Research Paper No. 2126

Does Going Public Affect Innovation?

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December 2012

RESEARCH PAPER SERIES

STANFORD
GRADUATE SCHOOL OF BUSINESS

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October 14, 2012

Abstract

This paper investigates the effects of going public on innovation by comparing the innovative activity of firms that went public with firms that withdrew their IPO filing and remained private. NASDAQ fluctuations during the book-building phase are used as an instrument for IPO completion. Using patent-based metrics, I find that the quality of internal innovation declines following the IPO and firms experience both an exodus of skilled inventors and a decline in productivity of remaining inventors. However, public firms attract new human capital and acquire external innovations. The analysis reveals that going public changes firms' strategies in pursuing innovation.

*Stanford University, e-mail: shaib@stanford.edu. I am deeply grateful to Fritz Foley, Josh Lerner, Andrei Shleifer, and Jeremy Stein for their invaluable guidance and encouragement. I also thank Philippe Aghion, Malcolm Baker, Bo Becker, Effi Benmelech, Lorenzo Casaburi, Josh Coval, Laura Field, Paul Gompers, Robin Greenwood, Sam Hanson, Oliver Hart, Naomi Hausman, Victoria Ivashina, Dirk Jenter, Lawrence Katz, Bill Kerr, Jacob Leshno, Gustavo Manso, Ramana Nanda, Francisco Perez-Gonzalez, David Scharfstein, Antoinette Schoar, Amit Seru, Andrea Stella, Adi Sunderam, Rick Townsend and Rodrigo Wagner for helpful comments. I am grateful to seminar participants at Columbia University, Dartmouth College, Entrepreneurial Finance and Innovation Conference, Harvard Business School, Hebrew University, London Business School, London School of Economics, NBER Productivity Lunch, Northwestern University, Searle Conference on Innovation and Entrepreneurship, Stanford University, Tel-Aviv University, University of British Columbia and University of Pennsylvania for helpful comments and suggestions. Andrew Speen provided superb research assistance. I am grateful for funding from the Ewing Marion Kauffman Foundation.

1. Introduction

Does the transition to public equity markets affect innovation? This question is particularly relevant given the the critical role of innovation in promoting economic growth (Solow 1957) and the prevalence of technological firms in the initial public offerings (IPOs) market over the last decades.[1] Although a large body of research examines the performance of firms around their IPO, little is known about the effects of going public on innovation. This paper's main contribution is to show that going public affects three important dimensions of innovative activity: internally generated innovation, productivity and mobility of individual inventors, and acquisition of external innovation.

Theoretically, in frictionless financial markets selling equities publicly should have no bearing on subsequent innovative activity. However, two broad views suggest that going public should in fact matter.

The "financing" view suggests that going public may enhance innovation by overcoming financing frictions and easing access to capital. As argued by Arrow (1962) and demonstrated empirically,[2] R&D is likely to be more sensitive to financing constraints than other forms of investments due to information problems, skewed and uncertain returns, and the potentially scant collateral value of intangible assets. Transferring idiosyncratic innovation risk to diversified investors through public equity markets may ease financing constraints allowing firms to enhance internally generated innovation, attract human capital, and facilitate technology acquisitions.

Alternatively, the "incentives" view suggests that ownership dilution and changes in governance may lead to a change in the composition of innovative projects, focusing on more incremental type of innovation. Following the IPO, inventors may face weaker incentives to pursue novel projects due to dilution of their claims on subsequent innovations and increases

[1] Approximately 40 percent of all firms that went public were technological firms in the period of 1980 to 2011. The definition of a technological firm is based on Loughran and Ritter (2004).

[2] See, for example, Brown, Fazzari and Petersen (2009), Himmelberg and Petersen (1994), and Mulkay, Hall, and Mairesse (2001). For detailed surveys of the literature see Bond and Van Reenen (2007) and Hall and Lerner (2010).

in wealth may lead to their departure. In addition, career concerns may pressure managers to select rather incremental projects that may be more easily communicated to stock market investors (Stein, 1989; Ferreira, Manso, and Silva, 2010). In fact, managers may prefer to exploit improved access to capital to acquire ready-made technologies, as this strategy is more transparent to the stock market and potentially less prone to failure.

To shed light on these two views and estimate the long-run effects on innovation I use standard patent-based metrics. Estimating these effects, however, is challenging due to an inherent selection bias associated with the decision to go public. A standard approach in the literature uses within-firm variation to study the dynamics of firm outcomes around the IPO. But, as noted by Jain and Kini (1994), firms choose to go public at a specific stage in their life cycle, and therefore this approach will produce biased estimates of the IPO effect. For instance, firms may choose to go public following an innovative breakthrough, as argued by Pastor, Taylor, and Veronesi (2009). Indeed, Chemmanur, He, and Nandy (2009) find empirically that firms go public following productivity improvements. In this case, the post-IPO performance may reflect reversion to the mean thereby mixing life cycle effects with the IPO effect.

To overcome this selection bias, I construct a dataset of innovative firms that filed an initial registration statement with the SEC in an attempt to go public, and either completed or withdrew their filing. This sample allows me to compare the innovative activity of firms that went public with that of private firms that are at a similar stage in their life cycle, namely, intended to go public. However, comparing complete and withdrawn IPO filings introduces a new bias associated with the decision of firms to withdraw the IPO filing and remain private.

To address this concern, I use NASDAQ fluctuations in the two months following the IPO filing date as an instrument for IPO completion, relying on filers' sensitivity to aggregate stock market movements during the book-building phase. Consistent with prior literature,[3]

[3] See for example Benveniste et al. (2003), Busaba, Benveniste and Guo (2000), Busaba (2006), Dunbar (1998), Dunbar and Foerster (2008), Edelen and Kadlec (2005), and Hanley (1993).

I find that these short-run NASDAQ fluctuations strongly predict IPO completion and the effect is concentrated at market declines. In the analysis, the IPO effect is identified from differences in long-run (five years) of innovation between firms that filed to go public in the same year, but experienced different post-filing NASDAQ returns.

For the instrument to be valid, it needs to satisfy the exclusion restriction; i.e., that two-month NASDAQ returns relate to long-run innovation measures only through the IPO completion choice (see section 2.C for a detailed discussion). There are several reasons for which this condition may hold. First, since the analysis compares between firms that filed to go public in the same year, they are likely to be subject to similar changes in innovative opportunities if such are reflected by the instrument. Second, I find that filers that experienced a NASDAQ drop during the book-building phase are not significantly different from other filers in the same year. Third, to ensure that the effects I identify are driven by firms' public ownership status and not aggregate changes reflected by the instrument, all innovation measures are scaled by the average innovation measures of all patents granted in the same year and in the same technology class.[4] Since firms that conduct research in the same technology are likely to be similarly affected by aggregate changes (such as changes in innovative opportunities), even if the instrument may reflect such changes, they are unlikely to affect scaled innovation measures.

Using short-run NASDAQ returns as an instrument in the first stage of a two-stage least square specification, I find a significant link between public ownership and innovation: going public causes a substantial decline of approximately 40 percent in innovation novelty as measured by patent citations. At the same time, I find no change in the scale of innovation, as measured by the number of patents. These results suggest that the transition to public equity markets leads firms to reposition their R&D investments toward more conventional

[4]Technology classes are defined by the United States Patent and Trademark Office (USPTO), and capture technological essence of an invention. Technological classes are often more detailed than industry classifications, consisting of about 400 main (3-digit) patent classes, and over 120,000 patent subclasses. For example, under the "Communications"category one can find numerous sub-categories such as wave transmission lines and networks, electrical communications, directive radio wave systems and devices, radio wave antennas, multiplex communications, optical wave guides, pulse or digital communications, etc.

projects.

To verify that the two-month NASDAQ returns do not affect scaled innovation through channels other than IPO completion choice, I also conduct a placebo test. I substitute the instrument with NASDAQ returns outside the book-building phase, during which the IPO completion choice is fixed. I find that these returns have no effect on long-run innovation, in contrast to NASDAQ returns during the book-building phase. This finding is consistent with the notion that short-term NASDAQ returns during the book-building phase affect long-run scaled innovation only through the IPO completion choice.

Having shown that going public drastically affects the composition of innovative relative to conventional projects, I proceed to uncover the IPO effect on additional dimensions of firms' innovative activity. First, I study the effects of going public on individual inventors' productivity and mobility over time. I find that the quality of innovation produced by inventors who remained at the firm declines following the IPO and key inventors are more likely to leave. These effects are partially mitigated by the ability of public firms to attract new inventors.

I also find a stark increase in the likelihood that newly public firms acquire companies in the years following an IPO. To better understand whether these acquisitions are used for purchasing new technologies, I collect information on targets' patent portfolios. I find that public firms acquire a substantial number of patents through M&A: acquired patents constitute almost a third of firms' total patent portfolio in the five years following the IPO. The acquired patents are of higher quality than the patents produced internally following the IPO.

These results illustrate that the transition to public equity markets affects the strategies firms employ in pursuing innovation. While publicly traded firms generate more incremental innovation internally, they also rely more heavily on acquiring technologies externally. This shift takes place during a substantial inventor turnover after the IPO.

While these results cannot be fully explained by the financing view, I find supportive evidence that managerial incentives matter. Firms with more entrenched managers,[5] whose greater job security makes them less likely to be sensitive to market pressures, experience a smaller decline in innovation novelty, and interestingly, their inventors are less likely to leave the firm.

The paper is related to several strands in the literature. First, the IPO literature documents a post-IPO decline in firm performance measures such as profitability (Degeorge and Zeckhauser, 1993; Jain and Kini, 1994; Mikkelson, Partch, and Shah, 1997; Pagano, Panetta, and Zingales, 1998; and Pastor, Taylor, and Veronesi, 2009) and productivity (Chemmanur, He, and Nandy, 2009). The paper contributes to the literature by proposing an identification strategy to estimate the IPO effect. Additionally, the paper contributes by its focus on firms' innovative activities around the IPO. In that regard the paper is closely related to contemporaneous research by Aggarwal and Hsu (2012) who examine similar question in the context of venture capital-backed biotechnology firms. Similarly to this paper they find a post-IPO long-run decline in innovation quality. This study differs from Aggarwal and Hsu (2012) by its focus on a cross-industry analysis and the use of an identification strategy that exploits NASDAQ fluctuations as an instrument for IPO completion.

