Are Public Firms Really Myopic?

Evidence from Matching IPO Firms at Birth

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Abstract

We track firms at birth and compare the growth and responsiveness to demand shocks of IPO firms and their birth-matched counterparts. Firms that are larger at birth with faster initial growth are more likely to go public. Firms in the top percentile of predicted propensity to go public grow 29 times larger fifteen years later than matched firms if they actually become public, and 14 times larger if they stay private. We show that public firms, especially those public firms backed by venture capital, grow faster, respond more to demand shocks and gain higher efficiency post-IPO. Our results show that the growth patterns of public firms are predictable before their IPOs and are inconsistent with public firms being short-term orientated.

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I. Introduction

In the United States, most large firms are publicly traded, while smaller firms tend to be held privately. Public status comes with several distinct advantages, such as access to public capital markets, and the ability to diversify ownership.[1] There are also potential costs of public status, including costs of dispersed ownership, misaligned investment and growth incentives, and costs from public market oversight. Several authors, such as Stein (1989), Froot, Perold, and Stein (1992), as well as the *New York Times*,[2] have suggested that misaligned investment and growth incentives have the potential to cause myopic investment distortions, whereby public firms under-respond to market opportunities. However, since public status in endogenous, comparing private firms with public firms is difficult and risks confounding differences in the effects of public status with inherent differences in quality and life stages between firms. In this paper, we show that firm quality is persistent and that initial conditions at birth predict their future growth trajectories and public status.[3] Controlling for this measure of firm quality, public firms are as, or more responsive to growth opportunities when compared to private firms in subsequent years.

We examine how public and private firms respond to industry demand shocks over the first 15 years after birth. We ask: controlling for initial characteristics, does staying private versus going public impact differential growth, efficiency, and responses to growth opportunities? If so, is the differential effect permanent, or concentrated around a firm's decision to go public? Finally, are any differences between our results and the previous literature attributable to sample selection issues when researchers do not control for initial conditions? To address these questions, we use confidential data from the Longitudinal Business Database (LBD) maintained by the U.S. Census Bureau to obtain size, growth, labor productivity and other relevant characteristics for a large sample of firms (892,000 firms and 5,952,500 firm-years between 1978 and 2008) starting from their first year, regardless of public and private status, to match firms at birth.

[1] See Ritter and Welch (2002) for an overview of both rational and behavioral rationales for why firms go public and the IPO timing. These theories include life-cycle theories (Zingales (1995) and Chemmanur and Fulghieri (1999) and market-timing theories (Lucas and MacDonald (1990), and Baker and Wurgler (2000).

[2] See New York Times, July 6, 2010, Smith and Parentau –"Are Profits Hurting Capitalism?"

[3] Our approach is similar to Lemmon, Roberts and Zender (2008), who argue that there are persistent firm-specific effects that influence firm capital structures among public firms over time, and that this persistence exists for IPO firms prior to going public.

We establish a number of new results that show the importance of selection and initial conditions that impact how researchers should compare public and private firms. First, we show that initial firm characteristics that predict growth also predict a firm's propensity to go public. One standard deviation increase in initial size, initial wage, and first-year growth rate increases the probability of an IPO by 300%, 250%, and 170%, respectively. Moreover, this higher propensity to go public also predicts higher growth. A firm within the top one percent propensity to subsequently go public employs, on average, 16 times more employees at the age of ten than an average firm whose propensity to go public is outside the top one percent. Among firms within this top one percent propensity, those that eventually became public are 29 times larger, whereas those that stay private are only 14 times larger than the remaining firms fifteen years later. This difference can be interpreted as an upper bound on the benefits of public status.[4] These estimates indicate the large role initial conditions play in predicting firm size over time and the significant effect of selecting a public listing.

Second, when we match firms on initial conditions and compare outcomes of public firms and private firms around the times of the IPOs, we find a distinctive pattern. IPO firms grow faster before the IPO, and in the first five years after the IPO. However, their growth rate subsequently converges to that of always-private firms five years after the IPO. This result is consistent with the notion that the IPO firms are of higher quality. They initially have a growth spurt until reaching their optimal size, and their growth afterward converges back to the economy average. The transition from private status occurs on average around midway through the firm's high growth trajectory.

Third, in the five years after the IPO, publicly listed firms react more positively to product-market growth opportunities than matched private firms do. As with growth, this advantage dissipates over time but does not reverse. This result contrasts with recent work on capital market myopia, which argues that misalignment incentives are powerful enough to induce public firms to respond less to industry growth than private firms (Asker, Farre-Mensa, and Ljungqvist (2015)). We show that the seemingly under-reactions of public firms arises from problematical matching choices that lead to adverse selection, whereby very successful private firms are matched with under-performing public firms.[5] In a given

[4] The difference of 12 times is explained by the benefits of public status, differences in initial quality not observed by us, and events, such as an unexpectedly good outcome of an R&D program, that may have occurred prior to deciding to go public.

[5] The summary statistics in Asker, Farre-Mensa and Ljungqvist also show matched public firms decrease in performance (average ROA = -2.8%) versus the full sample of public firms (ROA = 6.4%) while the reverse is true for the ROA of matched private firms (ROA= 11.1%) versus the full sample of private firms (ROA =-11.8%).

year, a sizable sample of very large and efficient mature public firms cannot be matched to private firms. At the same time, unsuccessful older public firms on a downward path are likely to be matched to more successful private firms with an upward trajectory. Examination of a cross-sectionally matched sample of public firms with private firms using Census data confirms this conjecture.

Fourth, we show that during the period of high responsiveness to growth opportunities (first five years after the IPO), the labor productivity of listed firms is higher than or equal to that of matched always-private firms. This is consistent with the efficient growth of public firms observed in this interval, after which public firms attain an efficient scale based on their characteristics. Further growth and efficiency from that point are not statistically different from that of always-private firms. Additionally, we show that the closure rates of public firms are lower than that of private firms. Thus, public firms do not attain their higher growth by following riskier growth strategies.[6] In addition, we observe similar differences in closure rates for firms that became public on or off IPO waves.

Fifth, to further clarify the role of selection and treatment effects for firms that go public, we compare firms with Venture Capital (VC) investments with firms that do not. VC investors may have additional information about the firm and may provide additional inputs to the firms that they sponsor. Thus, VC sponsorship can serve as a signal for firm quality. We show that IPO firms that are supported by VC earlier in life exhibit even greater responsiveness to demand shocks following their IPO. This result suggests that higher-quality firms are selected by venture capitalists, and are more responsive to demand shocks. A portion of the higher responsiveness of public firms compared to private firms is the result of quality differential that we do not measure by firms' data at birth but may be evident to VCs before the IPO. Critically, however, IPO firms that are not sponsored by VCs are no less responsive to demand opportunities than private firms.

We perform several tests to examine the potential determinants of responsiveness to growth opportunities. We show that the differential responses to growth opportunities of public firms are greater in industries that rely more on external financing. Public firms in more financially dependent industries grow faster in periods when financing costs are high, which suggests that public status gives firms better access to financial markets when money is tight. We also use shocks to the capital raised at IPO due to

[6] The firms in Jovanovic (1982) exhibit similar dynamics. In that model firms initially do not know their productivity. As their productivity is revealed in the market place, the more efficient firms grow faster. Our data shows, however, that early characteristics are informative of quality and predict future growth. However, since there is residual uncertainty about quality and growth opportunities, similar dynamics arise.

unanticipated price changes in the NASDAQ market to further examine if financial access is important to new public firms. We show that IPO firms that raise additional capital due to an unanticipated price increase in the NASDAQ market exhibit higher sensitivity to investment opportunities, and the effect persists for up to four years. However, the economic magnitude of the impact is small and moderately significant.

We also perform several tests to address potential concerns with our comparison between public and private firms. First, since IPO and acquisition are the two most common exit strategies for successful private firms, the differences we observe can be driven by the acquisition of successful private firms by public firms, which creates a downward bias for the matching sample. We show that while initially matched private firms that are subsequently acquired by public firms also grow faster before acquisition than matched firms that remain private, they do not exhibit the same higher sensitivity to growth opportunities over time as firms that go public. Thus, the effects we identify are specific to firms that go public and are not driven by sample attrition due to acquisitions. Second, we show that public firms' higher sensitivity to growth opportunities holds both when we consider firms' total growth including acquisitions, and when we measure only the growth of firms' original establishments. Thus, the greater responsiveness of public firms does not rely exclusively on their greater participation in the market for assets.

Overall, our results indicate that firm quality is observable very early in a firm's life and that its effect is persistent. Higher quality firms go public, and they attain a larger size. A significant part of the size differential between samples of public and private firms is predictable from initial conditions. When matched by initial quality, the growth path of firms that become public diverges from that of always-private firms both before and after the IPO. For a period after the IPO, public firms grow faster and are more responsive to growth opportunities. Predictions of firm size based on initial conditions suggest a lower bound of 49% of differences in firm size at year 15 due to initial conditions and the remaining 51% of differences in firm size due to the benefits of public status or unobserved initial differences in quality or luck.

We contribute to the research that examines real side differences between public and private firms. It is well recognized that managers of public firms may have suboptimal incentives. See, for example, the theoretical models by Holmström (1982), Narayanan (1985), Miller and Rock (1985), Stein (1989), and von Thadden (1995). Such incentives may motivate attempts by managers to misinform their dispersed shareholders or faulty signals due to mispricing in the public markets. In particular, managers may underinvest in investment opportunities if doing so increases their compensation – resulting in managerial myopia. The opposite view about public markets is given by Edmans (2009). He shows theoretically how increased stock-market liquidity and transient blockholders can increase market efficiency and reduce managerial myopia. More recent work by Edmans, Fang, and Llewelyn (2017) and Ladika and Sautner (2018) argues that long-term compensation of managers can control tendencies towards myopia.

Brav (2009) finds that private firms have lower investment rates than public firms in a sample of British firms. Gilje and Taillard (2016) show that relative to private firms, public firms in the gas industry are more responsive to investment opportunities. Lyandres, Marchica, Michaely, and Mura (2013) show how private and public firms' owners' diversification differentially impacts firms' investment decisions. Maksimovic, Phillips, and Yang (2013) find economically significant differences between public and private firms in mergers and acquisitions. Bernstein (2015) examines how public and private firms differ in innovation after their IPOs. Gao and Li (2013) find that public firms have higher pay sensitivity to accounting performance than do private firms. Phillips and Sertsios (2017) show that public firms in the medical device industry have higher financing responses and develop more new products than private firms do. Borisov, Ellul, and Sevilir (2019) show that comparing to matched private firms, IPO firms experience higher employment growth after going public and the effect on human capital investment is persistent.

Our paper is related to Lemmon, Roberts, and Zender (2008), who argue that there are persistent firm-specific effects that influence firm capital structures among public firms over time and that this persistence exists for IPO firms before going public. We show that characteristics that predict firm growth trajectories and responsiveness to growth opportunities are set early after firm formation. These characteristics are consistent with the models of entrepreneurship by Lucas (1978) and others. Our paper is also related to recent papers that document the role of initial conditions (Moreira (2017) and Sedlacek and Sterk (2017). A major distinction is that we show firms are born with different capabilities while those papers look at how shocks experienced at birth can lead to substantial differences in the long-run.[7]

We argue that there is also a strong "foundation effect" in which the entrepreneur's ability is embodied in the firm's structure and influences the exploitation of future growth opportunities in the

[7] Ayyagari et. al. (2017) investigate how the interaction between firm characteristics at formation and institutions in a developing country affect outcomes.

long run. Thus, our paper also relates to the literature that traces the effects of managerial characteristics on firm performance. Bertrand and Schoar (2003), Cronqvist, Makhika, and Yonker (2012), and Benmelech and Frydman (2015), among others, trace the connection between the personal characteristics of managers and firm decisions.

Our paper also draws on the literature on decisions to go public. Researchers have both analyzed the trade-offs between public and private status (e.g., Bhattacharya and Ritter (1993), Chemmanur and Fulghieri (1999), Maksimovic and Pichler (2001)), and the benefits to the entrepreneurial firm of a sale to public investors or strategic acquirers (e.g., Bayar and Chemmanur (2010), Chemmanur and He (2011), Gao, Ritter and Zhou (2013), and Chemmanur, He, and Nandy (2010)). These papers focus on the product market and study how information flow and strategic interactions determine the firm's value to outside investors and potential competitors. By contrast, we focus on how a firm’s initial characteristics, as perceived by the founding team and initial investors, contain information that is predictive of the firm's future value and growth, and how the subsequent transition from private to public status affects the firm's responses to growth opportunities.

We organize the rest of this paper as follows. Section II describes our data. Section III motivates our study by highlighting the role of initial conditions and predicts public status using initial conditions. Section IV describes our matching to create a matched sample of IPO firms and matched private firms. Section V presents our main results comparing birth-matched public and private firms on growth, efficiency, and survival. Section VI further explores the role of public status on growth related to selection and financial dependence. Section VII presents findings from robustness checks for different samples of firms and different types of investment. Section VIII uses a cross-sectionally matched sample of public and private firms to show issues with ex-post matching and to reconcile our results with previous results. Section IX concludes.

