)^{\alpha\eta}. \tag{A16}$$

The above expression shows no difference in the price function for stars versus nonstars. Hence, we expect the revenue function (PY) to comove with the output function (Y) in the same way for stars and nonstars, all other things being equal.

Appendix C. Variation in ROIC wrt μ, ν, and γ:

The general expression for ROIC in Equation (13) is given by

$$ROIC = \left(\frac{\mu-(1-\alpha)}{\alpha} - \gamma\eta\right)\left(\frac{1-\eta}{R_1} + \frac{\nu\eta}{R_2}\right)^{-1}. \tag{A17}$$

The derivative of *ROIC* wrt μ, ν and γ are given below:

$$\frac{\partial ROIC}{\partial\mu} = \frac{R_1R_2}{\alpha(\eta\nu R_1 + R_2(1-\eta))} > 0, \tag{A18}$$

$$\frac{\partial ROIC}{\partial\nu} = \frac{(1+\alpha(\eta\gamma-1)-\mu)\eta R_1^2R_2}{\alpha(\eta\nu R_1 + R_2(1-\eta))^2} < 0, \tag{A19}$$

$$\frac{\partial ROIC}{\partial\gamma} = \frac{-\eta R_1R_2}{\eta\nu R_1 + R_2(1-\eta)} < 0. \tag{A20}$$

Thus we see that ROIC is increasing in markups μ, and decreasing in the proportion of intangibles capitalized ν and the proportion of intangibles expensed γ.

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