This analysis focuses on the ex-post consequences of becoming a publicly traded firm rather than the general equilibrium effects of the IPO market on innovation. The findings illustrate a complex trade-off between public and private ownership forms. In that regard, the paper is also related to a growing literature that compares the behavior of public and private firms along various dimensions such as investment sensitivity (e.g., Asker, Farre-Mensa, and Ljungqvist, 2010; and Sheen 2009), debt financing and borrowing costs (Saunders and Steffen, 2009; and Brav, 2009), dividend payouts (Michaely and Roberts, 2007), and CEO compensation (Gao, Lemmon, and Li, 2010). This work also contributes to a growing theoretical and empirical literature that explores the role of governance, capital structure,

[5] I use cases in which the CEO also serves as the chairman of the board as a proxy for managerial entrenchment.

and ownership concentration on corporate innovation.[6]

The rest of the paper proceeds as follows. Section 2 outlines the main empirical strategy and Section 3 describes the sample. Section 4 presents the effects of going public on internal innovation, inventors' mobility and productivity, and firm reliance on external technologies. Section 5 discusses several theoretical explanations and Section 6 provides a conclusion.

2. Empirical Strategy

In this section, I discuss the standard patent-based metrics used in the analysis to measure firm innovation and then I describe the empirical strategy used in the paper.

2.A Measuring Innovative Activity

An extensive literature on the economics of technological change demonstrates that patenting activity reflects the quality and extent of firm innovation. While the literature acknowledges that patents are not a perfect measure,[7] their use as a measure of innovative activity is widely accepted (Hall, Jaffe, and Trajtenberg, 2001; Lanjouw, Pakes, and Putnam, 1998). Importantly for this analysis, patent information is available for both public and private firms, unlike R&D expenditures, and allows measuring firm innovative output along several dimensions, rather than merely expenditures.

The most basic measure of innovative output is a simple count of the number of patents granted. However, patent counts cannot distinguish between breakthrough innovation and incremental discoveries (e.g., Griliches, 1990). The second metric, therefore, reflects the importance or novelty of a patent by counting the number of citations a patent receives

[6] A few recent examples include Acharya and Subramanian (2009), Aghion, Van Reenen, and Zingales (2009), Atanassov, Nanda, and Seru (2007), Belenzon, Berkovitz, and Bolton (2009), Bhattacharya and Guriev (2006), Chemmanur and Tian (2007), Fulgheieri and Sevilir (2009), Fang, Tian, and Tice (2010), He and Tian (2012), Lerner, Sorensen, and Stromberg (2010), Seru (2011) and Tian and Wang (2010).

[7] For example, inventions may be protected by trade secrets.

following its approval.[8] Hall, Jaffe, and Trajtenberg (2005) illustrate that citations are a good measure of innovative quality and economic importance.[9]

Both citation rates and patent filing propensity vary over time and across technologies. Variations may stem from changes in the importance of technologies or from changes in the patent system. Therefore, a comparison of raw patents and citations is only partially informative. To adjust for these variations, I follow Hall, Jaffe, and Trajtenberg (2001) and scale each patent citation count by the average citations of matched patents. Matched patents are defined as patents that are granted in the same year and in the same technology class. Similarly, to adjust for variations in patent-filing likelihood, each patent is weighted by the average number of patents granted by firms in the same year and technology. Hence, patents that were granted in technologies in which firms issue more patents receive less weight. The *scaled patent count per year* is a simple sum of the scaled patents a firm generates in a year.

The final measures, Originality and Generality, use the distribution of citations to capture the fundamental nature of research (Trajtenberg, Jaffe, and Henderson, 1997). A patent that cites a broader array of technology classes is viewed as having greater originality. A patent that is being cited by a more technologically varied array of patents is viewed as having greater generality.[10] Similarly to patent counts and citations, *scaled originality* and *scaled generality* are normalized by the corresponding average originality or generality of all patents granted in the same year and technology class.

2.B Empirical Design

Identifying the effects of going public on innovation and firm outcomes in general is challenging due to inherent selection issues that arise from the decision of firms to go public.

[8]I count citations in the year of patent approval and three subsequent calendar years. In the robustness checks section, I verify that the results are not sensitive to the choice of the citation horizon window.

[9]Specifically, they find that an extra citation per patent boosts firm's market value by 3%.

[10]The originality (generality) measure is the Herfindahl index of the cited (citing) patents, used to capture dispersion across technology classes. I use the bias correction of the Herfindahl measures, described in Jaffe and Trajtenberg (2002) to account for cases with a small number of patents within technological categories.

To overcome the selection bias, I construct a dataset that includes innovative firms that submitted the initial registration statement to the SEC in an attempt to go public. Following the IPO filing, firms engage in marketing the equity issuance to investors during the book-building phase and have the option to withdraw the IPO filing. I compare the long-run innovation of firms that went public (henceforth 'IPO firms') with firms that filed to go public in the same year, but ultimately withdrew their filing and remained private (henceforth 'withdrawn firms'). This setup is attractive as it allows the comparison of the post-IPO performance of firms that went public with that of private firms at a similar stage in their life cycle. My baseline specification of interest is

$$Y_i^{post} = \alpha_1 + \beta_1 IPO_i + \gamma_1 Y_i^{pre} + X_i' \delta_1 + \nu_k + \mu_t + \varepsilon_{1i} \tag{1}$$

Y_i^{post} is the average innovative performance in the five years following the IPO filing: average scaled citations, average scaled originality/generality and average scaled number of patents per year. Y_i^{pre} is the equivalent measure in the three years prior to the IPO filing.[11] IPO_i is the dummy variable of interest, indicating whether a filer went public or remained private. Under the null hypothesis that going public has no effect on innovation, β_1 should not be statistically different from zero. This model includes industry (v_k) and IPO filing year (μ_t) fixed effects.

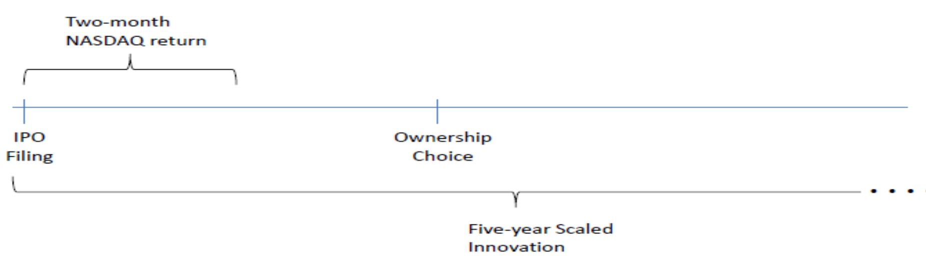
If the decision to withdraw an IPO filing is related to unobserved firm innovation policy or innovative opportunities (captured in the error term), then β_1 estimate may be biased. Therefore, I instrument for the IPO completion choice using NASDAQ returns in the first two months of the book-building phase, as issuers are highly sensitive to stock market fluctuations during the book-building phase (Benveniste et al., 2003; Busaba, Benveniste, and Guo, 2001;

[11] Adding a constraint of $\gamma_1 = 1$ in the model specified in equation (1) implies that the dependent variable is equivalent to innovative performance difference before and after the IPO filing. However, absent of this constraint, the above specification is more flexible and capable of capturing potential reversion to the mean that may arise following the IPO filing. Additionally, this model allows the inclusion of Y_i^{pre} in the first stage regression when correcting for endogeneity, and allows exploring whether pre-filing innovation explains IPO filing outcome.

Dunbar, 1998; Dunbar and Foerster, 2008; Edelen and Kadlec, 2005). This sensitivity is also illustrated in Figure 1 which plots the fraction of monthly filings that ultimately withdrew against the two months of NASDAQ returns calculated from the middle of each month, which approximates the stock market fluctuations during the initial part of the book-building phase.[12]

The decision to use two-month NASDAQ returns following the IPO filing is somewhat arbitrary. One could use the NASDAQ returns during the entire period of the book-building phase and still predict strongly the decision of whether or not to complete the IPO filing (see Table 4). However, the length of the book-building phase is often correlated with the likelihood to withdraw. Therefore, the NASDAQ returns window needs to be fixed, and also needs to be shorter than the length of the book-building periods in the sample.

The figure below illustrates the time line of the IPO filing and the NASDAQ fluctuations during the book-building phase. On average, the ownership choice is made within four months following the IPO filing. The firm-level innovation is measured over the five-year horizon after the IPO filing.[13]



To implement the instrumental variables approach, I estimate the following first-stage regression:

$$IPO_i = \alpha_2 + \beta_2 NSDQ_i + \gamma_2 Y_i^{pre} + X_i' \delta_2 + \nu_k + \mu_t + \varepsilon_{2i} \tag{2}$$

where $NSDQ_i$ is the instrumental variable. The second-stage equation estimates the impact

[12]The correlation of the two plots equals -0.44, or -0.34 if considering only the pre-2000 period. Both correlations are significantly different from zero at the 0.01% level.

[13]The results of the analysis remain unchanged if innovation measures are calculated from the ownership choice date rather than IPO filing date, as patent filings during the book-building period are not common.

of IPO on firm innovative activity:

$$Y_i^{post} = \alpha_3 + \beta_3 \widehat{IPO}_i + \gamma_3 Y_i^{pre} + X_i' \delta_3 + \nu_k + \mu_t + \varepsilon_{3i} \tag{3}$$

where $\widehat{IPO}_i$ are the predicted values from (2). If the conditions for a valid instrumental variable are met, β_3 captures the causal effect of an IPO on innovation outcomes. I implement the instrumental variable estimator using two-stage least squares. I also use a quasi-maximum likelihood (QML) Poisson model to estimate the IV specification (Blundell and Powell, 2004), which is the standard estimation method used in the innovation literature and count data analysis more generally.

To illustrate the advantage of using this instrumental variables approach in this setting consider a simple example.[14] Assume that firm innovation following the IPO filing is the sum of future innovation opportunities (which are unobserved at the time of the IPO filing) and the effect of ownership structure (being public or private). Specifically, the post-IPO innovative performance can be written as $Q + c \cdot IPO$, where Q stands for the unobserved quality of the issuer's future innovative projects, and IPO is a dummy that indicates whether the issuer completed the IPO filing ($IPO = 1$) or remained private ($IPO = 0$). The goal is to estimate c, the effect of public ownership on firm innovation.