II. Data

We use data from the Longitudinal Business Database (LBD),[8] maintained by the Center for Economic Studies (CES) at the Bureau of the Census to track growth for both public and private firms. The LBD covers non-farm establishments with paid employees in all industries and all states in the U.S. beginning in 1976. It has about 8.5 million records in 2012 and contains information on ownership, location, status (active or inactive), industry, employment, and total payroll on the establishment level. In their review of PSED data, Hurst and Pugsley (2011) conclude that "most individuals who start a small business have little desire or expectation of growing their business beyond a few employees." To avoid confounding our results with these firms, we drop very small firms with fewer than four employees.[9] For firms born after 1976, the first year of the LBD, we identify the birth year of the firm as the first year that the firm identifier appears in the data. Since the LBD keeps separate identifiers for the firm and the establishments, we can separate organic growth from acquisitions by tracking identifiers for existing and new establishments.[10]

We use the IPO data provided by Jay Ritter's website.[11] We collect information on IPO firms from 1981 to 2005, including company name, CRSP Permanent ID, offer date, ticker at the offering, founding date, and VC funding status. We then use the existing bridge file created by the CES staff to identify the IPO firms in the LBD. To construct the bridge file, firms are matched by employer identification number (EIN) and name in each year from 1980 to 2005.[12] To ensure the accuracy of the match, we impose several additional restrictions. We exclude firms from the sample if the founding date provided by Jay Ritter differs from the LBD initial year by more than five years (in both directions), or the difference in employment in the IPO year is more than 25% between the COMPUSTAT and the LBD. These additional criteria eliminate 20% of the matched IPO firms. In order to guard against including leveraged buyouts, we also eliminate IPOs of firms that were previously public. Our initial matched

[8] The LBD reports a snap shot of firm conditions on March 12 every year and contains all firms that have at least one paid employee.

[9] There is a vast group of firms with very few employees at birth in the LBD and the probability of becoming public for this group is dismal.

[10] For more information about LBD, see https://www.census.gov/ces/pdf/CES-WP-02-17.pdf.

[11] See Jay Ritter's website at https://site.warrington.ufl.edu/ritter/ipo-data/

[12] Not all IPO firms during this period are matched through the bridge file. We lost about one third of the sample due to missing Census' firm id in the bridge file.

sample consists of 2,900 IPO firms with initial conditions identified in the LBD, giving us a match rate of 48%.

Compared to the overall sample, our matched IPO firms are smaller and younger at the IPO compared to Ritter's IPO sample.[13] However, they have very similar distribution across industries and over IPO years compared to unmatched IPO firms. In unreported tables, we also find that the matched and unmatched IPO firms experience a similar growth rate in sales post IPO using COMPUSTAT data.

Since the LBD does not differentiate new firm creation from spinoffs and those from organic birth, also we eliminate firms that are formed in their first year with establishments that existed before, and firms with more than 200 employees reported at birth in the LBD. These last criteria eliminate 29% of the matched IPO firms.

To predict the decision of going public based on initial conditions, we create a birth sample that contains all firms in the LBD born after 1978 with 4 to 200 employees in the first year reported in the LBD. Our lower cutoff is used to exclude a large group of firms in the LBD that were born with very few employees, and the probability of IPO for this group is almost zero. We also manually check firms born with more than 100 employees to make sure they are not created through spinoffs. We also eliminate industry-years (based on 3-digit SIC codes) that yield no IPO firms. We then specify a dummy variable that equals one if a firm is in our matched IPO sample and zero otherwise. We excluded the unmatched IPO firms. The growth rates between matched and unmatched IPO firms are not significantly different.

Our final sample has about 892,000 firm births (given we only include industry-years in which there was an IPO), and the probability of going public is about 0.2%, with variation over time and industries using industries with at least one IPO. We identify the age at the IPO as the difference between the offering date and the birth year reported by the LBD. We use the birth sample to run our regressions to predict the probability of going public using initial birth conditions. We then construct a panel data by tracking firms in the birth sample overtime for up to 15 years. Our panel data has approximately 5.9 million firm-year observations.

[13] The match rate is higher for single-establishment firms and lower for firms with multiple establishments.

For cross-sectional matching, we use the same bridge file constructed by Census staff to identify all public firms in the LBD. We have a bigger sample of public firms in the cross-section matching since we no longer apply the restriction on initial conditions.

III. Initial Conditions, Firm Growth and Public Status

III.A. Initial Conditions and the Lifecycle of the Firm

In this section, we provide some initial motivating evidence using a comprehensive sample of 892,000 post-1978 firm births from the Census Bureau. Figure 1 presents the size distribution of public firms at birth and then ten years later. It shows that the initial size at the end of the first year already differs between private and, subsequently, public firms. This difference grows over time — ten years after their birth, public firms are substantially larger. The increase in observed differences in size between public and private firms in Figure 1 can reflect the difference in initial firm quality and also treatment effects from differential access to financing.

[Insert Figure 1 Here]

Figure 2 shows that initial conditions are persistent and related to long-run firm growth. We sort firms by their initial conditions, including size and wage in the first year we observe them, and the first full-year employment growth, which occurs between the first and second year when a firm appears in the LBD.[14]

For each variable, we separate firms that are in the top one percent of their distribution from the rest of the firms from the same industry-year cohort. Then we compare the average employment size from these two groups going forward — not taking into account whether these firms are public or not. Figure 2 shows that firms that are born at a larger size pay higher wages, and have high initial growth continue to grow faster for fifteen years post-birth. The observed persistence in initial conditions is consistent with the idea that the entrepreneurs have different skills, and those skills influence long-run firm growth.

[Insert Figure 2 Here]

Table 1 presents a similar pattern in regression setting where we control for industry and year fixed effects. We examine whether firms' initial characteristics predict future firm size (measured in employment) five, ten, or fifteen years after birth, respectively. Initial employment measures the number

[14] The LBD is created using information collected on March 12 every year. For firms born after March 12, the first time it appears would be subsequent year. Thus, the newly-born firms we identify can be up to 11 months old.

of full-time employees in the first year reported by the firm. Initial wage is calculated as the average wage paid by a firm in the first year. Initial growth measures the growth of employment from the first to the second year. Industries are defined at the 3-digit SIC level, and we cluster error by industry-year. Table 1 shows that firms' initial conditions predict future growth over all three horizons. This suggests that a component of the firm's quality is observable early in the life of the firm and persists for up to 10-15 years. This observable characteristic is perceived by entrepreneurs and early financial backers of the firm, while the firm is still private. We next investigate whether these initial indicators of firm quality also predict the firm's decision to go public.[15]

[Insert Table 1 Here]

In subsequent sections, we break up our analysis into four parts. First, we examine whether firms that are larger and more productive immediately after birth are on a higher long-run growth trajectory than initially smaller and less productive firms and whether the same initial conditions also predict future public status. We also derive a propensity score for measuring the "public quality" of all young firms using initial size, growth, and productivity. Second, we create a matching sample of IPO firms and private firms based on the predicted "public quality." Third, we show that firms that in fact, do become public show a distinctive growth trajectory pre- and post- IPO that differs from those of firms with the same initial propensity but remain always-private. We perform a variety of robustness checks on our main results. Last, we reconcile our findings with previous findings that public firms underinvest in response to product market opportunities.

III.B. Predicting Public Status

Since firms select to become public, it is reasonable to infer that going public provides value to the firm, or at least to the founders and initial investors. Public firms can raise equity in public markets. The enhanced access to capital markets helps investors to achieve optimal diversification and allows the firm to raise capital at a lower cost. Access to publicly traded equity also helps the firm finance acquisitions with stock and reward employees with traded stock. On the other hand, dispersed ownership in public firms may lead to unresolved agency conflicts and investment myopia (e.g., Stein (1988)).

[15] It is also possible that all firms are initially of the same quality, and that some firms were luckier than others in getting more resources at the very beginning. If so, the interpretation of our results would change slightly, to show that initial luck in obtaining financing affects firms' trajectories in predictable ways over the long term. We do not emphasize this interpretation, however, given the results in Howell (2016) that show that windfalls of capital do not alter firms' trajectories in this way.

Edmans (2009) shows theoretically how large blockholders in public firms can attenuate managerial myopia through their trading, and how liquidity and transient shareholdings can increase a public firm's investment by increasing market efficiency. The net advantage of public status thus depends on firm size, as the fixed costs of attaining and maintaining public status, and the comparative advantage of access to public markets is likely to make public status more attractive to larger firms. Our focus in this paper is on the firms that decide to become public and whether the public status has, on balance, a positive or a negative effect on the firm's ability to respond to demand shocks. To establish this, we also investigate the productivity and survival of birth-matched public and always-private firms after presenting initial growth and demand shock responsiveness.

Our central hypothesis is that given inherent talent, the benefits of public status are higher for firms on a fast growth trajectory that expects to engage in greater financing and investment. Thus, firms that select to become public are likely to be of higher quality, and they will respond more strongly to growth opportunities. To evaluate the effects of public status, we must control for the differences between the firms that select to become public and the firms that do not.

We first begin by predicting which firms will become publicly traded later in life. Defining Y_{it} to be an indicator variable for public status with $Y_{it} = 1$ for publicly traded firms and 0 for private firms, we model the firm's decision to go public as follows:

$$
\begin{aligned}
Y_{it} &= 0 \qquad \text{if} \quad V(P \mid Talent, Costs) < 0, \\
&= 1 \qquad \text{if} \quad V(P \mid Talent, Costs) > 0.
\end{aligned}
$$

Here *V(P | Talent, Costs)* is the value of becoming public given the firm's industry, its underlying talent, and its costs of becoming public and maintaining public status. We thus regress the public market indicator on a firm's inherent initial talent and industry conditions. To capture the inherent talent, we use birth conditions, which include initial employment (in log form) and the first annual growth rate for which we have data. The former hypothesis is motivated by Lucas (1978) who predicts that firms that were born larger are led by more talented entrepreneurs and the latter by Jovanovic (1982) with the prediction that controlling for size, young firms perceived to be of higher quality grow faster. We also use the initial wage (in log form) to control for human capital embedded in the entrepreneurial firm. As Figure 2 shows, these initial conditions are very persistent over time. We also include squared terms of these variables to account for non-linearity. We estimate this equation using a linear probability model.[16] This specification enables us to test whether initial conditions predict the tendency to go public later in life. Specifically, it enables us to test whether larger and faster-growing young firms become public. In addition, this specification also yields a "public quality" index based on the propensity of becoming public. We can use this index to control for initially observable firm characteristics when comparing subsequent outcomes between firms that become public and those that stay private.[17] Since this index is calculated using firms' initial conditions, it does not rest on the timing of the IPO and therefore is not influenced by changes in growth opportunities at the time of the IPO and by IPO waves (Pastor and Veronesi (2003)), which we verify empirically below.

In a second specification, we also include industry control variables that capture industry growth, the percentage of firms engaged in mergers and acquisitions, and the percentage of small firms in the industry. The M&A rate proxies for the time-varying incentive to go public in order to facilitate expansion through acquisitions.[18] Small firms are defined as firms with less than 50 employees following the Department of Commerce categories. Firms may have less incentive to go public in an industry that is dominated by small firms in which they can reach optimal scale without raising much funds externally.

[Insert Table 2 Here]

Table 2 shows that firms that are initially larger and pay higher wages at birth are more likely to be public later. One standard deviation increase in initial size and initial wage leads to a 300% and 250% increase in the predicted public quality index from the mean, respectively. Firms with higher first-year growth also have a higher public quality index. One standard deviation increase in growth rate leads to a 170% increase in the probability of becoming public from the mean. The industry variables, industry growth, percentage M&A are both significantly positive. Firms in industries with high growth and where there is a high frequency of M&A activity are likely to be public, consistent with public firms that find it advantageous to use external capital to grow and to use equity to buy other firms.

[16] LPM does as good a job approximating marginal effects as a non-linear model as a marginal effect is just a slope and is less subject distributional problems than a logit or probit model as emphasized by Angrist and Pischke (2009) in Chapter 3.4.2.

[17] This index parallels for firm quality the indices used to measure financial constraints, for example Kaplan and Zingales (1998) and Hoberg and Maksimovic (2015).

[18] Merger-motivated IPOs are studied in Celikyurt, Sevilir, and Shivdasani (2010) and Hovakimian and Hutton (2010).

III.C. Public Status and Firm Growth

Using the predicted public quality index from Column 1 in Table 2, we now examine graphically how initial conditions relate to firm growth over time.

[Insert Figure 3 Here]

In Figure 3, we examine the firms in the top 1% of the predicted public quality index and graph their growth (in number of employees) over time. Several results are worth highlighting. First, both always-private and eventually-public firms that are in the top 1% of the predicted public quality index become sharply larger than other firms. Fifteen years later, firms that started in the top 1% of the public quality index have 955 employees on average, more than 16 times bigger than the average for the rest of the distribution. Moreover, private firms in the top 1% have 831 employees by year fifteen compared to 59 employees on average for all other firms—14 times larger. This measures the *lower* bound for the selection effect.

Second, firms in the top 1% of the predicted public quality index that do go public have an average of 1,696 employees and are 29 times bigger than the average firm outside of the top 1%. The difference between this size difference of 29 times and the previous private size difference of 14 times can be interpreted as the *upper* bound of the treatment effect, as part of this difference may still be due to selection based on unmeasured attributes.

We investigate the predictive power of our public quality index for high-quality firms in a regression setting in Table 3. The dependent variable is the annual employment growth. We define high public quality index, HPI, equal to one when the estimated public quality index based on initial conditions (estimated in Table 2 Column 2) is in the top 1% of all firms at birth and zero otherwise. We interact HPI with a measure of industry demand and a measure of the tightness of access to financing. Our measure of industry level (at 3-digit SIC) demand shock, DS, is constructed based on changes of shipment from downstream industries. We also have estimated and used Tobin's *q* as our alternative measure of industry demand, calculated using all public firms in the same 3-digit SIC code. We obtain similar results and these alternative results are available from the Census on request. We use and report the downstream measure of demand as it captures a measure of demand for both public and private firms. We obtain the value of industrial production by industry from the Federal Reserve[19], aggregate

[19] These data are available at http://www.federalreserve.gov/releases/g17/table1_2.htm, starting from the year 1919.

it to the three-digit SIC level, and calculate the annual change of demand. We then link these data to each industry by "downstream" industries using the input-output matrix of the U.S. economy from the Bureau of Economic Analysis in the closest lagged census year using the "use" tables, where a downstream industry is one that uses 1% or more of the industry's output. Given that most industries sell to multiple downstream industries, to construct our final measure of demand shock, we weigh the percentage change of each downstream industry by the percentage sold to that industry. The DS variable is used and described in detail in Phillips and Zhdanov (2013). It is likely to be a more independent measure of demand than own industry movements, as shown by Shea (1993). We focus on positive demand shocks as we wish to measure how firms respond to increases in growth opportunities.