Suppose that the unobserved quality of future projects is heterogeneous and affects the likelihood of completing the IPO filing. Specifically, there are three types of firms: *Sure Thing* firms, with highest-quality of future innovative projects ($Q = q_H$), will complete the IPO irrespective of book-building market conditions; *Sensitive* firms, with medium-quality innovative projects ($Q = q_M$), will not complete the IPO filing if NASDAQ drops during the book-building phase, but will go public otherwise; and *Long Shot* firms, with the poorest innovative prospects ($Q = q_L$), will withdraw irrespective of the NASDAQ change.[15] For

[14] This example is based on Bennedsen et al. (2012)

[15] The decision to withdraw or complete the IPO filing is complicated and driven by many observed and unobserved factors. For simplicity, in this example I assume that the decision depends only on one factor, the unobserved quality of innovative projects.

simplicity, assume that NASDAQ can be either *high* or *low* each with probability of 1/2, and firm types are equally likely. The table below summarizes the innovative outcomes in the six cases:[16]

	NASDAQ returns	
Firm Type	High	Low
Sure Thing	*Complete*	*Complete*
	$q_H + c$	$q_H + c$
Sensitive	*Complete*	*Withdraw*
	$q_M + c$	q_M
Long Shot	*Withdraw*	*Withdraw*
	q_L	q_L

The OLS estimate simply compares firms that completed the IPO filing (the upper triangle) and firms that withdrew the IPO filing (the bottom triangle) and reflects the sum of the IPO effect as well as a selection bias:

$$\gamma_{OLS} = E\left[Y|IPO = 1\right] - E\left[Y|IPO = 0\right] = c + \frac{2}{3}(q_H - q_L) > c \tag{4}$$

Thus OLS will overestimate the effect of going public in this example because better firms are more likely to complete the IPO filing.[17]

The instrumental variables approach uses the variation in the NASDAQ – which affects the decision to complete the IPO filing – to estimate the effects of an IPO on innovative outcomes. Specifically, simply comparing outcomes based on the NASDAQ returns generates the "reduced-form" regression which is equivalent to calculating the difference in performance

[16]I assume in this example that innovative opportunities (i.e.,q_H,q_M,q_L), are independent of NASDAQ fluctuations. This assumption is part of the exclusion restriction, which I discuss in detail in section 2.C.

[17]If one assumes that lower quality firms are more likely to complete the IPO filing then the sign of the bias reverses.

across columns:

$$E\left[Y|NSDQ = High\right] - E\left[Y|NSDQ = Low\right] = \frac{1}{3}c \tag{5}$$

The "first-stage" regression captures the likelihood to complete the IPO as a function of the NASDAQ variation:

$$E\left[IPO|NSDQ = High\right] - E\left[IPO|NSDQ = Low\right] = \frac{1}{3} \tag{6}$$

Scaling the reduced-form result by the first-stage regression coefficient generates the desired outcome:

$$\gamma_{IV} = \frac{E\left[Y|NSDQ = High\right] - E\left[Y|NSDQ = Low\right]}{E\left[IPO|NSDQ = High\right] - E\left[IPO|NSDQ = Low\right]} = c \tag{7}$$

The example illustrates that the IV estimator uses only the *sensitive* firms whose IPO completion depends on NASDAQ conditions. In other words, the estimates are coming from a comparison of IPO and withdrawn firms that belong to the sensitive group. In fact, this is a general result, as any instrumental variables estimator uses only the information of the group of firms that responds to the instrument (Imbens and Angrist, 1994).

In the example I assumed for the sake of simplicity that NASDAQ returns can take two values. Clearly, NASDAQ returns vary considerably. When the instrument is multi-valued, the IV estimate is a weighted average of the sensitive subpopulation estimates along the support of the instrument (Angrist and Imbens, 1995).[18]

So far, I made two important assumptions. First, I assumed that NASDAQ conditions are not correlated with firm characteristics, and second that NASDAQ returns do not affect future innovative performance. These assumptions determine the validity of the instrument.

[18]Different firms have different thresholds of NASDAQ changes for which they complete the IPO filing. Roughly speaking, the IV estimate is an average of the estimates of sensitive firms along different values of NASDAQ returns. The average is weighted by the impact of NASDAQ returns on completing the IPO filing, and by the likelihood of observing the NASDAQ returns.

In the next section I discuss these assumptions in detail.

2.C NASDAQ Fluctuations and the Exclusion Restriction

For the instrument to be valid, it must strongly affect IPO completion choice, as I show in section 3.D and Figure 1. Additionally, it must not affect the scaled innovation measures through any channel other than the decision to complete the IPO filing.[19] Formally, this requires that the instrument must be uncorrelated with the residuals in equation (1). To alleviate concerns about the exclusion restriction, I take several steps:

(1) I explore whether significant differences in observables occur between firms that experienced a NASDAQ drop and other firms that filed to go public in the same year. I discuss this test in Section 3.D.[20]

(2) Within year comparison - In the analysis, I compare the long-run innovative activity of firms that filed to go public in the same year, but experienced different short-term NASDAQ fluctuations during the book-building phase. Firms that filed to go public in the same year are likely to be similarly exposed to changes in innovation opportunities, if reflected by NASDAQ returns, since R&D expenditure is a slow-moving process (Hall, Griliches, and Hausman 1986; Lach and Schankerman, 1989).

(3) Additional controls - To further address concerns about within-year compositional shifts, I control also for the three-month NASDAQ returns leading to the IPO filing, and for firms' location within the IPO wave.[21]

[19]These two requirements are sufficient if treatment effects are homogeneous. In case of heterogeneous treatment effects, monotonicity is also required to estimate a local average treatment effect. In other words, it is required that, other things equal, there is no firm that whose likelihood to complete the IPO filing increases as NASDAQ returns decline.

[20]These characteristics include: innovation measures in the three years before the IPO filing, firm financials at the time of the IPO filing, venture capital backing, age, underwriter ranking, and location in the IPO wave.

[21]I follow Beneveniste et al. (2003) definition of location within the IPO wave. A firm is defined as a "pioneer" if its filing is not preceded by filings in the same Fama-French industry in the previous 180 days (using all IPO filings, irrespective of patenting activity). "Early followers" are those that file within 180 days of a pioneer's filing date.

(4) Scaled innovation measures - Any aggregate changes, such as changes in innovative opportunities, reflected by the two-month NASDAQ returns, should affect all firms conducting research in the same technology. Since scaled innovation measures are expressed in terms relative to all patents granted in the same year and technology, these measures are not likely to be affected by aggregate changes if such are reflected by the instrument.[22]

(5) Placebo test - If the two-month NASDAQ returns affect long-run innovation through alternative channels, these should be apparent also when exploring NASDAQ returns outside the book-building phase, when firms' ownership choice is fixed. In section 3.D, I conduct a placebo test by exploring whether two-month NASDAQ returns outside the book-building phase can significantly affect long-run innovation.

(6) Innovation trends test - I also investigate directly whether the instrument can explain changes in aggregate innovative trends in filers' core technologies, using all patents granted by the U.S. Patent and Trademark Office. I describe this test in section 3.D.

3. Data

The data in this analysis is constructed from several data sources combining information on IPO filings, patents, hand-collected financial information and other firm characteristics. In this section I describe the steps in constructing the dataset and provide summary statistics. Following the introduction of the data, I discuss in detail the IV related tests described in section 2.C.

[22]Consider for example a firm that submitted an IPO filing in 1995 and was awarded a patent three years later in 1998 in the fiber optics technology. The novelty of the patent is scaled by the average novelty of all patents granted in 1998 in the fiber optics technology. If the two-month NASDAQ returns following the IPO filing reflected a change in innovative opportunities in fiber optics in coming years, this change should affect the novelty of all patents within this technology class. Hence, relative patent novelty is unlikely to be affected by the instrument, even if the instrument reflects changes in innovative opportunities.

3.A IPO Filings

To apply for an IPO, a firm is required to submit an initial registration statement to the SEC (usually S-1 form), which contains the IPO filer's basic business and financial information. Following the submission of the S-1 form, issuers engage in marketing the equity issuance to investors (the "book-building" phase) and have the option to withdraw the IPO filing by submitting the RW form. Filing withdrawals are common in IPO markets, as approximately 20 percent of all IPO filings are ultimately withdrawn, when "weak market conditions" is the most common stated reason for withdrawing. A survey by Brau and Fawcett (2006) finds that CFOs that withdrew an IPO registration indeed recognized that market conditions played a decisive role in their decision.

If market conditions are the reason for IPO filing withdrawals, why wouldn't firms simply wait for more favorable market conditions? There are several reasons. First, a filing registration automatically expires 270 days after the last amendment of the IPO filing, which limits the time to complete the IPO filing (Lerner, 1994). Additionally, waiting is costly: as long as the application is pending, firms cannot issue private placements, and are forbidden to disclose new information to specific investors or banks. In fact, firms are required to update the registration statement periodically to reflect the current affairs of the company. These considerations lead firms to withdraw at an even earlier date prior to the automatic expiration of the IPO filing.

I identify all IPO filings using Thomson Financial's SDC New Issues database. The sample starts in 1985, when SDC began covering withdrawn IPOs systematically, and ends in 2003 since the analysis explores the innovative outcomes of firms in the five years after the IPO filing. Following the IPO literature, I exclude IPO filings of financial firms (SIC codes between 6000 and 6999), unit offers, closed-end funds (including REITs), ADRs, limited partnerships, special acquisition vehicles, and spin-offs. I identify 5,583 complete IPOs and 1,599 withdrawn IPO filings in the period of 1985 - 2003.

3.B Patent Data

The patent data is obtained from the National Bureau of Economic Research (NBER) patent database, which includes detailed information on more than 3 million patents submitted to the U.S. Patent and Trademark Office (USPTO) from 1976 to 2006 (Hall, Jaffe, and Trajtenberg, 2001).

I use the NBER bridge file to COMPUSTAT to match patents to firms that completed the IPO filing, and manually match patents to withdrawn IPO filings.[23] I restrict the sample to firms with at least one successful patent application in the period of three years before and five years after the IPO filing. This yields 1,488 innovative firms that went public and 323 that withdrew the IPO application.

The goal is to collect information on firms' innovative activity in the five years after the IPO filing regardless of whether they are acquired or go public in a second attempt, to avoid biases that may arise from truncating firm activity. After all, firm exits are yet another consequence of the IPO effect that influences firms' innovative paths. Collecting patent information subsequent to firm exits is feasible since in most cases, even if a firm is acquired, its patents are still assigned to the acquired rather than the acquiring company.[24]

I calculate the number of citations a patent receives in the calendar year of its approval and in the subsequent three years. This time frame is selected to fit the nature of the sample. Since many of the IPO filings in the sample occur toward the end of the 1990s, increasing the time horizon of citation counts will reduce sample size. Given that citations are concentrated in the first few years following a patent's approval and the considerable serial correlation in

[23]Since withdrawn firms are not included in COMPUSTAT, I match these firms based on company name, industry, and geographic location, all of which are available in SDC and IPO registration forms. In ambiguous cases where firm names are similar but not identical, or the location of the patentee differs from the SDC records or SEC registration statements, I conduct web and FACTIVA searches to verify matches.

[24]Using firm identifiers in the five years following the IPO filing to track patenting activity allows me to capture firm patents in more than 90 percent of firm-year observations, irrespective of whether a firm was acquired. In the remaining firm-years, a firm was acquired and no patent was assigned to it. In these cases, the acquired firm either did not generate additional patents, or any patents generated were assigned to the acquiring company. To identify missing patents in these remaining years, I use inventor identifiers and geographic location to locate patents that were produced by the inventors of the acquired rather than the acquiring company.

citation rates (Akcigit and Kerr, 2011), three years is reasonably sufficient to capture the patent's importance.