Our measure of liquidity, CS, measures the credit spread between A3 and Baa corporate bonds. Credit spreads have been shown to be a good proxy for overall liquidity or ease of financing in the economy (Lown et al. (2000), Harford (2005), and Maksimovic, Phillips, and Yang (2013)). We control for industry-year fixed effects in all regressions and cluster the error at the industry-year level.

[Insert Table 3 Here]

Column (1) shows that firms with high public quality grow faster than other firms, most specifically in years when demand increases in their industry. The coefficient of the interaction between HPI and liquidity in the economy is insignificant, suggesting that firms with a high public quality index do not grow faster at times of higher credit spreads. This is not surprising since the majority of the firms in the HPI category stay private throughout the sample period. In column (2), we restrict the sample to firms that never go public and again find that firms that have a high public quality index grow differentially faster when their industry receives a positive demand shock. It further confirms that the index we construct captures firm quality. In columns (3) to (6), we again examine all firms and split the sample by firm age. We find that the predictive power of the public quality index is highest in the firm's first five years. In unreported tables, we define the HPI using the top 5% or 10% of the firms and find qualitatively similar results. Our results are also robust when we use the continuous measure of the estimated public quality index based on initial conditions.

In summary, the figures and tables above present a consistent relation between a firm's initial characteristics and its subsequent growth. In particular, regardless of whether a firm goes public or stays private, firms that are initially larger, grow faster and are more productive respond more strongly to industry growth opportunities. This effect is strongest early in the firm's life-cycle. Meanwhile, larger, fast-growing, and more productive firms are more productive are also more likely to become public later in life. Thus, to examine the difference between public and private firms, one has to control for the selection into public status. We next investigate whether the firms that go public respond differently to growth and financing opportunities than private firms with similar initial characteristics.

IV. Matching IPO Firms and Private Firms

Having established the finding that firms with better initial quality are more likely to grow faster and become public subsequently, we first match IPO firms with always-private firms at birth based on initial quality. For each IPO firm in our sample, we select up to 5 closest-matches from private firms from the same industry and birth year based on the predicted public quality index (using Column 1 in Table 2). As robustness, we also used up to 10 matching private firms at birth for each IPO firm. The results were qualitatively similar. We also require the matched private firms to survive at least up to the IPO year and the relative size of the matched private firm to the IPO firm is within the range of (0.5, 2). We exclude IPO firms with fewer than three matches to obtain common support. Our results are robust if we restrict to exactly five matches. Our final sample has about 1,600 IPO firms and about 8,000 matched private firms. Table 4 provides summary statistics comparing IPO firms with matched and unmatched private firms.

[Insert Table 4 Here]

Table 4 shows that IPO firms and matched private firms have a very similar predicted public quality index. The Kolmogorov-Smirnov test for an equal distribution has a p-value of 0.51, suggesting that the distribution of the predicted public quality index between public and matched private firms is not significantly different. Both eventually public and matched private firms are much more likely to go public later in life – the estimated probability of being public is about 40 times higher for these two groups compared to the unmatched private firms. We also present statistics for the number of employees, the initial wage in thousands of dollars, and the initial year growth rate – both for public firms and matched and unmatched private firms. IPO firms and matched private firms are also similar in size and initial growth rate in their initial years, although private matched firms tend to have higher average wages. In unreported tables, we match firms based on individual characteristics (size, wage, and growth rate) instead of the estimated propensity of becoming public, and find qualitatively similar results. In contrast, there is a stark difference between matched and unmatched private firms. Unmatched private firms are much smaller at birth, have lower wages, and experience a much slower initial growth rate compared to matched private firms. Table 4 highlights the selection effect in public status and emphasizes the need for controlling for firm quality when comparing the difference between public and private firms.

Figure 4 presents the distribution density in size for IPO firms and their matched private counterparts. The two groups have a similar size at birth, a result of matching, but deviate over time. At the IPO, the public firms are already bigger than the matched private firms. The difference keeps growing five and ten years following the IPO.

[Insert Figure 4 Here]

It is worth noting that despite our effort to match initial, observable conditions, firms that are ultimately public may still differ from matched private firms in unobservable characteristics that could affect their future growth. Hence, we provide estimates for a lower bound of the selection effect.

As a robustness check, we also create an alternative matched sample based on initial conditions that do not rely on our index of public quality. There, for each IPO firm, we select five private firms based on initial size, initial wage, and first-year growth rate using the nearest neighbor matching, not using the index-based match. All of our subsequent results are qualitatively the same.

V. Public and Private Firms – Matched Sample

V.A. Responses to Growth Opportunities

We now examine whether and how IPO firms differ in their growth and responsiveness to demand shocks compared to their matched private counterparts. We estimate the following basic specification using annual data in the sample of IPO firms and their matched always-private firms:

$$Growth = \beta_0 + \beta_1 Pub + \beta_2 DS + \beta_3(DS \times Pub) + \beta_4 CS + \beta_5(CS \times Pub) + \gamma\ control\ variables \qquad (1)$$

where *Pub* is an indicator variable for actual public status. Growth is measured in employment winsorized at one percent on both ends. As before, we use changes in shipments in downstream industries to capture exogenous shocks to industry demand. Since we hypothesize that being public facilitates response to changes in industry demand that require expansion of the firm scale, we focus on the positive part of the industry demand shocks, *DS*. All of our results are robust when we use industry demand shocks in both directions. As discussed previously, we also have estimated and used Tobin's *q* as our measure of industry demand, calculated using all public firms in the same 3digit SIC code. We obtain similar results, and these alternative results are available from the Census on request. Here, we use and report the downstream measure of demand as it captures a measure of demand for both public and private firms, while Tobin's q is calculated using just public firms.

Public and private firms may also be affected differently by financial market shocks. Public firms can access public financial markets, especially for long-term capital, at more favorable or easier terms, while private firms rely more on short-term financing from financial intermediaries (Brav (2009)). We thus examine whether credit conditions in the debt markets impact public firm growth and thus include a credit spread variable (*CS*). Lown, Morgan, and Rohatgi (2000) find that credit spreads are strongly correlated with the tightening of liquidity measured from the Federal Reserve Senior Loan Officer (SLO) survey. We calculate credit spread as the difference in interest rate between the A3 and Baa rated-bonds.

We control for a variety of firm characteristics. *Log(Emp)* is the logarithm of firm employment. *Log(Wage)* is the logarithm of the average wage. *Age* measures the firm's age following birth. All variables are lagged. Our results are robust when we exclude firm characteristics.

Figure 5 presents the growth rates of IPO firms around the IPO. Regardless of firm age at IPO, there is one common pattern. IPO firms grow faster before the IPO, and in the first five years after the IPO. The growth rate subsequently converges to the economy average. In comparison, the average growth rate of all private firms is close to zero. Given the observed difference in growth over time, in all of our later analysis, we estimate our regressions separately in three time periods – before the IPO, first five years after the IPO, and five years after the IPO.

[Insert Figure 5 Here]

Thus, for each IPO firm, we break up the time interval to three separate periods, (-5,-1), (1, 5) and (6, 10) where 0 denotes the IPO year, to examine the event windows around the IPO. The first-period tracks firms in their private, pre-IPO period and the other two windows track the early and late public years, respectively. We follow the same time frame and use the IPO year of their public match to define event windows for matched private firms.

In Table 5, columns (1) - (4), we estimate equation (1) using all firm-years and then separately for each of the three sub-periods. The coefficient β_1 yields the differential growth rates for firms that become public. The coefficient β_3 and β_5 enable us to estimate the difference in growth sensitivity to demand shocks and financial market shocks, respectively, between public and private firms. Similar specifications are used in Gilje and Taillard (2016) and Asker, Farre-Mensa, and Ljungqvist (2015).

The interpretation of these coefficients differs across event windows. Since the IPO decision occurs at time 0 and is likely to be based on performance in the immediately prior period, coefficients estimated over the period (-5,-1) compare the performance of firms ultimately selected to become public with firms with similar conditions at birth but did not become public before IPO. The window (1, 5) describes early IPO years for public firms. Since decisions (to become public) have already been made, any excess performance over this period does not cause an IPO. Instead, it will describe the possible effects of recently acquired public status, but will be an upper bound for any treatment effect, as part of the difference in performance may be due to quality differences we do not measure. Over the window (6, 10), excess performance, if any, is more likely to reflect steady-state effects.

We define industry by 3-digit SIC and include industry-year fixed effects. Since *DS* varies by industry-year and *CS* is an annual measure, the main effects of both variables drop out after including industry-year fixed effects. In columns (5) and (6), we adopt a fixed-effects specification, where we treat each firm in our IPO sample and its matched always-private firms as a separate cohort. For each cohort, we further separate firm-years into three periods, namely up to five years before the IPO (-5, 0), first five years following the IPO (1, 5), and six to ten years after the IPO (6, 10). Thus, we have 1600 x 3 firm-cohort-period fixed effects. This procedure controls for shocks that affect the growth of each IPO firm and the matching always-private firms at different points of their life cycle. Since the matching firms are of the same age and industry as the IPO firms, this fixed effect, in addition to year fixed effects, removes the possibility that the differences are cohort-specific and persist over particular periods.[20] Thus, this fixed effect structure provides for stringent control of factors that might confound cross-sectional differences in performance between public and private firms. Robust standard errors allow for clustering at the industry-year level are reported in parentheses.

[Insert Table 5 Here]

Column 1 of Table 5 shows that public firms grow faster and are more responsive to growth opportunities, as measured by demand shocks *DS*. There is also evidence that public firms grow relatively faster in periods when credit spreads are high.

Examining the results broken out by the years surrounding a firm's IPO in columns (2) - (4), we can see some interesting patterns. The public indicator variable is positive and significant for the five years

[20] Our results also hold with conventional firm fixed effects but we use separate cohort effects because these capture possible technological changes in the industry that are specific to IPO firms and their particular cohort.

before the firm's IPO and the five years after but becomes insignificant for years greater than five. Examining the interaction of eventual public status with the demand shock, we find that it is in the earlier years (before year five) following the IPO that public firms react more positively to changes in demand than private firms. IPO firms grow 1.7% more than their private counterparts for every one standard deviation increase in positive demand shock. This result is consistent with public firms growing faster pre-IPO to reach a specific size with internal and private funds and using the funds from their IPO and their access to public markets to better take advantage of industry growth opportunities. However, growth and sensitivity to demand shocks fall back to their private market matched firms after the first five years. In an unreported table, when we re-run the specification in Table 5 year by year following year five, we do not find that public firms significantly differ from their private counterparts, either in growth rate or response to demand shocks. The other control variables in the regression show that basic economics holds for these firms. The positive coefficient on wages indicates that firms, perhaps indicating higher human capital, grow more. There are negative coefficients on age and employment, consistent with growth slowing down over the firm's life and there being some decreasing returns to scale. We show, in an unreported table, that our results are robust without controls such as size and age.

In columns (5) and (6), we report specifications, including firm-cohort-period fixed effects. In column (5), we show that public firms that become public at some point grow faster and are more responsive to growth opportunities, without considering their pre- and post-IPO periods separately. In column (6), we focus on the post-IPO period and split it into years 1 to 5 (1, 5) and years 6 to 10 (6, 10) by including two indicator variables, *PostIPO_1to5* and *PostIPO_5+*. It shows that public firms grow faster and respond to growth opportunities more strongly than private firms in the first five years after the IPO. The estimated coefficients have a similar magnitude as those reported in column (3). However, the differential effect disappears after that, consistent with the specification in column (4).

These results indicate a natural life-cycle process for firms. Firms that become public grow fast for up to five years following the IPO, but their growth is similar to their matched private firms afterward. It is worth noting that public firms are much larger at this point. These results are consistent with firms obtaining a larger, optimal firm size after five years post-IPO.

Interactions of *Pub* x *CS* provide very limited evidence that public firms benefit differentially from access to financing during periods of low liquidity. Some of these firms may not have credit ratings, which may potentially explain the insignificance. In addition, benefits from access to financial markets is likely to be a result of their underlying quality and size and therefore captured by the fixed effects.

In unreported tables, we repeat our analysis using change of industry median Tobin's q as an alternative measure for demand shock and find qualitatively similar results.[21] We use and report the downstream measure of demand as it captures a measure of demand for both public and private firms, while Tobin's *q* is calculated using just public firms.

V.B. Productivity of Public Firms

We have shown that public firms respond more to positive demand shocks in the first five years after their IPO. While these results are suggestive of an efficient investment strategy, it is also possible that public firms may over-expand beyond their optimal scale, given their access to less-expensive public capital. We now examine efficiency for IPO firms in the post-IPO period, especially during periods when they grow more following a positive demand shock. Ideally, we would like to use profits or total factor productivity measures, but those items are only available for manufacturing firms, while the vast majority of the IPO firms during this period are outside of manufacturing industries. Thus we resort to a labor productivity measure based on sales per employee ratio. It is also consistent with our growth measure based on employment. Foster, Haltiwanger, and Krizan (1998) show that the sales-employee ratio highly correlates with total factor productivity in U.S. manufacturing firms.

[Insert Table 6 Here]

Inspection of Table 6 reveals very little evidence that the higher growth rates and higher responsiveness to growth opportunities of public firms come at the cost of lower labor efficiency. On the contrary, public firms are more efficient when their industry receives a positive demand shock, especially in the first five years after the IPO. The interaction between the public status indicator and demand shock is positive and significant at the one percent level in columns (3) and (6). It indicates that public status helps firms to adapt to changing industry conditions and become more efficient in expansion.

[21] These results can be disclosed from the Census Bureau.

Interestingly, we find that the labor efficiency of public firms increases relative to private firms in years when the financing is more readily available (i.e., credit spread is low) before and immediately after IPO. This finding contrasts with the result in Table 5 that the growth rate of firms is unaffected by the credit spread over these life-stages. It suggests that while the growth of early-stage public and pre-public firms is not affected by credit spreads, public firms facing low financing costs may be able to invest correspondingly in capital assets to maintain their labor productivity.