Since the NBER patent database ends in 2006, I supplement it with the Harvard Business School (HBS) patent database, which covers patents granted through December 2009. This enables calculating the citations of patents granted toward the end of the sample. Overall, the sample consists of 39,306 granted patents of IPO firms and 4,835 granted patents of withdrawn firms.

Panel A of Table 1 summarizes the distribution of IPO filings by year. IPO filings are concentrated in the 1990s and drop after 2000, with 95 of the 323 withdrawn filings occurring in 2000. The absence of transactions conducted before 1985 and after 2003 reflects the construction of the sample. Panel A also displays the patent applications and awards of IPO firms and withdrawn firms separately. Each patent is associated with an application date and grant date, reflecting the lag in patent approvals. In the analysis, I attribute a patent to the year it was applied, as it captures more closely the innovation date. Panel A illustrates that since the sample includes only patents granted by December 2006, the number of approved patent applications declines in 2005 and 2006.

Panels B and C detail the composition of firms and patents across industries and technology classes. The majority of the firms in the sample are concentrated in technological industries such as electronic equipment, software, drugs, and medical equipment. Similarly, most patents are concentrated in industries that rely on intellectual property, such as computer, drugs, and electronics industries. As illustrated in Panels B and C, IPO and withdrawn firms are similarly distributed across industries and technologies.

Panel D compares the patenting activity of withdrawn and IPO firms in the three years prior to the IPO filing. I find no significant differences across any of the patenting measures. Since a value of one in the scaled citations measure implies that a firm is producing patents of average quality, it is interesting to note that both IPO firms and withdrawn firms produce patents that substantially more cited than comparable patents in the same year and technology (80 percent higher for withdrawn firms and 89 percent higher for IPO firms). This evidence suggests that firms that select to go public are likely to do so following innovative breakthroughs, which may raise concerns of post-IPO reversion to the mean and motivates the empirical approach in this paper.

3.C Financial Information and Firm Characteristics

The analysis of private firms is complicated due to data limitations. While patents are useful in capturing the innovative activity of both public and private firms, no financial information is readily available for withdrawn firms in standard financial databases. To partially overcome this constraint, I collect withdrawn firms' financial information from initial registration statements, by downloading the S-1 forms from the SEC's EDGAR service, which is available from 1996. For IPO firms, I rely on standard financial databases such as COMPUSTAT and CapitalIQ to collect firm financial information. This allows me to compare withdrawn and IPO firms' characteristics at the time of filing.

Additional information on firm characteristics is collected from various sources. I obtain data on venture capital (VC) funding from SDC, VentureXpert, and registration statements. I supplement the data with information on firms' age at the time of the IPO filing and its underwriters' ranking obtained from registration forms, VentureXpert, Jay Ritter's webpage, and the SDC database. Finally, I collect information on firms' exits, i.e., events in which firms were acquired, went public in a second attempt (for withdrawn firms), or filed for bankruptcy. I use COMPUSTAT and CapitalIQ to search for acquisitions and bankruptcies, and the SDC database to identify second IPOs of withdrawn firms. I perform extensive checks to verify the nature of private firms' exits using the Deal Pipeline database, Lexis-Nexis and web searches.

Panel E compares the characteristics of IPO firms and withdrawn firms at the time of filing. I find no significant differences in firm size (measured by log firm assets) and R&D spending (normalized by firm assets). However, withdrawn firms have a higher cash-to-assets ratio and have lower net income to assets.

The literature often uses the reputation of the lead underwriter as a proxy for firm quality, based on the rationale that higher-quality firms are more likely to be matched with a higher-quality underwriter.[25] I find no significant differences between the two groups using this firm quality proxy. Moreover, there is no significant difference in firm age at the time of filing.[26]

There are stark differences, however, in the NASDAQ fluctuations that firms experience after the IPO filing. Specifically, firms that went public experienced on average a 3 percent increase in the two-month NASDAQ returns following the IPO filing, while firms that selected to withdraw experienced, on average, a sharp drop of 6 percent over a similar period. However, the differences in NASDAQ returns in the three months prior to the IPO filing are fairly small (5 percent increase for firms that ultimately remained private versus 7 percent for those that went public).

Panel F of Table 1 describes firm exit events in the five years following the IPO filing. These include acquisitions, bankruptcies, or IPOs of withdrawn firms. I find that 18 percent of the withdrawn firms ultimately go public in a second attempt in the five years following the IPO filing. Additionally, 29 percent of the withdrawn firms and 24 percent of the IPO firms are being acquired over this period. Only 2 percent of both IPO and withdrawn firms went bankrupt.

The resulting small fraction of withdrawn firms that return to public equity markets in a second attempt was highlighted in the literature (Dunbar and Foerster, 2008; Busaba, Beneviste, and Guo, 2001). While somewhat surprising, when incorporating acquisitions as an alternative form of exit, the fraction of withdrawn firm exits in the five years following the event rises to 50 percent. Several additional explanations exist for the low fraction of second attempt IPOs. It may be the case that returning to the IPO markets in a second attempt

[25]The underwriter ranking is based on a scale of 0 to 9, where 9 implies highest underwriter prestige. The ranking is compiled by Carter and Manaster (1990), Carter, Dark, and Singh (1998), and Loughran and Ritter (2004). I use the rating that covers the particular time period when the firm went public. If the rating for that period is not available, I employ the rating in the most proximate period.

[26]Firm age is calculated from founding date. The firm age of issuers that went public is kindly available at Jay Ritter's webpage. I collected firms' age of issuers that remained private from IPO prospectuses.

is difficult as the window of opportunities may close due to the boom and bust nature of the IPO markets (Ibbotson and Ritter 1995). Brau and Fawcett (2006) interview CFOs and found that those that withdrew an IPO expressed greater concern about the uncertainty and costs associated with the IPO process. These perceptions may deter firms from a second attempt at going public. Brau and Fawcett (2006) also find that the most important signal when going public is a firm's past historical earnings. If going public requires several years of fast growth to attract investors' attention, such growth may be difficult to regenerate in a second attempt. Finally, Dunbar and Foerster (2008) suggest that there are reputational costs associated with the decision to withdraw which prevent firms from returning to equity markets.

3.D Instrumental Variable Related Tests

Having introduced the data, this section presents the tests described in section 2.C to explore the validity of the instrumental variables approach. I start by exploring whether firms that experience a NASDAQ drop are significantly different from other firms that filed to go public in the same year. A firm is said to have experienced a NASDAQ drop if the two-month NASDAQ returns after the IPO filing are within the bottom 10 percent (or bottom 25 percent) of filers in a given year. Using both thresholds in table 2, I find no significant differences between the two sets of firms across a list of observables such as firm financial information at the time of filing, age, VC backing, IPO filing characteristics, and importantly, innovation measures in the three years before the IPO filing. These findings are not surprising given that similar firms are likely to cluster and attempt to go public at the same time in an attempt to exploit information spillovers (Beneveniste et al. 2003).

In a second set of results I conduct a placebo test by exploring whether two-month NASDAQ returns *outside* the book-building phase, when ownership choice is fixed, can predict long-run innovation. I explore this conjecture in Table A.1 in the Appendix. First, in column (1) I report the significant correlation between post-filing NASDAQ returns and long-run scaled citations.[27] If the exclusion restriction holds, then this effect is generated only through the ownership choice channel. In column (2) I find that the two-month NASDAQ returns immediately following the IPO completion choice do not predict long-run innovative performance. In columns (3) and (4), I similarly find that in the year before (or year after) the IPO filing, the two-month NASDAQ returns are insignificant and do not predict long-run innovation. In columns (5) to (7) I repeat the analysis by including both post-filing NASDAQ returns and NASDAQ returns outside the book-building phase. I find that in contrast to the NASDAQ returns following the IPO filing, outside the book-building window they are not correlated with long-run innovation. These findings are consistent with the story that short-run NASDAQ returns affect long-run innovation only through firms' ownership choice.

Finally, I investigate directly whether the instrument can explain changes in long-run innovation trends in firms' core technologies. A firm's core technology is defined as a technology class whose share of patents in the three years before the IPO filing is above the median share of the technology classes of the firm. I calculate innovative trends for each core technology using all patents granted by the USPTO in the five years after the IPO filing relative to the three years before the IPO filing.[28] As illustrated in Table A.2 in the Appendix, I find that the instrument does not predict changes in innovative trends measured by either changes in average patent citations, number of patents or number of patents weighted by patent citations. Clearly, firms may switch to different technologies following the IPO. However, this test suggests that whether or not such a switch occurred, it is not likely to be driven by the two-month change in the NASDAQ.

[27]This result is also reported in Table 6 column (2).

[28]Specifically, the change in average patent quality of each core technology is the average scaled citations of all patents in the specific technology class in the five years after the IPO filing, divided by the average scaled citations in the three years prior to the IPO filing in the corresponding technology class. Similarly, I construct the change in the total number of patents in the core technology, and also the change in the weighted number of patents, when patents are weighted by the number of citations. Since firms may have multiple core technologies, I weight the measures outlined above by the share of patents a firm produced in each core technology class.

4. Results

4.A Within-Firm Relationship Between IPOs and Innovation

Before turning to the instrumental variables analysis, in this section I explore the within-firm changes in innovation of firms that successfully completed the IPO filing. The specification presented in Table 3 uses the various innovation measures as dependent variables and has the following form:

$$Y_{it} = \beta_0 + \sum_{\substack{k=-3 \\ k\neq 0}}^{k=5} \gamma_k EventYear_{i,k} + \tau_i + \mu_t + \varepsilon_{i,t}$$

$EventYear_{i,k}$ is a dummy variable indicating the relative year around the IPO in which a patent was submitted for approval (year zero is the year of the IPO and the omitted category). All specifications are estimated using OLS and include firm fixed effects (τ_i) and year fixed effects (μ_t). Standard errors are clustered at the firm level.[29]

The unit of observation in columns (1) to (6) of Table 3 is at the patent level. The dependent variable in column (1) is the raw count of patent citations. I find a monotonic decline in patents' novelty that starts two years before the IPO event, and continues in the five years thereafter. Since citation rates vary over time and across technology classes, in column (2) I use the scaled citations measure. The coefficients represent the change in relative innovation quality, and demonstrate a similar pattern to the one found in column (1). The post-IPO decline in scaled citations is displayed in Figure 2. The magnitude of the effect is substantial. For example, the coefficient of the year dummy three years after the IPO equals -0.597, implying a decline of 31.64 percent in innovation quality relative to the pre-IPO filing period (pre-IPO average scaled citations is 1.89).

In column (3) I repeat the same specification, but use patent originality as a dependent variable. Patent originality deteriorates significantly, starting two years after the IPO event.

[29] In an unreported analysis I verify that these results remain unchanged when the estimated model is quasi maximum likelihood Poisson, the standard model used in count data analysis.