V.C. Survival and Firm Risk

A natural question to ask is whether the higher growth we have documented for public firms comes at the expense of higher risk. We investigate this question by examining the failure rate of public firms and their matched private counterparts. In Panel A of Table 7, we estimate a Cox Proportional Hazard model – where the hazard is defined as "death." In this model, a negative coefficient indicates a lower chance of death and thus a higher probability of survival.

We identify the "death" of a firm as the case in which the firm is out of business, and none of its establishments is active. "Death" is thus the closure of all establishments of a particular firm. Since the LBD has different identifiers for firms and establishments, we can separate acquisitions from plant closures. We do not count cases when a firm ceases to exist and its plants are subsequently acquired and continue to be operated by other firms as "death." Therefore, our definition captures the economic survival rather than the business survival. We begin our analysis of survival from the IPO year (year 0); thus, we restrict our sample to only include matched private firms that survive at least to the IPO year.

[Insert Table 7 Here]

Column (1) of Panel A of Table 7 shows that public firms are more likely to survive. The survival rates are tabulated in Panel B. The difference between public and private firms is more pronounced in the early years. Five years after the IPO, 21% of public firms close, as compared to 32% for matched private firms. In an unreported table, we also find that public firms are more likely to be acquired than private firms.

One potential concern for breaking out periods surrounding the IPO is that firms may have timed their public offering in response to expected financial market factors, thereby introducing sub-optimal growth patterns relative to firms that always remain private. For example, firms may choose to grow too fast too early in order to be able to take advantage of anticipated financial market mispricing, as might occur during hot markets. In Column 2 we show that the effect of public status on survival is not affected whether or not the firm goes public during IPO waves. We define IPO waves as years in which the number of IPOs is two standard deviations above the average in our sample period using Ritter's data.[22]

Taken together, Tables 5-7 show that public firms are more responsive to industry growth opportunities and that their growth is efficient and does not lead to riskier strategies.

VI. The Role of Public Status

VI.A. Financially Dependent Industries

One potential explanation for our finding that public firms are more responsive to demand shocks early in their public life is that the public status allows firms to raise capital more easily to respond to changing opportunities. To test this hypothesis, we separate industries into two groups based on their financial dependence. If the advantage of being public comes from better access to financing to fund high capital expenditures, then we would expect a more significant difference between public and private firms in industries with higher financial dependence.

We use Quarterly Financial Reports (QFR) data at Census in every 5th year, which are the years available to us, to compute industry level financial dependence measures.[23] The QFR has both income and balance sheet data for a stratified random sample of public and private firms. While only a sample of 200,000 firms exist in each year, thus preventing most firms in the LBD from being matched, there are sampling weights which allow us to create population estimates. We use this data to construct our indicator of industry financial dependence. We measure financial dependence using the rate of external financing calculated as the difference between capital expenditure and internal operating cash flow over total assets. We then separate all industry-years into two groups – those that are financially dependent (*FD*) and those that are not financially dependent (*Non_FD*) – based on whether the median rate of the industry is higher than the median of all industries in that year. Specifically, we estimate the following specification:

[22] We use Ritter's data to define IPO waves so that we can capture all IPOs in a given year.

[23] For example, we use financial dependence identified in year 1982 for year 1982 to 1986, and financial dependence identified in 1987 for 1987-1991.

$$Growth = \beta_0 + \beta_1 Pub \times FD + \beta_2 Pub \times Non\_FD + \beta_3(DS \times Pub \times FD)$$
$$+\beta_4(DS \times Pub \times Non\_FD) + \beta_5(CS \times Pub \times FD) + \beta_6(CS \times Pub \times Non\_FD)$$
$$+\gamma\ control\ variables \qquad (3)$$

β_1 and β_2 capture the difference in growth rates between IPO firms in financially dependent or non-dependent industries and matched private firms, respectively. β_3 and β_4 capture the difference in responsiveness to demand shocks, and β_5 and β_6 capture the difference in responsiveness to financial shocks. As in our main regressions, we control for industry-year fixed effects. Table 9 presents our findings.

[Insert Table 8 Here]

The examination of the results presented in Table 8 reveals some interesting patterns. First, the differential growth between public and private firms post IPO is not higher in more financially-dependent industries. However, public firms in financially dependent industries are more responsive to industry growth opportunities than private firms. Again, the effect is most pronounced in years (1, 5), early in their public life. The estimated coefficient on demand shocks for financially dependent industries is higher in magnitude than that from our main regression in Table 5 – 0.694 vs. 0.485, and the estimated coefficient on demand shocks for financially non-dependent industries is positive but not significantly from zero. It suggests that the higher responsiveness to demand shock is mostly driven by public firms in financially dependent industries. Interestingly, we do see that pre-IPO and in early years post-IPO, public firms in financially dependent industries grow faster in periods when financing is tight (i.e., higher credit differential). There is no corresponding differential in non-dependent industries. This result is consistent with the hypothesis that there is an advantage of being public when alternative sources of finance are more expensive. However, the effect disappears with firm age.

VI.B. IPO Firms and Industry Earnings Responsiveness

We now present results where we investigate whether the responses of public firms to growth opportunities are affected by industry earnings response coefficients. The central premise in AFL is that driven by short-termism pressures, managers in public firms invest inefficiently and respond less to opportunities. To support their argument, they show that the lack of sensitivity of investment to opportunities is the most severe for public firms in industries with higher Earning Response Coefficient (ERC) where share prices are more responsive to earnings.

We perform a similar test using our birth-matched sample. We follow Easton and Zmijewski (1989) and Asker et al. (2015) to estimate ERC for each Fama French 48 industry-year by regressing unexpected stock returns on earnings surprises over the 3 years before the analysis. Unexpected returns are determined by subtracting the three-day announcement return around earning release from market model. Earnings surprise for year t is equal to the actual EPS for t as reported by I/B/E/S, less the EPS forecast at t-1 for t. Our results are robust when we (1) use the 5-year rolling average ERC or (2) use indicators to classify industries into high or low-ERC industries. Our results are also robust to using either 5 or 10 matching private firms for each IPO firm.[24]

[Insert Table 9 Here]

Table 9 presents our findings. We do not find any evidence that public firms are less sensitive to investment opportunities than public firms, even in industries with high ERC. We find that the higher responsiveness to industry demand shocks in public firms (relative to their private counterparts) is stronger in low ERC industries. At the same time, there is no evidence that public firms are less responsive to demand shocks compared to private firms in high ERC industries. [25] Thus, there is little reason to believe that capital market myopia is causing investment inefficiency or under-investment relative to private firms.

VI.C. VC Investments and IPO Firm Growth

We match our sample of IPO firms with private firms at birth based on measurable firm characteristics such as industry, size, wage, and initial growth. However, an unmeasurable difference may still exist between IPO firms and always-private firms. VC investors may have additional soft information about the firm quality, and VC sponsorship can serve as another indicator of firm quality. Puri and Zarutskie (2012) show that in their sample, VC-financed firms grow faster and outperform matched firms that are not financed by VC. Such an effect may occur both because VCs select higher quality small firms and because they provide mentoring and monitoring services (Bernstein, Giroud, and Townsend (2016)) or because they set up more investor-friendly governance structures (Hochberg

[24] All robustness results can be viewed at the Census Bureau but were not disclosed at this point given Census requirements to limit disclosure to the main tables and results. These results will be disclosed on project reactivation with a request. We will disclose all robustness tables requested.

[25] ERC has a mean of 0.9921 and a standard deviation of 1.328 in our sample. For public firms in industries with ERC one standard deviation above the mean, the coefficient of Pub x DS equals to (0.670 – 0.181 x 2.32) = 0.249 in the first five years following the IPO.

(2012)). Thus, on average, our birth measures of firm quality may systematically understate the quality of VC sponsored firms relative to unsponsored firms. We next use VC sponsorship as an additional indicator of firm quality prior to the IPO and examine whether or not VC sponsorship predicts responsiveness to growth opportunities. In particular, we examine whether non-VC backed firms respond similarly to demand shocks as private firms.

We use VC-investment information from Ritter's database to separate public firms into two groups—VC-sponsored (*VC*) or non-VC-sponsored (*Non_VC)*—to examine the effect of VC-sponsorship on the differential growth between public and private firms. Specifically, we estimate the following specification:

$$Growth = \beta_0 + \beta_1\, Pub \times VC + \beta_2\, Pub \times Non\_VC + \beta_3(DS \times Pub \times VC)$$
$$+\beta_4(DS \times Pub \times Non\_VC) + \beta_5(CS \times Pub \times VC) + \beta_6(CS \times Pub \times Non\_VC)$$
$$+\gamma\ control\ variables \qquad (4)$$

β_1 and β_2 capture the difference in growth rates between IPO firms in VC- or non-VC sponsored IPO firms and matched private firms, respectively. β_3 and β_4 capture the difference in responsiveness to demand shocks, and β_5 and β_6 capture the difference in responsiveness to financial shocks. As in our main regressions, we control for industry-year fixed effects. Table 10 reports our findings.

[Insert Table 10 Here]

Both VC and non-VC backed firms grow faster than matched always-private firms in their pre-IPO period. However, in the period after the IPO, the differential opens up, and VC sponsored pre-IPO firms outperform their matched always-private firms both in growth rates and responsiveness to growth opportunities. The evidence is consistent with VC firms selecting better firms who go public or helping firms before their IPO. The VC backing helps the firms before their IPO, and they respond more than private firms to demand shocks. We emphasize that non-VC backed firms still grow faster than their always-private firms and do not have lower responsiveness to demand shocks than private firms.

VI.D. Unexpected Shocks to Supply of Capital and IPO Firm Growth

To further examine whether there is a potential treatment effect of public status on the responsiveness to growth opportunities versus a selection effect where better firms go public, we examine unexpected changes to the supply of capital from the IPO affects a firm's growth. We present these results in the appendix as Appendix Table A-1. We present these results in the appendix as these tests involve a different setup than our main tests and involve comparing within firms that file to go public. The rationale for these tests is to examine if increases in financial access gained by going public affects responsiveness to growth opportunities by examining IPO firms that had an exogenous increase in the funds that they raise. The identifying assumption for these results is following increases in the general NASDAQ index, firms will adjust upwards their offer price and thus have exogenous increases in their the supply of capital at the time of the IPO. These increases would be independent of differences in firm's quality that drove the decision to file to become public and that any effects of these shocks on subsequent growth reflect treatment effects of listed status and not prior selection effects. This method is related to Bernstein (2015) who used unexpected changes to NASDAQ that cause firms to withdraw their IPO to distinguish between treatment and selection effects of public status on firm patenting. [26]

For this test, we run a two-stage regression. In the first stage, we instrument the gap between proposed and actual IPO price using the NASDAQ fluctuations during the book-building phase. Then, in the second stage, we regress firm growth after IPO based on the estimated price gap (i.e., additional capital raised at the IPO). The results are presented in Table A-1 of the appendix. It shows that NASDAQ return during the book-building period has a positive effect in predicting the price gap, significantly at a 1% level. The F-stat for the first stage regressions are all greater than 30, suggesting strong instruments. In the second stage, we find that the price gap has no significant effect on firm growth (both IPO firms and private counterparts) in general. On the other hand, firms with additional capital raised at the IPO exhibit higher sensitivity to demand shocks. The estimated coefficients are at a 5 to 10% significance level, thus marginally significant. Our results from the IV approach thus suggest a statistically weak treatment effect of having additional capital raised at the IPO on firm growth in the immediate years. These results, combined with the previous findings, are consistent with access to capital markets acting in the same direction as the selection of the best firms into public status and increasing investment responsiveness to demand shocks. Overall, these results, combined with the previous findings, are consistent with selection being the primary driver of firm growth and response to demand shocks and a relatively weaker positive treatment effect stemming from better access to capital

[26] We examine unexpected changes in the capital raised rather than unexpected changes in public firm status due to withdrawn IPOs, as in Bernstein (2015), because a large percentage of withdrawn offerings in our sample subsequently refile and go public later in our sample horizon, making a clear interpretation impossible given our hypothesis that decisions to become public are driven by initial conditions.

markets. The results are not consistent with public firms being myopic and less responsive to demand shocks than private firms.

VII. Robustness Checks

VII.A. Sample Attrition due to the Acquisition of Private Firms

Since IPO and acquisition are the two most common exit strategies for successful private firms (Bayar and Chemmanur (2011)), one potential concern is that successful private firms may be acquired by other public firms and thus exit the sample, creating a downward bias for the matching sample. To gain further understanding of this process, we separate matched private firms into three groups based on their acquisition status: never acquired (baseline), acquired by private firms (*Prv_Acq_Prv*=1), and acquired by public firms (*Prv_Acq_Pub*=1). We then track growth and responsiveness to shocks of each group compared to the baseline. For firms that are subsequently acquired, we exclude firm-years after the acquisition, as the establishments then belong to another firm. Table 11 reports our findings.

[Insert Table 11 Here]

Inspection of columns (1) - (3) shows that both the IPO-firms and those that are cash-out through acquisition grow faster on average during their private phase than the always-private never-acquired firms. However, only the IPO firms exhibit a heightened responsiveness to growth opportunities.

Interestingly, there is also some evidence that private firms that were eventually acquired by other private firms grow more slowly in periods of high credit spreads, particularly in their early years. Thus, entrepreneurial firms that are taken over by private firms are encountering financial distress. This is consistent with the finding in Maksimovic, Phillips, and Yang (2013) that the productivity gains from private acquisitions are lower than when the acquirer is public.

VII.B. Internal vs. External Growth

Table 5 above shows that firms grow faster in the years before their IPO and the first five years post-IPO. This growth may be internal or through acquisitions. We would expect public firms to have an advantage in growth through acquisition through the issuance of shares, as documented by Celikyurt, Sevilir, and Shivdasani (2010). We thus examine whether the higher growth of IPO firms arises from acquisitions that are directly facilitated by public status or through the expansion of existing operations.

We identify internal (or organic) growth by tracking the growth of establishments that firms had from the very beginning. It includes the growth of the firm's existing establishments and from newly built establishments and excludes additions to the firm that occur through acquisitions. We can separate establishments that are newly built from those acquired, as Census keeps separate identifiers for firms and establishments. Since acquirers often only keep a portion of the establishments from acquisitions and sell off the rest (Maksimovic, Phillips, and Prabhala (2008)), we exclude growth from acquired establishments in all years after the acquisition. Our approach is likely to create a downward bias for estimating internal growth. Since public firms are more likely to engage in acquisitions (Maksimovic, Phillips, and Yang (2013)), it would under-estimate internal growth from public firms compared to private counterparts. Table 12 examines internal growth in the matched sample over a different time horizon surrounding IPO.

[Insert Table 12 Here]

Table 12 follows the same structure as that in Table 5. The only difference is that it uses the ratio of internal growth as the dependent variable instead of overall growth. Column 1 shows that as for the overall growth, IPO firms also differ significantly in how they exploit growth opportunities using their assets in place, in that they are more responsive to growth opportunities. Interestingly, the magnitude for the coefficients on *Pub*DS* in column 1 is very similar to that reported in Table 5 when we include both internal and external growth – 0.295 vs. 0.317. On the other hand, the estimated coefficient on public status is noticeably smaller than in Table 5 – 0.053 vs. 0.089. These findings suggest that although acquisitions account for an important part of the difference between public and private firms, the greater responsiveness of public firms does not only rely on their greater participation in the market for assets.

As in Table 5, public firms' greater responsiveness to growth occurs mostly in the first five years after the IPO. Another interesting contrast between Tables 5 and 12 is in the growth rates of IPO and private firms. In both tables, the growth rates of firms that become public in the pre-IPO period (-5, -1) is higher than that of matched private firms. However, after the IPO, there is a divergence in overall growth rates and the growth rates of the assets that IPO firms possessed at birth. Specifically, five years after the IPO the growth rate of the public firms' initial assets declines below that of private firms. This result is consistent with the finding that public firms are much more active in acquisition markets than private firms (Maksimovic, Phillips, and Yang (2013), Arikan and Stulz (2016)) and that larger firms grow by acquisition rather than by organic growth (Maksimovic and Phillips (2008)). This finding also suggests that a focus on capital expenditures in comparison to public and private firms' investment patterns may miss important distinctions between these categories of firms.

Column 5 and 6 estimate the model with firm-cohort-period fixed effects, similar to that used in Table 5 and find consistent results.

VIII. Firm Growth with Cross-Sectionally Matched Public and Private Firms

Using a panel of public and private firms matched in 2001, Asker, Farre-Mensa, and Ljungqvist (2015) find that public firms respond significantly less to demand shocks than do private firms. Given that we find different results using birth-matched samples, we now explore whether their result may at least be partially attributable to matching in cross-section rather than at firm birth.

Similar to Asker et al., we match in the year 2001 using the same matching criteria that they use. For each public firm in 2001, we select up to five private firms closest in size and age in the same 3-digit SIC industry. For size, the requirement is that each private firm's total assets are within 2 times the size of the matched public firms, i.e., $\max(TA_{public}, TA_{private}) / \min(TA_{public}, TA_{private}) < 2$). We discard the sample public firms if we cannot find any match. Once a match is formed, as in Asker et al., we follow the firms over time and keep the panel structure intact. We then use this matched sample to run our main specification to predict firm growth.

Table 13 Panel A presents summary statistics for our four subsamples - public and private firms, matched and unmatched. We match about 5,800 public firms with 26,600 private counterparts. This sample and their matched private counterparts are much larger than the Asker et al. sample as our data includes nearly all public firms in 2001. In our matched sample, public firms and private firms are similar in size, wage, and productivity, while public firms have lower growth rates in the previous three years and the trend continues after 2001. There is also an interesting pattern across different samples. Among all four groups, unmatched public firms are the biggest in size, most efficient, and have the highest growth rate. There are 550 (8.7%) very large, very efficient public firms for which we cannot find matching private firms. In contrast, unmatched private firms are the smallest among all groups, least efficient, and have lower growth than matched private firms. The comparison suggests that when we match mature public firms in cross-section in the same year to private firms, we tend to match the less successful public firms with the more successful private firms.

[Insert Table 13 Here]

In Panel B, we examine firm growth in response to demand shocks using the sample matched in 2001. Column 1 includes all firm years while Columns 2 - 5 split the sample by firm age with cutoffs set at five, 10, and 20 years. We find some limited evidence that the matched public firms respond less to demand shocks relative to their cross-sectionally matched private counterparts. While negative, the effect is only marginally significant in our data. Comparing firms by age splits, we find that the negative coefficient is most prominent for firms in the age group of (11, 20). We attribute these findings to the fact that finding a size match to already public firms is difficult in many cases, resulting in adverse selection in the matched set of public firms. As shown in Panel A, it is more likely to find a match for public firms that have not done very in the well in the preceding periods, and those firms grow at a significantly lower rate than their matched private counterparts going forward. In addition, in our sample, in 2001, public firms have an average age of 17 years, and many have long passed their IPO year. Table 5 shows that there is little difference in growth between public and private firms five years after the IPO.

IX. Conclusions

We examine the growth of IPO firms and private firms using a sample of 892,000 firms. We follow the growth of these firms throughout their life-cycle – from their early years when all firms are private, to later years when some of the firms choose to go public and beyond. We show that there are economically important measurable differences in the quality of firms that are evident early in the firms' lives. These quality differences predict future growth and public status.

We find that initial conditions at the time of firm formation explain at least half of observed size difference between public and private firms and that firms with higher initial quality also grow faster and are more responsive to growth opportunities. We further use pre-IPO VC sponsorship as evidence of higher quality among IPO firms and show that VC sponsored firms are indeed more responsive than matched private firms. Controlling for these quality differences, we find that public firms grow faster before and approximately five years post the IPO and are more responsive to positive growth shocks for the first five years post-IPO. After that point, they grow at the same rate and have similar responsiveness to positive demand shocks as their initially matched private counterparts, albeit with the public firms being of a much larger size.

We present evidence that these differences may be due to differences in access to financial resources. We show that the difference in responsiveness to growth opportunity between public and private firms is more significant in financially dependent industries. In addition, using IPO price adjustments after initial filings due to price changes in the NASDAQ market, we show that exogenous cash shocks to newly public firms have a small, moderately significant positive impact on sensitivity to growth opportunities that persist for four years after the IPO.

We test the robustness of our findings in several different ways. We show that the greater responsiveness of public firms to growth opportunities in the early years after the IPO also holds when we match public and private firms one year before the IPO. We also show that our findings are not caused by high-quality matched private firms subsequently exiting through acquisition.

We show that contrary to the results documented in Asker et al. (2015), public firms in industries with higher earnings response coefficients do not respond less to investment opportunities relative to private firms, even controlling for quality differences in our birth-matched sample. Moreover, the growth of post-IPO firms in response to shocks increases labor productivity and does not lead to a higher risk of firm exit. Thus, our results are not consistent with public firms being short-sighted or myopic and responding less than private firms to investment opportunities.

We reconcile our results with earlier research that finds that public firms are less responsive to growth opportunities. Using a cross-sectional match, we show that the differences in results are likely because the earlier literature is not able to match very successful, large public firms with comparable private firms in cross-section. Cross-sectional matches rely on matches of equally-sized public and private firms, whereby relatively larger, more successful private firms tend to be matched to relatively less successful public firms that are much smaller.

Overall, we show that once the initial quality of the firms is controlled for, there is no evidence that public firms are less responsive to demand shocks than private firms. In fact, it is quite the contrary. We show that public firms grow faster and respond more positively to positive demand shocks in the first five years post-IPO than birth-matched private firms. Thus, the evidence suggests that managerial myopia, which some believe that characterizes public firms' responses to investment opportunities, is not likely to be a significant counterweight to the benefits of being public for firms deciding to go public.

Appendix: Unexpected Shocks to Supply of Capital and IPO Firm Growth

To measure the unexpected supply of capital from the IPO, we use the difference between the actual offering price and the original filing expected price, i.e., $PriceGap = \frac{Offering\ Price}{Estimated\ Price} - 1.$ The estimated price is based on the midpoint between the highest and lowest price disclosed in the first prospectus. [27]

One concern with this approach is that the unexpected supply of capital from the IPO can be driven by information about firm's growth prospects. For example, investors are willing to pay a higher price for shares if they expect better growth potential. To mitigate this concern, we instrument the actual price gap using the NASDAQ fluctuations during the book-building phase. [28] Specifically, we follow Bernstein (2015) and use the NASDAQ returns during the 60 days following an IPO filing (*NASDAQ*) to instrument for the *PriceGap* for the firm and also instrument the (*Price Gap x DS*) with ($NASDAQ\ x$ *DS*). Our results are robust when we use the 90-day NASDAQ returns.

We thus estimate the following first-stage regressions for firm *i* in industry *j* overtime period *t:*

$$PriceGap = \alpha_1 + \omega_1 NASDAQ + \phi_1(NASDAQ \times DS) + \gamma_1 CV + \varepsilon_1 \qquad (1A)$$

$$PriceGap\ x\ DS = \alpha_2 + \omega_2 NASDAQ + \phi_2(NASDAQ \times DS) + \gamma_2 CV + \varepsilon_2 \qquad (1B)$$

where $NASDAQ$ and $NASDAQ \times DS$ are the instrumental variables. As in our earlier tables, *DS* is the industry level demand shock, and *CV* are the control variables that include firm age, the log of firm employment, the log of firm wage per employee, and industry-year fixed effects.

The second stage regression estimates the effect of the price gap on firm growth (*Growth*) for firm *i* in industry *j* in time period *t* (t=2 to 5 years). We include years 2 to 5 as the data is measured at the end of the first quarter of the year, and thus the first year of the IPO may only represent part of a year. We estimate:

$$Growth = \beta_0 + \beta_1\ \widehat{PriceGap} + \beta_2\left(\widehat{PriceGap_j} \times DS\right) + \gamma\ Control\ Var. + \varepsilon_3 \qquad (2)$$

where $\widehat{Price\ Gap}$ and $\widehat{PriceGap} \times DS$ are the predicted value from (1A) and (1B). If the conditions for a valid instrumental variable are met, β_1 captures the causal effect of having an additional supply of

[27] We thank Jay Ritter for this data, whose format is further described in Loughran and Ritter (2004). We also thank Tania Babina who linked the data to the Census and provided the links to us. The data links consist of a subset of our years as her data only began in 1990.

[28] Our results are robust when we use an indicator for price gap (above median or 75th percentile) or an indicator for positive price gap only.

capital on firm growth and β_2 captures the causal effect of having an additional supply of capital on a firm's sensitivity to demand shock.

Table A-1 shows that $NASDAQ$ has a positive effect in predicting the price gap - $\omega_1 > 0$ significantly at 1% level. At the same time, $\phi_2 > 0$, significant at 1% level. The F-stat for the first stage regressions are all greater than 30, suggesting strong instruments.

In the second stage, β_1 is insignificant from zero in all time horizons, suggesting that there is no significant effect on growth in general. On the other hand, β_2 is positive for the three of the four years reported, suggesting that firms that raise additional capital at the IPO exhibit higher sensitivity to demand shocks. The estimated coefficients are at a 5 to 10% significance level, thus marginally significant. Our results from the IV approach thus suggests a statistically weak treatment effect of having additional capital raised at the IPO on firm growth in the immediate years. Overall, these results, combined with the previous results, are consistent with selection being the primary driver of firm growth and response to demand shocks and relatively weaker treatment effect stemming from better access to capital markets.

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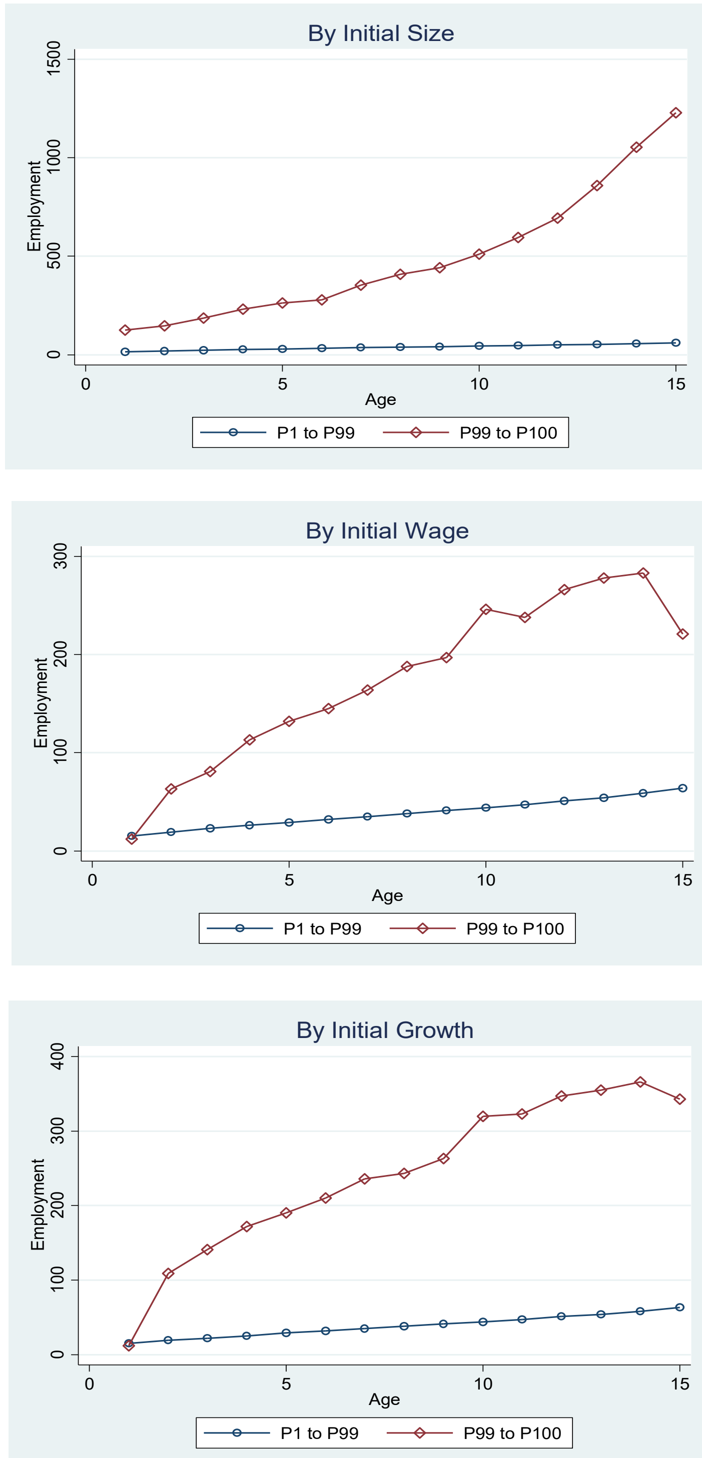
Figure 1: Size Distribution of Public and Private Firms (Unmatched Sample)