In column (4) the effect becomes even more significant when I estimate it using scaled originality. In columns (5) and (6), similar patterns arise when I estimate the effects on generality and scaled generality. Lastly, in columns (7) and (8) I consider changes in innovation measured by number of patent applications per year in the years around the IPO event. I find no change in the number of patents produced after the IPO, measured by either simple patent counts or scaled number of patents.

Taken together, the results indicate a change in the composition of patents around the IPO. The quality of innovation declines, as do the generality and originality measures, indicating that research becomes less fundamental. Additionally, I find no evidence for an increase in innovative scale following the IPO. However, these results could be driven by reversion to the mean and life cycle effects, irrespective of the IPO filing. To better understand whether this decline is driven by the IPO, the following sections present the results using the instrumental variables approach.

4.B Internal Innovation

In this section I use the instrumental variables approach, described in Section 2, to study the effects of going public on internally generated firm innovation.

4.B.1 First Stage

The first-stage results, presented in Table 4, demonstrate the effect of NASDAQ returns during the book-building phase on IPO completion. The dependent variable is equal to one if a firm completed the IPO filing, and zero otherwise. All specifications include filing year and industry fixed effects using OLS.[30] In column (1), I find that the coefficient of the two-month NASDAQ returns equals 0.704 and is significant at 1 percent. A decline of one standard deviation in NASDAQ returns translates into a decline of 8.72 percent in the likelihood of completing the IPO. Moreover, the F-statistic equals 47.79 and exceeds the threshold of

[30]Probit model generates similar estimates.

$F = 10$ which suggests that the instrument is strong and unlikely to be biased towards the OLS estimates (Bound, Jaueger, and Baker, 1995; Staiger and Stock 1997).

A concern with the post-IPO filing returns is that its variation may be either capturing the pre-IPO filing fluctuations that motivate firms to submit the initial registration statement, or reflecting the state of the IPO market. Therefore, I add additional control variables such as the three-month NASDAQ returns prior to the IPO filing and the location of the filer within the IPO wave. I also control for the number of pre-filing patents, and a dummy variable indicating whether the firm is backed by a VC fund and re-estimate the model in column (2). The coefficient of the post-IPO filing NASDAQ returns is still significant at 1 percent with a higher F-statistic of 52.03 reflecting the greater accuracy of the first stage. The sensitivity to market fluctuations slightly increases, and equals 0.763. This result suggests that the two-month NASDAQ returns play an important role in determining IPO completion, and is almost orthogonal to the added control variables, confirming the findings in Table 2. Moreover, in columns (3) and (4) I verify that the variation of the instrument is not driven only by the year 2000 by repeating the specifications above, and limiting the sample to pre-2000 years.

In the remainder of the table I explore alternative specifications of the instrument. In columns (5) and (6) I calculate the NASDAQ returns over the entire book-building period, from the first day of the IPO filing until the IPO completion or withdrawal dates.[31] Although the coefficient is still significant at 1 percent, and the F-statistic is sufficiently high, the magnitude of the coefficient declines, as one standard deviation change reflects a 6.17 percent change in the likelihood that the firm will complete the IPO filing.[32] In columns (7) and (8), I construct a dummy variable that equals one if the two-month NASDAQ returns experienced by a filer are among the lowest 25 percent of all filers within the same year. The dummy

[31] When the IPO withdrawal date is not available, I calculate it as the 270 days after the last IPO filing amendment (Lerner 1994)

[32] The weaker effect may reflect the importance of the first months in the book-building period, where most of the marketing efforts are concentrated. This is consistent with Welch's (1992) argument of "information cascades": later investors are more likely to rely on earlier investors' choices, leading to the rapid success or failure of the equity offering.

variable in column (7) is highly significant, reflecting a 10.6 percent decline in the likelihood that a firm will complete the IPO filing. Column (8) adds additional control variables and results remain unchanged.

Figure 3 illustrates the non-parametric relation between the two-month NASDAQ fluctuations and the likelihood of completing the IPO filing. The figure shows that as long as the NASDAQ fluctuations are negative, there is a positive and monotonic association between NASDAQ returns and the likelihood of completing the IPO filing. When NASDAQ returns are positive, filers become less sensitive to market conditions and the likelihood of completing an IPO filing becomes more or less stable around 85 percent.

Overall, the first-stage results indicate that NASDAQ fluctuations have a strong effect on IPO completion, and the effect is concentrated in market declines. Moreover, the two-month NASDAQ effect seems to be orthogonal to the added control variables.

4.B.2 Simple Illustration of Reduced Form Results

Before proceeding to the multivariate analysis, I illustrate the results by a simple comparison of the post-IPO innovative performance of firms that experienced a NASDAQ drop relative to other filers within the same year. This comparison is equivalent to the reduced-form estimation illustrated in the example in Section 2.B when the instrument is binary and equals one if a firm experienced a NASDAQ drop. This approach is attractive because of its simplicity and the absence of any distributional or functional form assumptions. If experiencing a NASDAQ decline affects the decision to complete the IPO but does not affect the long-run scaled measures of innovation, differences in averages illustrate the effects of going public on innovative activity.

For this analysis, a firm is said to have experienced a NASDAQ drop if the two-month NASDAQ returns after the IPO filing are within the bottom 25 percent of filers in a given year. Column (6) of Table 2 illustrates that there are no significant differences between the two groups in any of the firm characteristics and innovation measures at the time of the IPO filing. However, a comparison of post-IPO filing performances reveals significant differences.

Table 5 illustrates a strong correlation between two-month NASDAQ declines and subsequent five-year innovative performance. The likelihood that the IPO will be completed declines by 11.1 percent for firms experiencing low NASDAQ returns. These firms produce patents with higher average scaled citations in the subsequent five years and generate patents with higher average scaled originality. The difference in patent quality is also apparent when one considers the most-cited patent produced after the IPO filing (rather than the average citation rates). I find no differences in the number of patents produced following the IPO filing.

These reduced-form results illustrate that declines in short-run NASDAQ returns translate into changes in long-run innovation activity, leading to a more incremental type of innovation. These effects are likely to take place through the IPO completion choice, demonstrating the effects of going public on internal innovation. The remainder of the section makes use of the continuous value instrument, using the entire variation in the two-month NASDAQ returns, and studies separately each of the innovative performance measures.

4.B.3 Innovation Novelty

The first set of results explores the effect of IPO on innovation novelty. The dependent variable is the average scaled citations in the five years following the IPO filing, controlling for equivalent measure in the three years prior to the IPO filing. All specifications follow the model described in Section 2.B, controlling for filing year and industry fixed effects. Additionally, I control for the three-month pre-IPO filing NASDAQ returns, a dummy variable indicating whether the issuer is backed by a VC, and location within the IPO wave. Robust standard errors are reported in parentheses.[33]

In column (1) of Table 6, I report the endogenous OLS model and find no differences between IPO firms and withdrawn firms as the IPO coefficient is insignificant and close to zero. Column (2) presents the reduced-form estimation, obtained by substituting the endogenous IPO variable with the instrument. I find a strong and negative correlation between two-month NASDAQ returns and average scaled citations in the subsequent five years.[34] This strong correlation is plausibly generated through the effect of the two-month NASDAQ fluctuations on the decision of firms to complete the IPO filing, which in turn translates into long-run innovation. This result corresponds to the findings in Table 5. In column (3), I report the estimates of the two-stage least squares. The coefficient of the IPO variable is significant and equals -0.831, implying that average scaled citations of IPO firms drops after the event by 43.51 percent (=0.83/1.91, when 1.91 is the average number of scaled citations in pre-event years). In column (4) I use the quasi maximum likelihood (QML) Poisson model to estimate the IV specification. The estimates are similar to column (3), as the coefficient of interest is significant, negative, and of a similar magnitude.

It is interesting to note that the OLS coefficient overestimates the effect of going public on the quality of innovation, compared to the IV estimate. As illustrated in the example in Section 2.B, this suggests that the selection bias associated with the decision to complete the IPO filing is positive, and on average, more innovative firms are more likely to complete the IPO filing.

[33] It may be natural to cluster standard errors at a quarter level since the selection to complete the IPO filing may be correlated across issuers filing in proximity to one another. In an unreported analysis I run this specification and find that clustered standard errors decline in such cases relative to the robust estimates. This may indicate that there is no need to cluster firms at that level. As illustrated by Kezdi (2004), clustering may generate a bias toward over-rejection and overestimated t-statistics when there is no need for clustering. Using a robust standard errors in my setting may be a more conservative approach with lower t-statistics.

[34] This negative correlation goes against the notion that two-month NASDAQ returns predict long-run innovation opportunities. If that was the case, one would expect positive correlation between short-run NASDAQ returns and long-run innovation.

4.B.4 Fundamental Nature of Research

In this section I explore whether the decline in patent citations is associated with a change in the nature of projects. Specifically, firms that pursue less basic or fundamental research may produce less influential innovations. In Table 7, I use the originality and generality measures to capture the fundamental nature of patents. The estimation follows the same specification used in the previous section, substituting average scaled citations with average scaled originality or generality.

Columns (1)-(3) provide the results with respect to average scaled originality of patents in the five years following the IPO filing. In column (1), I estimate the endogenous variable specification. I find no significant difference between withdrawn firms and IPO firms. The reduced-form estimation in column (2), which substitutes the IPO variable with the instrument, shows that the instrument is statistically significant with a magnitude of -0.081. The two-stage least squares estimates in column (3) demonstrate that the post-filing average originality of firms that completed the IPO significantly declines as the IPO coefficient equals -0.137 reflecting a decline of 13 percent ($=-\frac{0.13}{1.06}$, the average scaled originality in pre-event years is 1.06). These findings suggest that issuers who remained private produce patents that rely on a broader set of technologies. In columns (5)-(8) I repeat the analysis this time with respect to average scaled generality measure, and results demonstrate no significant effects.

4.B.5 Scale of Innovation

The decline in innovation novelty may be driven by an increase in the scale of innovation, measured by number of patents. In that case, addition of low-quality innovative projects may generate the results rather than a repositioning of research to lower impact topics. The analysis in Table 8 addresses this conjecture by exploring changes in innovative scale. The dependent variable is the average scaled number of patents per year in the five years after the IPO filing. I control for the pre-IPO filing corresponding measure. The specification is similar to the estimation in the previous sections.[35]

The endogenous model in column (1) indicates that IPO firms produce significantly more patents per year following the IPO filing with a 37.75 percent increase relative to the pre-IPO average. Column (2), however, indicates that the above effect is insignificant when the reduced form specification is estimated. The 2SLS estimate in column (3) indicates that the coefficient of the IPO variable is insignificant and the magnitude declines to 28.17 percent. In fact, when using the IV Poisson specification in column (4), the coefficient of the IPO variable is close to zero and insignificant.