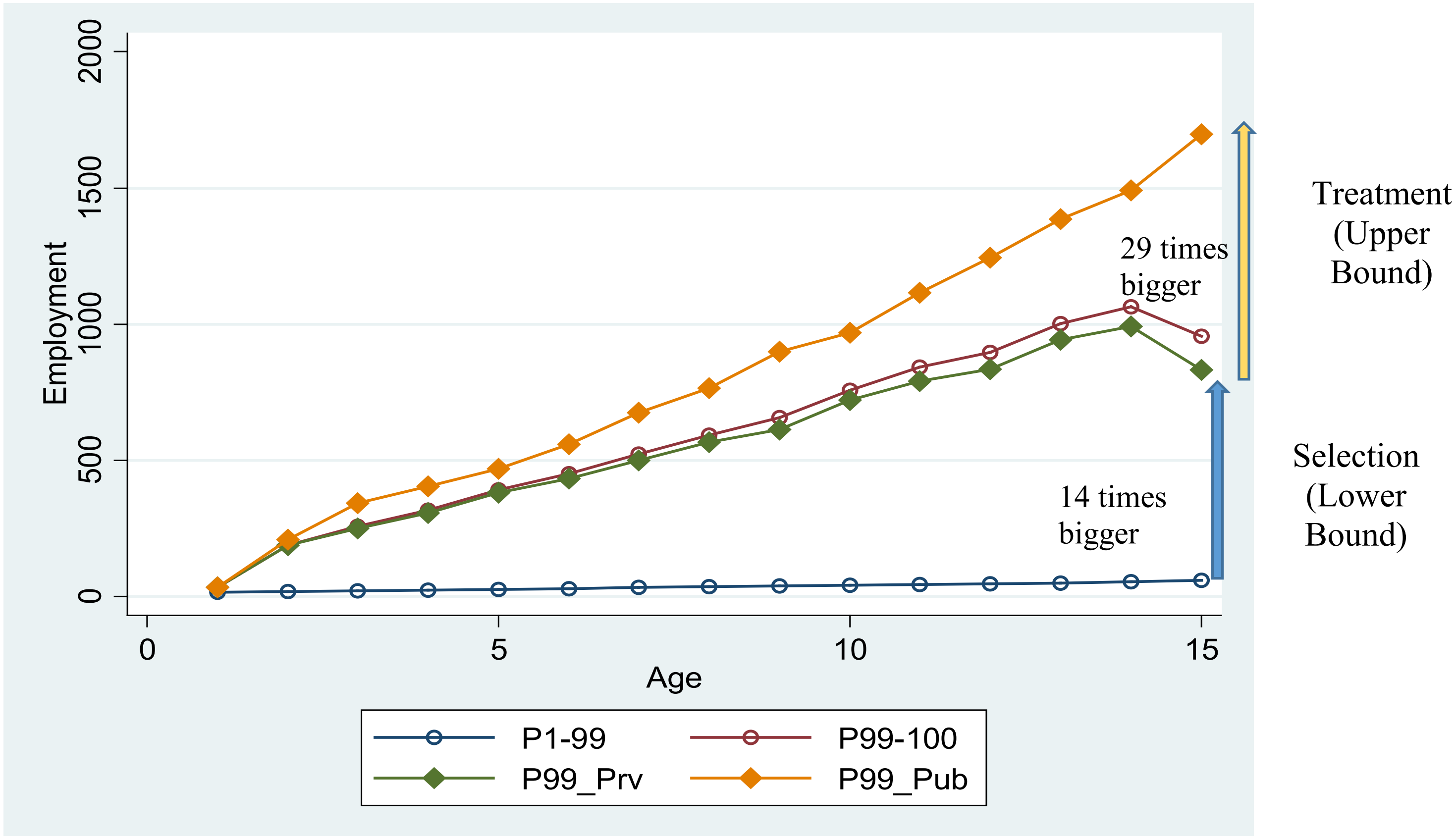
This figure presents the size distribution of public and private firms in our sample (unmatched) at birth (Panel A) and 10 years after birth (Panel B).

Figure 2: Initial Conditions and Firm Growth



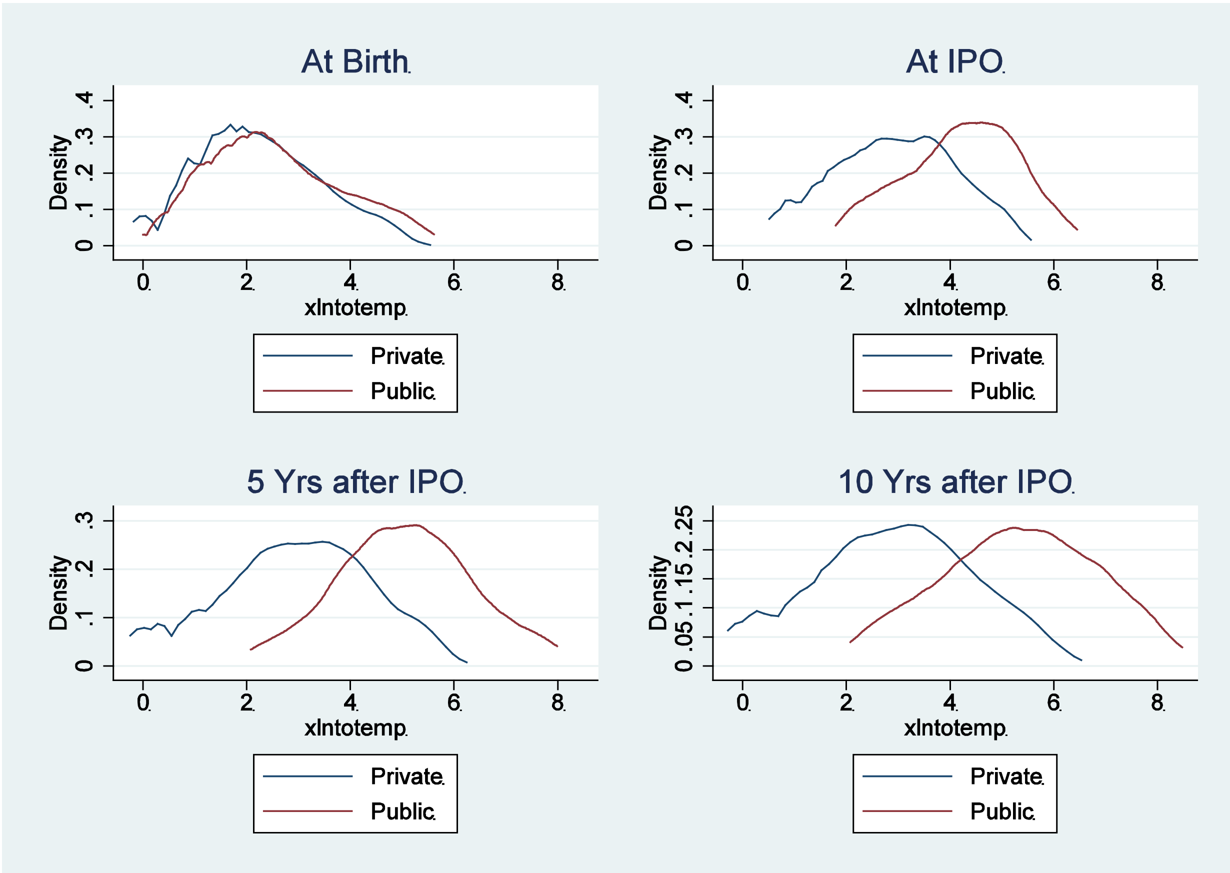
The figures compares firm size (number of employees) over time for firms in the 1st-99th percentile and firms above 99th percentile based on initial conditions - size, wage, and initial growth rate, respectively.

Figure 3: Top 1% Firms: Public vs. Private



This figure shows the average number of employees for firms at the top 1% of the predicted public quality (P99-100) and those in the rest of the population (P1-99) by their actual public status later in life. P99_Prv and P99_Pub refer to the top 1% firms that stay private and become public later, respectively. Thus, the difference between P99_Prv and P1-99 captures the lower bound of selection effect while the difference between P99_Pub and P99_Prv captures the upper bound of treatment effect.

Figure 4: Matched Sample



This figure represents the distribution density of the log of number of employees for public firms and their matched private counter parts over time - at birth, at IPO, 5 years after IPO, and 10 years after IPO. For each public firm, we choose up to 10 matched private firms from the same industry and same birth year based on the predicted probability of being public (based on Table 2 Column 2).

Figure 5: Growth around the IPO

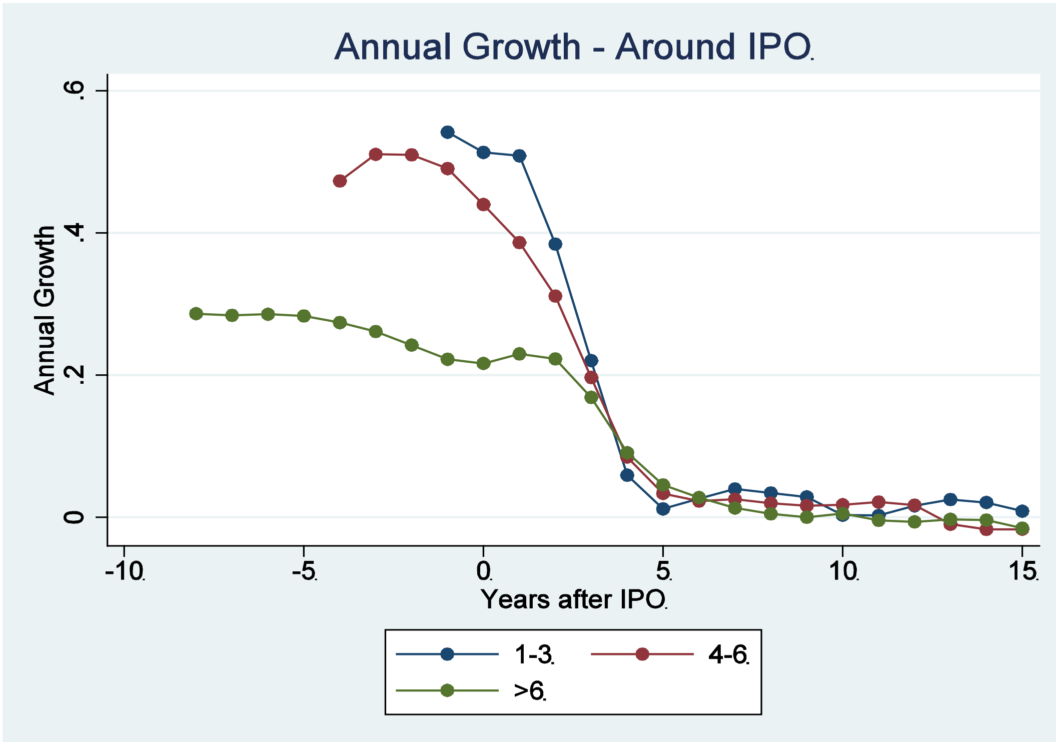


Table 1: Persistence in Initial Conditions

This table presents estimated coefficients from predicting a firm's size later in life based on macro, industry, and firm conditions at birth. The dependent variables are employment size 5, 10, or 15 years after birth, respectively. We include year and industry fixed effects in all specifications. Industries are defined using 3-digit SIC level. Initial employment measures number of employees in the first year reported by firm. Initial wage is calculated as the average wage paid by firm in the first year. Initial growth measures the growth of employment in the first year. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Var: Employment	Panel A: Year 5 (1)	Panel B: Year 10 (2)	Panel C: Year 15 (3)
Initial Employment	1.631 ***	2.639 ***	3.282 ***
	(0.010)	(0.038)	(0.121)
Initial Wage	0.637 ***	1.401 ***	2.042 ***
	(0.024)	(0.094)	(0.356)
Initial Growth (x 100)	0.350 ***	0.514 ***	0.771 ***
	(0.006)	(0.025)	(0.084)
Number of Observation	463,000	268,000	162,000
R-square	8.16%	3.90%	1.07%
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 2: Predicting Public Status

This table presents the estimated coefficients from predicting a firm's public status. The dependent variable equals to 1 if a firm becomes publicly traded later in life and 0 otherwise. Log(Initial_Emp) is the logarithm of the number of employees at birth. Log(Initial Wage) is the logarithm of average wage paid by the firm at birth. Initial_Growth is the firm's growth rate (in employment) in the first year. Pct_Small_Firms is the percentage of firms that have fewer than 50 employees in the industry. Ind_Growth is the average growth (in employment) in the industry, and Pct_M&A is the percentage of employment involved in mergers and acquisitions (from target firms) in the industry. Industries are defined using 3-digit SIC level. We control for industry (3-digit SIC) fixed effects and year fixed effects in all regressions. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: 1 (Public)	(1)	(2)
Log(Initial_Emp)	-0.003	0.005
	(0.058)	(0.058)
Log(Initial_Emp)^2	0.037 ***	0.036 ***
	(0.010)	(0.010)
Log(Initial Wage)	-0.570 ***	-0.578 ***
	(0.066)	(0.066)
Log(Initial Wage)^2	0.177 ***	0.178 ***
	(0.018)	(0.018)
Initial_Growth	0.354 ***	0.351 ***
	(0.032)	(0.032)
Initial_Growth ^ 2	0.211 ***	0.209 ***
	(0.023)	(0.023)
Ind_Growth		0.772 ***
		(0.263)
Pct_M&A		8.659 ***
		(2.123)
Pct_Small_Firms		-0.673 ***
		(0.133)
R-Square	0.016	0.016
Number of Observations	892,000	892,000
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 3: Public Index and Firm Growth

This table reports the estimated coefficients from regressing firm growth on an indicator of high public index. We define high public quality index (HPI) equal to 1 if the estimated public index based on initial conditions (estimated in Table 2 Column 2) is above the 99th percentile of all firms at birth and zero otherwise. The dependent variable is the annual employment growth. DS is an industry level (at 3-digit SIC) measure for demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread for the year. We control for industry and year fixed effects in all regressions. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Variable: Emp Growth	(1) All Firms	(2) Private Firms Only	(3) All firms Yr (1, 5)	(4) All Firms Yr (6, 10)	(5) All Firms Yr (11, 15)	(6) All Firms Yr (15+)
HPI	0.019 *	0.007	0.056 **	0.014	-0.009	-0.009
	(0.010)	(0.011)	(0.025)	(0.018)	(0.018)	(0.018)
HPI * DS	0.262 **	0.249 **	0.424 ***	0.017	0.302 *	0.099
	(0.106)	(0.114)	(0.154)	(0.159)	(0.162)	(0.233)
HPI * CS	0.002	0.002	-0.016	-0.002	0.011	0.009
	(0.008)	(0.008)	(0.022)	(0.015)	(0.014)	(0.010)
R-Square	0.009	0.009	0.011	0.006	0.007	0.009
# of Obs	4,449,000	4,435,000	1,757,000	1,286,000	760,000	645,000
Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Summary Statistics for the Matched Sample

This table presents the summary statistics for our matched sample. For each public firm, we choose up to 5 matched private firms from the same industry and the same birth year based on the predicted probability of being public (using Table 2 column 2). Column (3) and (5) present the t-statistics comparing the group mean between (1) and (2), and between (1) and (4), respectively. Standard errors are shown in parentheses.

	(1) Public Firms	(2) Private Firms (Matched)	(3) t-stat (1) vs (2)	(4) Private Firms (Unmatched)	(5) t-stat (1) vs (4)
Phat	0.83%	0.81%	1.56	0.28%	49.39
	(0.011%)	(0.005%)		(0.005%)	
Initial Employment	27.01	26.37	0.54	18.42	8.02
	(1.07)	(0.49)		(0.03)	
Initial Wage	61.79	65.45	-2.46	16.41	33.88
	(1.33)	(0.65)		(0.02)	
Growth Rate	0.767	0.794	-1.32	-0.058	44.80
	(0.018)	(0.009)		(0.0006)	
Number of Obs.	1,600	8,000		886,000	

Table 5: Response to Demand Shocks by Public Status

This table presents the estimated coefficients from regressing firm growth on public status and demand shocks for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the growth of employment for a firm in a specific year. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. We control for firm-cohort-period fixed effects in column (5) and (6). Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. PostIPO_1to5 is an indicator variable that equals to one for firm-years that are within the first five years following the IPO and zero otherwise. PostIPO_5+ is an indicator variable that equals to one for firm-years that are five years after the IPO date and zero otherwise. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the annual credit spread using the difference in rates between the A3 and Baa rated-bonds. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Firm Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)	(5) FE	(6) FE
Pub	0.089 ***	0.202 ***	0.070 **	-0.027	0.072 ***	
	(0.021)	(0.033)	(0.033)	(0.038)	(0.027)	
PostIPO_1to5						0.101 ***
						(0.032)
PostIPO_5+						-0.015
						(0.039)
DS					0.124	0.175 *
					(0.124)	(0.099)
Pub x DS	0.317 ***	0.091	0.485 ***	0.187	0.472 ***	
	(0.119)	(0.220)	(0.183)	(0.238)	(0.136)	
(PostIPO_1to5) x DS						0.468 ***
						(0.163)
(PostIPO_5+) x DS						0.128
						(0.241)
Pub x CS	0.036 *	0.023	0.019	0.009	-0.002	
	(0.020)	(0.028)	(0.032)	(0.031)	(0.025)	
(PostIPO_1to5) x CS						-0.005
						(0.031)
(PostIPO_5+) x CS						0.018
						(0.033)
Log(Emp)	-0.033 ***	-0.056 ***	-0.017 ***	-0.005 *	-0.026 ***	-0.026 ***
	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Log(Wage)	0.158 ***	0.179 ***	0.141 ***	0.115 ***	0.171 ***	0.171 ***
	(0.007)	(0.011)	(0.007)	(0.008)	(0.006)	(0.006)
Age	-0.013 ***	-0.035 ***	-0.002	0.002	-0.0534 ***	-0.065 ***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)
R-Square	0.15	0.23	0.11	0.09	0.08	0.08
Number of Obs.	89,000	30,000	42,000	18,000	89,000	89,000
Industry-Year FE	Yes	Yes	Yes	Yes		
Year FE					Yes	Yes
Firm-Cohort-Period FE					Yes	Yes

Table 6: Efficiency by Public Status

This table presents the estimated coefficients from regressing efficiency (measured as sales over employment) on public status and demand shocks for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the growth of employment for a firm in a specific year. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. We control for firm-cohort-period fixed effects in column (5) and (6). Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. PostIPO_1to5 is an indicator variable that equals to one for firm-years that are within the first five years following the IPO and zero otherwise. PostIPO_5+ is an indicator variable that equals to one for firm-years that are five years after the IPO date and zero otherwise. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the annual credit spread using the difference in rates between the A3 and Baa rated-bonds. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Sales/Emp	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)	(5) FE	(6) FE
Pub	0.048	0.239 *	0.160	-0.305	0.050	
	(0.126)	(0.137)	(0.158)	(0.261)	(0.153)	
PostIPO_1to5						0.188
						(0.159)
PostIPO_5+						-0.092
						(0.316)
DS					0.215	0.042
					(0.187)	(0.160)
Pub x DS	1.550 ***	1.166 **	1.972 ***	1.896	1.039 *	
	(0.476)	(0.543)	(0.551)	(1.505)	(0.593)	
(PostIPO_1to5) x DS						1.106 **
						(0.547)
(PostIPO_5+) x DS						1.583
						(1.674)
Pub x CS	-0.107	-0.266 **	-0.292 *	0.495	0.025	
	(0.110)	(0.105)	(0.154)	(0.210)	(0.142)	
(PostIPO_1to5) x CS						-0.219
						(0.150)
(PostIPO_5+) x CS						0.486 *
						(0.262)
Log(Emp)	-0.040 **	-0.081 ***	-0.064 ***	-0.016 **	-0.086 ***	-0.087 ***
	(0.018)	(0.016)	(0.021)	(0.026)	(0.019)	(0.019)
Log(Wage)	0.653 ***	0.512 ***	0.658 ***	0.853 ***	0.618 ***	0.617 ***
	(0.029)	(0.032)	(0.035)	(0.064)	(0.031)	(0.031)
Age	0.044 ***	0.049 ***	0.043 ***	0.017 ***	0.0459 ***	0.039 ***
	(0.003)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
R-Square	0.28	0.32	0.28	0.36	0.12	0.12
Number of Obs.	45,000	13,000	23,000	10,000	45,000	45,000
Industry-Year FE	Yes	Yes	Yes	Yes		
Year FE					Yes	Yes
Firm-Cohort-Period FE					Yes	Yes

Table 7: Survival by Public Status - Cox Proportional Hazard Model

This table reports the analysis of survival rate based on public status. Panel A describes the coefficients from a Cox Proportional Hazard Model estimated from the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. We include all firm years up to fifteen years following the IPO. Failure is defined as the event that a firm does not survive in the next year. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point of its life. IPO_wave is an indicator variable that equals one if the firm went public during IPO waves and zero otherwise. IPO waves are defined as years in which the number of IPOs is two standard deviations above the average in the sample period using Ritter's data. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. Panel B predicts the survival rate by public status and IPO age using estimates from column (2).

Panel A: Cox Proportional Hazard Model

	(1)	(2)
Pub	-0.194 ***	-0.230 ***
	(0.044)	(0.051)
IPO_Wave		0.061
		(0.045)
Pub * IPO_Wave		0.117
		(0.089)
Number of Obs	76000	76000
Log Likelihood	-38854	-38851

Panel B: Survival Rate following IPO by Public Status and IPO Age

# of Yrs. After IPO	Private Firms	IPO Firms
0	100%	100%
1	100%	100%
2	93%	98%
3	86%	94%
4	80%	89%
5	74%	83%
6	69%	78%
7	65%	73%
8	61%	67%
9	57%	62%
10	53%	58%
11	49%	53%
12	47%	50%
13	45%	48%
14	43%	44%
15	40%	41%

Table 8: Response to Demand Shocks by Public Status and Financial Dependence

This table presents the estimated coefficients from regressing firm growth on public status, demand shocks, and financial dependence for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the annual growth rate of employment in a specific year. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. PostIPO is an indicator variable that equals to 1 for public years and zero for private firms or public firms prior to the IPO. We include firm-cohort period fixed effects in column 5. FD (Non-FD) is an indicator that equals to 1 if the industry is (not) financially dependent. We measure financial dependence using the difference between capital expenditure and internal operating cash flow over total assets and define FD to be 1 if the median rate of the industry is higher than the median of all industries. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread using the difference between the A3 and Baa rated-bonds for the year. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Firm Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)	(5) FE
Pub x Non-FD	0.150 ***	0.278 ***	0.167 ***	-0.049	
	(0.026)	(0.038)	(0.044)	(0.068)	
Pub x FD	0.034	0.112 **	0.000	-0.008	
	(0.029)	(0.048)	(0.044)	(0.045)	
PostIPO x Non-FD					0.127 ***
					(0.035)
PostIPO x FD					0.028
					(0.033)
Pub x Non-FD x DS	0.120	0.094	0.103	0.283	
	(0.178)	(0.320)	(0.243)	(0.439)	
Pub x FD x DS	0.498 ***	0.183	0.694 ***	0.098	
	(0.151)	(0.295)	(0.223)	(0.288)	
PostIPO x Non-FD x DS					0.146
					(0.217)
PostIPO x FD x DS					0.485 ***
					(0.157)
Pub x Non-FD x CS	0.002	-0.037	-0.062	0.018	
	(0.024)	(0.034)	(0.043)	(0.060)	
Pub x FD x CS	0.067 **	0.091 **	0.076 *	-0.001	
	(0.028)	(0.038)	(0.044)	(0.037)	
PostIPO x Non-FD x CS					-0.044
					(0.032)
PostIPO x FD x CS					0.020
					(0.030)
Log(Emp)	-0.033 ***	-0.056 ***	-0.017 ***	-0.005 *	-0.026 ***
	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)
Log(Wage)	0.158 ***	0.179 ***	0.141 ***	0.115 ***	0.167 ***
	(0.007)	(0.011)	(0.007)	(0.008)	(0.006)
Age	-0.013 ***	-0.035 ***	-0.002	0.002	-0.017 ***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
R-Square	0.15	0.23	0.11	0.09	0.10
Number of Obs.	89,000	30,000	42,000	18,000	89,000
Industry-Year FE	Yes	Yes	Yes	Yes	
Year FE					Yes
Firm-Cohort Period FE					Yes

Table 9: Response to Demand Shocks by Public Status and Industry Earnings Responsiveness

This table presents the estimated coeffcients of regressing firm growth on public status, industry Earnings Response Coefficients (ERC) and demand shocks for the matched sample of public and private firms. For each public firm, we select up to 10 matched private firms based on initial conditions (industry, birth year, birth size, and initial employment growth rate) and survivial up to the IPO year. The dependent variable is the growth of employment for a firm in a specific year. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. We estimate ERC for each Fama French 48 industry-year by regressing unexpected stock returns on earings surprises. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread using the difference between the A3 and Baa rated-bonds for the year. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Firm Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)
Pub	0.123 ***	0.242 ***	0.081 ***	-0.011
	(0.010)	(0.015)	(0.015)	(0.014)
Pub x ERC	-0.007	-0.002	0.001	0.000
	(0.006)	(0.009)	(0.007)	(0.007)
Pub x DS	0.352 **	0.179	0.670 ***	0.104
	(0.137)	(0.244)	(0.210)	(0.229)
Pubx ERC x DS	-0.048	-0.053	-0.181 **	-0.025
	(0.081)	(0.104)	(0.090)	(0.131)
Log(Emp)	-0.035 ***	-0.064 ***	-0.019 ***	-0.008 ***
	(0.002)	(0.004)	(0.003)	(0.002)
Log(Wage)	0.160 ***	0.187 ***	0.146 ***	0.103 ***
	(0.005)	(0.009)	(0.006)	(0.005)
Age	-0.009 ***	-0.030 ***	-0.001	0.002 ***
	(0.001)	(0.002)	(0.002)	(0.001)
R-Square	0.12	0.18	0.09	0.07
Number of Obs.	186200	61700	74100	50400
Industry-Year FE	Yes	Yes	Yes	Yes