Given the length of research projects, the magnitude of increase in scale may appear only several years after the IPO. In column (5), I use as a dependent variable the innovative scale measure over years two to five after the IPO filing, and control for the scaled number of patents per year in prior years (in the three years before the IPO filing and one year thereafter). Similar to the results in column (4), I find no evidence of an increase in the number of patents produced by IPO firms. Overall, the results suggest that there is no causal evidence of an increase in the scale of innovation.

4.B.6 Robustness Checks

In this section I summarize several unreported supplemental analyses that test the robustness of the findings and explore alternative explanations. I start by exploring whether the decline in average quality of IPO firms can be driven by lower patenting threshold after the IPO. This may lead to the addition of low-quality patents and hence lower average patenting quality. I explore the best (most-cited) patent that firms produce, which is unlikely to be affected by such addition of low-quality patent filings. I find that the quality of the best patent of IPO firms is substantially lower, with a comparable magnitude to the decline

[35] One complication in this analysis is coming from the attrition problem that may arise due to patent approval lags, particularly toward the end of the sample. Such patents may have not been approved yet and therefore are not considered in the analysis. In that regard, scaling patent counts is important not only to account for variations in patent filings but also to correct for variations in patent approvals, thus alleviating the attrition problem. The attrition problem is further mitigated by the fact that patent approval lags are likely to affect similarly both IPO firms and withdrawn firms.

in the average innovation quality reported in Table 6. This evidence, which adds up to the finding that the overall number of patents does not significantly change, suggests that going public affects the entire patent distribution rather than simply driving average performance down by the addition of low-quality projects.

Second, I examine when differences between IPO firms and withdrawn firms first emerge. Since research is a long-term process, the effect should not take place immediately after the IPO. I repeat the instrumental variable estimation separately for each year in the years following the IPO filing. I find that, as expected, the differences in quality between IPO firms and withdrawn firms become significant only from the second year onward after the IPO filing.

Additionally, if cash-rich firms are less cited because citing firms may face higher litigation risk, this may mechanically generate the result that publicly traded firms are less cited relative to private firms. To test this concern directly, I focus on patents approved before the IPO-filing and explore whether the yearly citation rates change once firms become publicly traded (relative to firms that withdrew the filing). I find that changes in citation rates of existing inventions cannot be explained by the transition to public equity markets.

Next, I explore whether the results are mostly driven by the year 2000. As illustrated in Table 4, the instrument strongly predicts IPO completion even when all firms that filed in 2000 onward are excluded. I re-estimate the innovation novelty regressions after excluding all firms that filed to go public during the internet bubble in the years 1999 – 2000. Naturally, standard errors increase due to the decline in sample size, but the results remain significant and qualitatively the same.

I also verify that the results are robust to different citations horizons. As noted earlier, Akcigit and Kerr (2011) find that citations are concentrated in the first few years following a patent's approval; therefore, results should not vary substantially when using different citation horizons. I repeat the analysis, using citation horizons of two and four years after the patent's approval. I find that the results are qualitatively similar.

What if the results are driven by this particular grouping of firms? I shift the filing year fixed effects by six months and re-estimate the results. The findings remain unchanged.

Finally, I explore the robustness of the finding that the post filing two-month NASDAQ returns are not correlated with firm characteristics. I find similar patterns in an out-of-sample setting, when including all IPO filings, regardless of whether they generated patents.

4.C Inventor Mobility and Productivity Changes

A substantial portion of the R&D investment is in the form of wages for highly educated scientists and engineers, who encompass the firm's knowledge. The transition to public equity markets may have substantial ramifications for the firm's human capital. Retaining key employees may become difficult following the IPO as options are vested, ownership is diluted, and changes in firm governance may affect employees. However, stock options and improved access to capital may enable firms to attract new human capital. In this section, I study mobility choices and productivity changes of inventors following the IPO.

4.C.1 Inventor Level Data

The patent database provides an interesting opportunity to track inventors' mobility across firms, as each patent application includes both the name of the inventor and its assignee (most often the inventor's employer). The analysis of inventor-level data is, however, complicated for several reasons. First, patents are associated with inventors based on their name and geographic location. Inventors' names are unreliable, as first names can be abbreviated and different inventors may have similar or even identical names. Second, attempting to detect inventor mobility using patents is necessarily inexact. While it is possible to infer that an inventor changed firms (e.g., patented for company A in 1987 and for company B in 1989), the precise date of the relocation is unavailable. Additionally, transitions in which inventors did not produce patents in the new location are not observable. Nevertheless, this method identifies relocations of the more creative inventors who patent frequently and presumably matter the most.

To overcome the hurdle of name matching, I use the Harvard Business School patenting database, which includes unique inventor identifiers. The unique identifiers are based on refined disambiguation algorithms that separate similar inventors based on various characteristics (Lai, D'Amour, and Fleming, 2009). When patent applications include multiple inventors, I attribute a patent equally to each inventor. Overall, I have information on approximately 36,000 inventors in my sample. I restrict the analysis to inventors that produced at least a single patent both before and after the IPO filing and explore the patenting behavior of inventors in the three years before and five years after the IPO filing. I identify three inventor types:

1. Stayer – an inventor with at least a single patent before and after the IPO filing at the same sample firm.

2. Leaver – an inventor with at least a single patent at a sample firm before the IPO filing, and at least a single patent in a different company after the IPO filing.[36]

3. Newcomer – an inventor that has at least a single patent after the IPO filing at a sample firm, but no patents before, and has at least a single patent at a different firm before the IPO filing.

Out of the 36,000 inventors in my sample, I can classify 16,108 inventors by the above categories. These inventors account for approximately 65 percent of the patents in the sample.

In Panel A of Table 9, I compare the patenting activity of stayers, leavers and newcomers between IPO and withdrawn firms.[37] I first consider only IPO firms, and find that leavers produced more novel patents and a higher number of patents in the three years before the IPO filing than stayers, measured by scaled citations and scaled number of patents

[36] I verify that all inventor relocations are not mistakenly associated with acquisitions and name changes.

[37] An inventor can be classified as both a stayer and a leaver. In these cases, I classify her as a leaver. The results do not change in a meaningful way if I classify her as a stayer instead.

correspondingly. Interestingly, these patterns are reversed for withdrawn firms, as stayers produced higher quality patents before the IPO-filing while I find no significant differences in terms of number of patents. Next, I compare the post-IPO filing patents generated by stayers and newcomers. Newcomers in IPO firms produce more cited patents than stayers but fewer patents. Again, I find opposite results when considering withdrawn firms. The quality of patents produced by newcomers is lower than those of inventors who remained at the firm.

The results in Panel A, however, incorporate also the selection associated with the decision to complete the IPO filing. In Panel B, I consider the reduced form results, similarly to the approach used in Table 5. I compare firms that experienced a NASDAQ drop versus remaining filers in the same year. A firm is said to experience a NASDAQ drop if its post-filing NASDAQ returns are within the bottom annual 25 percent. As illustrated in Panel B of Table 9, leavers of firms that did not experience a NASDAQ drop (and thus are more likely to complete the IPO filing) produced higher quality innovation in the three years before the IPO filing, relative to stayers. This result is significant at the 1 percent level. However, no significant difference arises between stayers and leavers of firms that experienced a NASDAQ drop. Additionally, I no longer find significant differences between newcomers and stayers in either of the groups. Overall, the reduced form results illustrate that absent selection bias, going public leads to a departure of inventors that were responsible for higher-quality innovation than stayers, in contrast to withdrawn firms.

4.C.2 Inventor Level Analysis

I explore changes in inventor level activity using the instrumental variable approach introduced in Section 2.B. I start by investigating changes in innovation quality of stayers. Then, I examine inventor mobility by studying inventors' likelihood to leave or join the firm following the IPO filing.

The results are reported in Table 10, when the unit of observation is at the level of the inventor. In columns (1) and (2), I focus on the set of inventors that remained at the firm, and the dependent variable is the average scaled citations produced by inventors in the five years after the IPO filing. I control for the inventor's pre-IPO filing citations per patent, as well as filing year and industry fixed effects, VC-backed dummy, pre-IPO filing NASDAQ returns, and location within the IPO wave. Standard errors are clustered at the level of the firm, to allow for correlations between inventors in the same firm. I estimate the 2SLS-IV in column (1), and find that the IPO coefficient equals -1.094 and this effect is significant at a 1 percent level. The magnitude is large, corresponding to a 48 percent decline in inventors' innovation novelty in IPO firms relative to the pre-IPO filing period. I repeat the analysis in column (2) using the Poisson specification, and find a similar result. These findings suggest that the decline in IPO firms' innovative activity could be at least partially attributed to the change in quality of innovation produced by inventors who remained at the firm.

To estimate whether going public may affect inventors' departure, I focus on inventors that produced patents at the firm before the IPO filing, and explore their likelihood to leave. In column (3), the dependent variable equals one if the inventor is classified as a leaver, and zero if an inventor is a stayer. I control for the average quality of patents produced by an inventor in the pre-filing period, the number of patents produced, as well as other control variables used in previous specifications. Standard errors are clustered at the level of the firm. The 2SLS-IV estimates of column (3) illustrate that inventors in IPO firms are 18 percent more likely to leave the firm after the IPO, and the coefficient is significant at 1 percent.

A natural concern regarding the validity of the instrument in this setup is that NASDAQ returns may also reflect changes in the labor market conditions and thus correlate with the likelihood that an inventor will leave the firm. However, since the empirical exercise compares firms that filed in the same year and given the lengthy process of the job search, it may be reasonable to assume that employees of firms that filed to go public in the same year will face similar labor market conditions in the five years following the IPO filing. To verify the robustness of the results, I restrict the sample further by focusing only on stayers and late leavers, i.e., inventors who produced patents in a different firm for the first time at least three years after the IPO filing. This lag between the IPO filing event and the potentially late relocations may reduce the likelihood that the two-month NASDAQ change is correlated with future labor market conditions. I estimate this specification in column (4) and find that, in fact, the magnitude of the coefficient becomes larger, and employees at firms that went public are 27.5 percent more likely to leave the firm relative to withdrawn firms.[38] These results demonstrate that the decline in the quality of innovation of IPO firms is potentially driven also by the departure of inventors.

Finally, I explore whether IPO firms are more likely to attract new inventors. In order to address this question, in column (5) I restrict the analysis to inventors that generated post-filing patents in a sample firm and as a dependent variable I use an indicator that an inventor is a newcomer. Using the 2SLS-IV specification I find that IPO firms are substantially more likely to hire new inventors. The magnitude of the coefficient is large, corresponding to a 38.8 percent increase. In column (6), I repeat the same exercise as in column (4) and restrict attention to stayers and late newcomers who produce their first patent at least three years after the IPO filing. I find that the coefficient slightly decreases, but still highly significant, corresponding to a 35 percent increase in the likelihood of hiring newcomers.

The results reveal that the transition to public equity markets has important implications for the human capital accumulation process, as it shapes firms' ability to retain and attract inventors. Following the IPO, there is an exodus of inventors leaving the firm, and importantly, these inventors are those who are responsible for the more novel innovations before the IPO. Additionally, going public affects the productivity of the inventors who remained at the firm. The average quality of patents produced by stayers decline substantially at IPO firms. However, the effect is partially mitigated by the ability of IPO firms to attract new inventors who produce patents of higher quality than the inventors who remained at the

[38] The increase in frequency of inventor departure may reflect the vesting of the employees' stock options.

firm.

4.D Acquisition of External Technology

In this section, I explore how the transition to public equity markets affects firms' reliance on external technologies purchased through mergers and acquisitions. I collect information on all acquisitions conducted by IPO and withdrawn firms using the SDC database. As illustrated by Figure 4, I find that IPO firms exhibit a sharp increase in M&A activity following the IPO, while there is no meaningful effect for withdrawn firms. This pattern, which is consistent with Celikyurt, Sevilir, and Shivdasani (2010), is also evident in Panel A of Table 11, as the acquisition likelihood of IPO firms increases from 9 percent in the three years prior to the IPO to 66 percent in the five years following the event.

Acquisitions, however, are used for a variety of reasons. The question remains whether acquisitions are used to buy external technologies. I collect information on patents generated by target firms in the years prior to the acquisition, by matching acquisition targets to the NBER patents database. A complication arises since, as demonstrated in Panel B, approximately 30 percent of the acquisition targets are of firm subsidiaries. In these cases, it is difficult to identify whether assigned patents are generated by the parent firm or by the subsidiary. Therefore, I collect patent information on independent firms only. Given that almost all of the subsidiaries are acquired by IPO firms, the results underestimate the true contribution of acquisitions to the IPO firms' patent portfolio and provide only a lower bound.

The number of external patents acquired by IPO firms in the five years following the IPO filing is substantial. Approximately 7,500 patents were acquired through mergers and acquisitions in the five years following the IPO filing, relative to approximately 30,000 patents produced. As illustrated in panel C of Table 11, before the IPO filing both withdrawn and IPO firms rarely acquire external patents through M&A (the fractions of external patents in patent portfolio are 3 percent and 1 percent for withdrawn and IPO firms respectively).

However, in the five years following the IPO filing there is a dramatic change. The fraction of external patents in IPO firms' portfolio increases to 31 percent while it remains small for withdrawn firms (8 percent). This pattern is illustrated in Figure 5, demonstrating the annual likelihood of acquiring at least a single external patent per year.

The patterns described so far demonstrate a sharp increase in firms' reliance on external technologies following the IPO. Similar patterns arise when using the instrumental variable approach. Panel D of Table 11 shows that firms that experienced a NASDAQ drop, and thus are less likely to complete the IPO filing, acquire significantly fewer external patents relative to the rest of the filers in the same year (1.27 versus 4.70 patents in the subsequent five years). This pattern is also apparent in a multivariate IV analysis, even when controlling for industry acquisition propensity. In an unreported analysis, I find that in a multivariate regression analysis when instrumenting for IPO completion choice, IPO firms are 22.6% more likely to acquire external patents relative to withdrawn firms.

Given the substantial reliance on external patents, it is interesting to compare the external and internal patents of IPO firms. Panel E of Table 11 demonstrates that, on average, external patents exhibit higher quality than patents generated internally, measured by average scaled citations. Acquired patents are more likely to be in new technologies for which the firm had no patents before the IPO filing (and less likely to be in core technology classes) relative to the patents generated within the firm.

Overall, the results suggest that going public leads to enhanced reliance on external technologies. Interestingly, IPO firms acquired external patents mostly from private targets and patents acquired externally were of higher quality than patents produced internally.

5. Discussion and Interpretation

The empirical findings illustrate that going public has substantial effects on firms' strategies when pursuing innovation. The financing view suggests that the improved access to capital may allow firms to enhance their innovative activities by overcoming financial constraints. While I find that the transition to public equity markets enables firms to acquire external technologies and recruit new human capital, this view by itself cannot explain the decline in the quality of internal innovation, nor the departure of key inventors. In this section I consider two incentive-based explanations of the empirical findings.

A first explanation suggests that going public may affect managerial incentives which leads to a change in the type of innovative projects selected and a greater reliance on acquisitions of external technologies. For example, career concerns and takeover threats may pressure managers to select more conventional projects which can be more easily communicated to dispersed shareholders (Aghion, Van Reenen, and Zingales, 2009; Stein, 1989; Ferreira, Manso, and Silva, 2010). This effect may become even stronger if stock market misvalues innovation (Cohen, Diether, and Malloy, 2011). Similarly, He and Tian (2012) find that analysts coverage impede firm innovation as they exert pressure on managers to meet short-term goals.[39] These considerations may lead managers to exploit improved access to capital to acquire technologies externally, rather than developing them within the firm. The former strategy is attractive since acquisitions are easily observed, potentially less prone to failures, and quicker to implement. The shift in the focus toward more incremental projects internally and the greater reliance on external technologies may explain the departure of skilled entrepreneurial inventors. Thus, managerial incentives can explain the findings in the paper.

Going public may affect inventors' incentives as well. For example, the dilution in ownership claims of future innovations may lead inventors to pursue less ambitious projects, or alternatively leave the firm to implement their ideas in a private firm setting where they can capture a larger fraction of the returns for their innovation. Additionally, improved ability to cash out once stock options are vested may make key inventors less sensitive to financial

[39]When explaining the delay in Facebook's IPO, Mark Zuckerberg, founder and CEO, claimed that "being private is better for us right now because of some of the big risks we want to take in developing new products. ... Managing the company through launching controversial services is tricky, but I can only imagine it would be even more difficult if we had a public stock price bouncing around."(Facebook Blog, September 2010).

incentives.[40] This suggests that following the IPO it may be more difficult to provide appropriate incentives for inventors and therefore less feasible to induce them to pursue high quality innovation internally. This, in turn, may force managers, regardless of the change in their incentives, to rely more heavily on the acquisition of external technologies. Hence, changes in incentives to inventors, associated with the transition to public equity markets, can be similarly consistent with the findings of a decline in novelty of internal innovation, departure of skilled inventors, and greater reliance on acquisitions.

5.A Suggestive Evidence

While both incentive-based theories can explain the empirical findings, they have different implications. The managerial incentives explanation suggests that corporate governance considerations may lead managers to select more incremental innovative projects. The inventor incentives theory suggests that providing appropriate incentives to inventors is difficult in a publicly traded firm setting and therefore, irrespective of managerial preferences, leads to less productive internal innovation. Testing directly the inventor incentives hypothesis is difficult due to the lack of information on inventors' compensation. However, in this section I provide some suggestive evidence supporting the managerial incentives theory.

To explore whether managerial incentives affect innovation, I consider the case of managerial entrenchment. A more entrenched CEO may be harder to replace, and thus less likely to be sensitive to market pressures. I capture managerial entrenchment by investigating whether the CEO is also the chairman of the board (Shleifer and Vishny, 1989). The CEO's dual role as chief executive and chairman of the board implies that the CEO can direct board initiatives affecting the CEO's job security and compensation, as well as

[40]Google's IPO Prospectus provides some anecdotal evidence. As claimed in the risk factors section of its IPO filing: "The initial option grants to many of our senior management and key employees are fully vested. Therefore, these employees may not have sufficient financial incentives to stay with us."(Google's prospectus, p. 13).

responding to takeover threats.[41] Inventors' incentives, however, are plausibly not affected directly by whether the CEO is also the chairman of the board, making it possible to test the managerial incentives hypothesis separately from the inventor incentives hypothesis.

I manually collect information on board characteristics from S-1 filings, to determine whether the CEO is also the chairman at the time of the IPO. Since S-1 filings are available through the SEC Edgar system from 1996, the number of observations in this analysis is smaller. In Table 12, I repeat the IV analysis to explore the effect of going public on innovation novelty separately for IPO firms with and without an entrenched CEO. In column (1), I find that when the CEO is the chairman of the board, the decline in innovation novelty following the IPO is not significant with a magnitude of a 20.1 percent decline relative to the pre-IPO period. In column (2) I contrast this result with the case where the CEO is not the chairman of the board: here, going public is associated with a decline of 64 percent in the novelty of patents produced in the five years following the IPO, significant at 5 percent. In columns (3) and (4) I repeat the analysis with respect to the likelihood of inventors to leave the firm. In column (3), I find that when the CEO is the chairman, the likelihood of inventors leaving the firm is negative, yet insignificant, relative to firms that remained private. When the CEO is not the chairman, however, column (4) demonstrates that inventors are 10.8 percent more likely to leave, consistent with the decline in innovation quality. These results provide some evidence of the importance of managerial incentives in generating innovation, and its subsequent effect on individuals' behavior within the firm.

6. Conclusion

In this paper, I investigate an important but yet understudied aspect of initial public offerings, namely, the effect on firm innovation. I find that the transition to public equity

[41] An alternative test for managerial entrenchment applies in cases in which the CEO is also the founder. I collected information on firm founders from initial registration statements, and in unreported analyses explore the effects of CEO-founder on innovation. I find similar results to those found when the CEO is also the chairman of the board.

markets has a substantial effect on firms' innovative activities along three dimensions. First, it changes the nature of projects pursued by the firm as internal innovation becomes less novel, and relies on a narrower set of technologies. Second, going public generates substantial employee turnover. Key inventors are more likely to leave the firm, and the productivity of remaining inventors declines, while at the same time firms attract new human capital to the firm. Going public also affects firm boundaries, as firms rely more heavily on the acquisition of external technologies.

Estimating the IPO effects on innovation is challenging due to the inherent selection bias associated with the decision to go public. The empirical strategy in this paper compares firms that went public with firms that intended to go public, but ultimately withdrew their IPO filing and remained private. To overcome the selection to complete the IPO filing, I use NASDAQ fluctuations during the book-building phase as an instrument.

The findings in this paper reveal a complex trade-off between public and private ownership forms. While private firms are able to generate more novel innovation and retain skilled inventors, public firms can rely on acquisitions of external technologies and attract human capital. These results have implications for determining the optimal point at which a firm should go public during its life cycle.

The results also draw attention to the effects of IPO on both the ability of firms to retain and attract human capital and on the productivity of the remaining inventors. Seru's (2011) study of the impact of mergers on innovation has found that mergers affect mostly the productivity of inventors remaining at the firm, rather than affecting their likelihood to leave. The difference in results suggests that productivity changes that coincide with various corporate events such as mergers and IPOs are nuanced, heterogeneous, and require better understanding.

This paper does not address the general equilibrium effects of the IPO market on innovation and its corresponding welfare consequences. Yet, the results suggest that there may be important complementarities between public and private ownership structures. While private ownership may allow firms to pursue more ambitious innovations, improved access to capital may allow public firms to acquire technologies, mostly from private firms. This suggests that ownership structure plays an important role in shaping the market for technologies.