Table 10: Response to Demand Shocks by Public Status and VC Sponsorship

This table presents the estimated coefficients from regressing firm growth on public status, demand shock, and financial dependence for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the annual growth rate of employment in a specific year. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. PostIPO is an indicator variable that equals to 1 for public years and zero for private firms or public firms prior to the IPO. We include firm-cohort period fixed effects in column 5. Non-VC (VC) is an indicator variable that equals to 1 if the public firm does not (does) have VC sponsorship. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread using the difference between the A3 and Baa rated-bonds for the year. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Firm Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)	(5) FE
Pub x Non-VC	0.054 **	0.193 ***	0.044	-0.030	
	(0.027)	(0.041)	(0.042)	(0.055)	
Pub x VC	0.124 ***	0.192 ***	0.102 **	-0.004	
	(0.028)	(0.045)	(0.045)	(0.050)	
PostIPO x Non-VC					0.060 *
					(0.036)
PostIPO x VC					0.083 **
					(0.033)
Pub x Non-VC x DS	0.270 *	0.231	0.224	0.605 *	
	(0.146)	(0.229)	(0.207)	(0.349)	
Pub x VC x DS	0.299 *	-0.049	0.664 ***	-0.169	
	(0.164)	(0.280)	(0.252)	(0.322)	
PostIPO x Non-VC x DS					0.133
					(0.205)
PostIPO x VC x DS					0.477 ***
					(0.173)
Pub x Non-VC x CS	0.055 **	0.001	0.053	-0.010	
	(0.025)	(0.036)	(0.039)	(0.050)	
Pub x VC x CS	0.020	0.060	-0.020	0.008	
	(0.027)	(0.039)	(0.047)	(0.038)	
PostIPO x Non-VC x CS					0.009
					(0.033)
PostIPO x VC x CS					-0.022
					(0.031)
Log(Emp)	-0.033 ***	-0.056 ***	-0.017 ***	-0.005 *	-0.026 ***
	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)
Log(Wage)	0.157 ***	0.178 ***	0.141 ***	0.115 ***	0.166 ***
	(0.007)	(0.011)	(0.007)	(0.008)	(0.006)
Age	-0.013 ***	-0.035 ***	-0.002	0.002	-0.017 ***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
R-Square	0.15	0.23	0.12	0.09	0.10
Number of Obs.	89,000	30,000	42,000	18,000	89,000
Industry-Year FE	Yes	Yes	Yes	Yes	
Year FE					Yes
Firm-Cohort Period FE					Yes

Table 11: Response to Demand Shock by Public Status and Acquisition Status

This table presents the estimated coefficients from regressing firm growth on public status and demand shock for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the growth of employment for a firm in a specific year. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. Prv Acq_Prv is an indicator that equals to 1 if a firm never went public and was acquired by another private firm later in life and zero otherwise. Prv Acq_Pub is an indicator that equals to 1 if a firm never went public and was acquired by a public firm later in life and zero otherwise. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread using the difference between the A3 and Baa rated-bonds for the year. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Firm Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)
Prv Acq_Prv	0.149 ***	0.187 ***	0.091 **	0.060
	(0.028)	(0.042)	(0.039)	(0.046)
Prv_Acq_Pub	0.131 ***	0.112 **	0.129 *	0.122
	(0.043)	(0.054)	(0.070)	(0.132)
Pub	0.124 ***	0.237 ***	0.099 ***	-0.011
	(0.021)	(0.035)	(0.034)	(0.039)
Priv_Acq_Prv x DS	-0.138	-0.455 *	-0.022	0.312
	(0.152)	(0.253)	(0.197)	(0.336)
Priv_Acq_Pub x DS	-0.243	-0.399	0.061	-1.566 *
	(0.236)	(0.254)	(0.311)	(0.847)
Pub x DS	0.289 **	0.018	0.483 **	0.135
	(0.119)	(0.225)	(0.197)	(0.237)
Priv_Acq_Prv x CS	-0.070 **	-0.084 **	-0.012	-0.060
	(0.028)	(0.042)	(0.040)	(0.045)
Priv_Acq_Pub x CS	0.004	0.033	-0.005	-0.006
	(0.043)	(0.048)	(0.079)	(0.120)
Pub x CS	0.025	0.012	0.017	0.000
	(0.019)	(0.028)	(0.033)	(0.033)
Log(Emp)	-0.039 ***	-0.062 ***	-0.024 ***	-0.006 *
	(0.002)	(0.005)	(0.003)	(0.003)
Log(Wage)	0.154 ***	0.175 ***	0.137 ***	0.114 ***
	(0.007)	(0.011)	(0.007)	(0.008)
Age	-0.013 ***	-0.035 ***	-0.002	0.002
	(0.002)	(0.003)	(0.002)	(0.001)
R-Square	0.16	0.24	0.12	0.09
Number of Obs.	89,000	30,000	42,000	18,000
Industry-Year FE	Yes	Yes	Yes	Yes

Table 12: Response to Demand Shocks by Public Status (Internal Growth)

This table presents the estimated coefficients from regressing firm's internal growth on public status and demand shocks for the matched sample of public and private firms. For each public firm, we select up to 5 matched private firms based on initial conditions and survival up to the IPO year. The dependent variable is the growth of employment for a firm in a specific year. Column 1 includes all firm years (from up to five years before the IPO to up to 10 years after the IPO); column 2 includes firm years from up to five years prior to IPO; column 3 includes firm years that are up to five years following the IPO; and column 4 includes firm years that are between 6 and 10 years following the IPO. We control for firm-cohort-period fixed effects in column (5) and (6). Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. PostIPO_1to5 is an indicator variable that equals to one for firm-years that are within the first five years following the IPO and zero otherwise. PostIPO_5+ is an indicator variable that equals to one for firm-years that are five years after the IPO date and zero otherwise. DS measures the industry-level (3-digit SIC) demand shock constructed based on changes of shipment from vertical industries. CS measures the annual credit spread using the difference in rates between the A3 and Baa rated-bonds. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. Industries are defined using the 3-digit SIC codes. Robust standard errors are clustered at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep Var: Internal Growth	(1) All Years	(2) Yr. (-5, -1)	(3) Yr. (1, 5)	(4) Yr. (6, 10)	(5) FE	(6) FE
Pub	0.053 **	0.221 ***	-0.001	-0.134 *	0.010	
	(0.025)	(0.031)	(0.039)	(0.074)	(0.033)	
PostIPO_1to5						0.044
						(0.040)
PostIPO_5+						-0.117 **
						(0.059)
DS					0.123	0.146
					(0.015)	(0.116)
Pub x DS	0.295 **	-0.083	0.482 ***	0.470	0.502 ***	
	(0.139)	(0.225)	(0.165)	(0.301)	(0.148)	
(PostIPO_1to5) x DS						0.394 **
						(0.169)
(PostIPO_5+) x DS						0.562 *
						(0.321)
Pub x CS	0.057 **	-0.003	0.062	0.088	0.043	
	(0.025)	(0.025)	(0.042)	(0.074)	(0.032)	
(PostIPO_1to5) x CS						0.041
						(0.041)
(PostIPO_5+) x CS						0.076
						(0.055)
Log(Emp)	-0.028 ***	-0.057 ***	-0.004	0.000	-0.023 ***	-0.022 ***
	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
Log(Wage)	0.183 ***	0.216 ***	0.159 ***	0.123 ***	0.199 ***	0.199 ***
	(0.007)	(0.012)	(0.008)	(0.008)	(0.007)	(0.007)
Age	-0.016 ***	-0.038 ***	-0.005 ***	0.002	-0.0589 ***	-0.065 ***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
R-Square	0.16	0.26	0.12	0.11	0.08	0.08
Number of Obs.	80,000	27,000	37,000	16,000	80,000	80,000
Industry-Year FE	Yes	Yes	Yes	Yes		
Year FE					Yes	Yes
Firm-Cohort-Period FE					Yes	Yes

Table 13: Response to Demand Shocks by Public Status - Matched in 2001

This table presents the estimated coefficients of regressing firm growth on public status and demand shocks for the matched sample of public and private firms in 2001. For each public firm, we select up to 5 matched private firms based on size and age in 2001. The dependent variable is the growth of employment for a firm in a specific year. Panel A presents summary statistics for our subsamples. In Panel B, column 1 include all firm years up to 2010; column 2 - 5 split the sample by firm age - cutoffs are set at 5, 10 and 20 years. We define firm age using the difference between current year and birth year. Pub is an indicator that equals to 1 if a firm becomes publicly traded at some point in its life and zero otherwise. DS measures the demand shock constructed based on changes of shipment from vertical industries. CS measures the credit spread using the difference between the A3 and Baa rated-bonds. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. All dependent variables are lagged. We control for industry-year fixed effects in all regressions. Industries are defined using the 3-digit SIC codes. Robust standard error are clustered at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Group Mean for Subsamples used in Matching

	Total Emp	Wage (in $000)	Firm Age	Sales/Emp	Growth (last 3 years)	Growth (next 3 Years)	# of Firms
Public Unmatched	25703	45	21	10768	0.084	0.011	550
Public Matched	2479	62	17	2666	-0.104	-0.099	5,800
Private Matched	1343	43	17	1553	0.037	-0.008	26,600
Private Unmatched	22	29	12	135	0.000	0.000	1,559,500

Panel B: Firm Growth

	(1) All Years	(2) Age = (1, 5)	(3) Age = (6, 10)	(4) Age = (11, 20)	(5) Age >20 yrs.
Pub	-0.031 **	-0.190	-0.094	-0.020	-0.006
	(0.013)	(0.146)	(0.060)	(0.030)	(0.011)
Pub * DS	-0.226 *	0.365	-0.055	-0.606 *	-0.173
	(0.131)	(1.003)	(0.490)	(0.310)	(0.111)
Pub * CS	-0.008	0.034	-0.030	-0.044 *	-0.012
	(0.009)	(0.138)	(0.049)	(0.023)	(0.008)
Log(Emp)	0.000	-0.021	0.004	0.003 *	0.000
	(0.001)	(0.014)	(0.004)	(0.002)	(0.001)
Log(Wage)	0.059 ***	0.089 ***	0.088 ***	0.074 ***	0.041 ***
	(0.005)	(0.019)	(0.010)	(0.006)	(0.006)
Age	0.001 **	0.007	-0.003	0.002 *	-0.001
	(0.000)	(0.007)	(0.004)	(0.001)	(0.001)
R-Square	0.06	0.14	0.11	0.09	0.07
# of Obs.	171,000	7,000	13,000	35,000	115,000
Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Table A1: IPO Price Revisions and Firm Growth (2SLS)

This table presents the estimated coefficients from regressing firm growth on IPO price revisions measured as the difference between the actual IPO price and the original filing price (Price_Gap) experienced for a subsample of IPO firms between 1990 and 2005 in two-stage least square regressions. We instrument Price_Gap and Price_Gap x DS using the 60-day NASDAQ return following the first day of IPO filing (Ret) and Ret x DS. Panel A represents the second stage regression. The dependent variable is the growth rate of employment for the IPO firm 2 to 5 years following the offering, respectively. Panel B represents the first stage regression. Price_Gap is the log difference between actual price and the average price proposed in IPO filings. NASDAQ is the 60-day NASDAQ return following the first day of filing. DS measures the demand shock constructed based on changes of shipment from vertical industries. Log(Emp) is the logarithm of firm employment. Log(Wage) is the logarithm of firm's average wage. Age measures firm's age following birth. Standard Errors are clustered by year and are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1%, respectively.

Panel A: Second Stage

Dependent Variable = Growth	(1) Yr. (0, 2)	(2) Yr. (0,3)	(3) Yr. (0,4)	(4) Yr. (0,5)
Price_Gap	-0.459	-0.320	-0.232	-0.329
	(0.359)	(0.294)	(0.302)	(0.324)
Price_Gap x DS	0.096 *	0.081 **	0.053 *	0.045
	(0.049)	(0.037)	(0.032)	(0.034)
Log(Emp)	-0.016	-0.009	-0.007	0.027
	(0.034)	(0.029)	(0.022)	(0.020)
Log(Wage)	0.257 ***	0.261 ***	0.260 ***	0.255 ***
	(0.086)	(0.073)	(0.063)	(0.056)
Age	0.002	0.002	0.003	0.001
	(0.008)	(0.006)	(0.005)	(0.005)
Ind (SIC3) FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1000	1400	1700	2000
Adj. R-Square	0.08	0.13	0.13	0.12

Panel B: First Stage

Dependent Variable = Price_Gap	(1) Yr (0, 2)		(2) Yr (0,3)		(3) Yr (0,4)		(4) Yr (0,5)	
NASDAQ	0.646	***	0.653	***	0.593	***	0.545	***
	(0.111)		(0.115)		(0.113)		(0.114)	
NASDAQ x DS	0.016		0.017		0.027		0.033	*
	(0.022)		(0.021)		(0.019)		(0.018)	
Log_Emp	0.051	***	0.048	***	0.041	***	0.039	***
	(0.011)		(0.009)		(0.007)		(0.006)	
Log_Wage	0.037		0.038	*	0.036	***	0.041	***
	(0.025)		(0.020)		(0.018)		(0.016)	
Age	-0.008	***	-0.009	***	-0.009	***	-0.010	***
	(0.003)		(0.002)		(0.002)		(0.002)	
Ind (SIC3) FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
N	1000		1400		1700		2000	
Adj. R-Square	0.27		0.27		0.25		0.23	
F-test (Instruments)	45.47		51.89		54.43		49.5	

Panel B: First Stage (cont.)

Dependent Variable = Price_Gap x DS	(1) Yr (0, 2)		(2) Yr (0,3)		(3) Yr (0,4)		(4) Yr (0,5)	
NASDAQ	-0.614		-0.982		-1.411	*	-1.617	**
	(0.644)		(0.753)		(0.749)		(0.708)	
NASDAQ x DS	1.017	***	1.098	***	1.186	***	1.230	***
	(0.348)		(0.304)		(0.252)		(0.221)	
LN_EMP	0.378	***	0.364	***	0.315	***	0.269	***
	(0.132)		(0.098)		(0.077)		(0.064)	
LN_WAGE	0.332		0.347	*	0.322	*	0.334	**
	(0.214)		(0.189)		(0.166)		(0.142)	
AGE	-0.046	**	-0.039	**	-0.044	***	-0.041	***
	(0.022)		(0.017)		(0.016)		(0.013)	
Ind (SIC3) FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
N	1000		1400		1700		2000	
Adj. R-Square	0.17		0.12		0.13		0.14	
F-test (Instruments)	30.54		36.55		43.95		46.01	