Finally, corporate managers, bankers, and policy makers alike have expressed concerns that the recent dearth of IPOs marks a breakdown in the engine of innovation and growth (Weild and Kim, 2009). Some blame the Sarbanes-Oxley Act (SOX) for raising the costs of compliance for publicly traded firms.[42] Regardless of the role of SOX in explaining the recent IPO cycle, policy prescriptions of this sort raise the question of whether the transition to public equity markets affects innovation and if so how. This paper contributes to the debate by demonstrating that, ex-post, IPOs may affect overall innovation, and these effects may also be indirect. While internal innovation novelty declines following the IPO, it allows public firms to acquire entrepreneurial firms, and thus, potentially facilitates innovation through increased demand for new technologies.

[42]In the hope that IPO market stimulation will "jumpstart innovation and job creation," President Obama's Council on Jobs and Competitiveness has urged Congress to amend the Sarbanes-Oxley Act to allow small companies to tap public equity markets.

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Table 1 - Summary Statistics

The table reports summary statistics of the key variables in the analysis, defined in the Appendix. Panel A describes the distribution of IPO filings and patents over time. Panels B and C detail the distribution of firms across industries and the distribution of patents across technology classes. The industry classification is based on Fama-French 10, and the technology classification is based on Hall, Jaffe, and Trajtenberg (2001). Panel D describes average innovative measures in the three years up to (and through) the IPO filing year. Panel E provides information on firm characteristics at the time of filing. Panel F describes firm exit characteristics in the five years after the IPO filing, where firm exits are corporate events such as acquisition, bankruptcy, or an IPO for withdrawn firms. *, **, and *** indicate that differences in means are statistically significant at the 10%, 5%, and 1% levels.

Panel A - Distribution by year

	IPO Filing		Patent Applications		Patent Grants	
Year	Complete	Withdrawn	Complete	Withdrawn	Complete	Withdrawn
1983	N/A	N/A	4	2	0	0
1984	N/A	N/A	18	9	1	0
1985	4	2	16	8	9	8
1986	10	5	58	18	9	5
1987	11	6	111	17	39	11
1988	14	4	202	34	62	13
1989	42	6	356	74	147	27
1990	34	10	527	86	231	56
1991	120	2	715	62	321	59
1992	119	33	1169	125	525	68
1993	144	14	1457	106	797	89
1994	105	18	2152	162	1050	87
1995	140	8	3568	318	1309	94
1996	169	29	3220	262	1760	133
1997	114	25	3857	444	2298	199
1998	66	20	3672	509	3317	310
1999	169	15	4249	634	3658	388
2000	167	95	4225	586	3360	457
2001	17	13	4144	555	3448	531
2002	12	17	3082	431	3483	517
2003	21	1	1795	256	3678	533
2004	N/A	N/A	616	117	3547	465
2005	N/A	N/A	89	20	2943	376
2006	N/A	N/A	4	0	3314	409
Total	1478	323	39306	4835	39306	4835

Panel B - Distribution by industry

Industry	Complete	Withdrawn
Consumer Non-Durables	2.77%	3.10%
Consumer Durables	3.04%	2.17%
Manufacturing	10.15%	11.46%
Oil, Gas, and Coal Extraction	0.74%	0.93%
Computers, Software, and Electronic Equipment	49.32%	39.94%
Telephone and Television Transmission	1.89%	3.10%
Wholesale, Retail	2.71%	4.95%
Healthcare, Medical Equipment, and Drugs	24.22%	29.10%
Utilities	0.41%	0.31%
Other (Mines, Construction, Hotels, etc.)	4.74%	4.95%

Panel C - Distribution of patents across technology classes

Technology Class	Complete	Withdrawn
Chemical	9.43%	11.15%
Computers and Communication	35.11%	26.29%
Drugs and Medicine	21.84%	28.25%
Electronics	18.57%	17.91%
Mechanical	8.67%	7.40%
Other	6.38%	9.00%

Panel D - Average innovation measures in the three years before (and through) the IPO filing year

	Complete			Withdrawn			
	Mean	Median	S.D.	Mean	Median	S.D.	Difference
Citations	12.69	7.25	21.60	10.91	6.00	16.83	1.78
Scaled Citations	1.89	1.41	1.73	1.80	1.31	1.94	0.09
Number of Patents	8.20	2.00	50.06	7.00	2.00	15.00	1.21
Scaled Number of Patents	2.96	0.85	11.16	2.72	0.93	5.07	0.24
Generality	0.45	0.47	0.21	0.46	0.50	0.22	−0.01
Originality	0.47	0.50	0.21	0.48	0.49	0.23	−0.01
Scaled Best patent	4.30	2.89	5.71	4.00	2.49	4.92	0.31

Panel E - Firm characteristics and market conditions at the time of the IPO filing

	Complete			Withdrawn			
	Mean	Median	S.D.	Mean	Median	S.D.	Difference
Financial Information at IPO filing (from 1996)							
Log Total Assets	3.07	2.91	0.05	2.97	2.93	0.11	−0.09
R&D / Assets	0.29	0.21	0.31	0.29	0.19	0.31	0.01
Net Income / Assets	−0.31	−0.11	0.48	−0.44	−0.21	0.47	0.13***
Cash / Assets	0.28	0.20	0.26	0.36	0.32	0.29	−0.08***
IPO Characteristics							
Lead Underwriter Ranking	8.16	9.00	1.27	8.17	9.00	1.33	−0.01
Firm age	11.94	8.00	10.98	11.14	7.00	10.38	0.80
VC-Backed	0.46	0.00	0.50	0.51	1.00	0.50	−0.05*
Post-filing NASDAQ returns	0.03	0.03	0.11	−0.06	−0.05	0.14	0.09***
Pre-filing NASDAQ returns	0.07	0.06	0.12	0.05	0.05	0.16	0.02***
Pioneer	0.02	0.00	0.14	0.03	0.00	0.17	−0.01
Early follower	0.05	0.00	0.22	0.07	0.00	0.26	−0.02

Panel F - Firm exits in the five years after the IPO filing

Exit Type	Complete	Withdrawn
Bankruptcy	2.30%	2.48%
Second IPO	0.00%	18.10%
Acquisition	24.02%	29.10%

Table 2 - NASDAQ Drops and Firm Characteristics

The table presents differences in firm characteristics and innovative performance between IPO filers that experienced a NASDAQ drop and other filers in the same year. A firm is said to experience a NASDAQ drop if the two month NASDAQ returns it experienced following the IPO-filing is at the bottom of the distribution of all IPO filers in the same year. In column (1), *Bottom 10%* defines all firms that experienced the lowest 10% NASDAQ returns of all IPO filers within a year, and *Top 90%* in column (2) captures the remaining firms. In column (4), *Bottom 25%* defines all firms that experienced the lowest 25% NASDAQ returns within a year, and *Top 75%* captures all remaining firms. Innovative measures are based on the three years up to (and through) the IPO filing. Variables are defined in the Appendix. *, **, and *** indicate that differences in means are statistically significant at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
NASDAQ Returns Threshold:	Bottom 10%	Top 90%	Difference	Bottom 25%	Top 75%	Difference
Pre-Filing Financials Information						
Total Assets	3.16	3.06	0.104	3.13	3.05	0.077
R&D / Assets	0.26	0.26	0.007	0.26	0.26	−0.002
Net Income / Assets	−0.32	−0.33	0.008	−0.34	−0.33	−0.014
Cash / Assets	0.32	0.28	0.036	0.30	0.29	0.013
Sales / Assets	0.86	0.89	−0.024	0.85	0.90	−0.051
IPO Characterisitics						
Lead Underwriter Ranking	8.22	8.09	0.124	8.19	8.08	0.110
Firm age at filing	11.87	11.81	0.068	11.10	12.05	−0.946
VC backed	0.46	0.49	−0.029	0.49	0.50	−0.011
Pre-Filing Patents Characteristics:						
Citations	13.38	12.48	0.905	12.63	12.57	0.064
Scaled Citations	1.81	1.87	−0.070	1.92	1.85	0.072
Number of Patents	8.53	7.92	0.603	6.97	8.32	−1.354
Scaled Number of Patents	3.21	2.88	0.330	2.67	2.99	−0.326
Scaled Generality	1.11	1.12	−0.020	1.14	1.12	0.023
Scaled Originality	1.03	1.07	−0.039	1.06	1.07	−0.017
Scaled Best Patent	4.06	4.26	−0.197	4.45	4.17	0.277

Table 3 - Within-firm relationship between IPOs and Innovation

The table presents within-firm changes in innovative activity around the IPO of firms that completed the IPO filing. The dependent variables are stated at the top of each column. In columns (1) to (6), a patent is the unit of observation, while in columns (7) and (8) firm-year is the unit of observation. *Event Year* are dummy variables indicating the relative year around the IPO event (the omitted category is the year of the IPO). Variables are defined in the Appendix. The estimated model is Ordinary Least Squares (OLS), and standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Citations	Scaled Citations	Originality	Scaled Originality	Generality	Scaled Generality	Patents	Scaled Patents
Event Year -3	3.086***	0.209	0.014	0.048	0.033**	0.053	−0.330	−0.215*
	(1.035)	(0.185)	(0.021)	(0.039)	(0.014)	(0.047)	(0.438)	(0.113)
Event Year -2	3.752***	0.406***	0.022**	0.065***	0.019*	0.041	−0.192	−0.141
	(0.843)	(0.135)	(0.011)	(0.025)	(0.010)	(0.029)	(0.345)	(0.092)
Event Year -1	1.873***	0.214**	0.002	0.006	0.008	0.009	0.022	−0.039
	(0.475)	(0.089)	(0.012)	(0.027)	(0.008)	(0.026)	(0.282)	(0.065)
Event Year 1	−2.422***	−0.342***	−0.009	−0.018	−0.007	−0.001	0.069	0.060
	(0.450)	(0.077)	(0.006)	(0.016)	(0.007)	(0.023)	(0.209)	(0.062)
Event Year 2	−3.677***	−0.384***	−0.017**	−0.046***	−0.015*	−0.024	−0.265	−0.049
	(0.558)	(0.086)	(0.007)	(0.018)	(0.007)	(0.024)	(0.428)	(0.113)
Event Year 3	−4.748***	−0.597***	−0.017**	−0.054***	−0.026***	−0.063**	−0.197	−0.049
	(0.635)	(0.094)	(0.008)	(0.020)	(0.009)	(0.029)	(0.468)	(0.132)
Event Year 4	−5.739***	−0.662***	−0.022**	−0.072***	−0.032***	−0.063*	0.091	−0.002
	(0.789)	(0.110)	(0.009)	(0.022)	(0.011)	(0.036)	(0.486)	(0.150)
Event Year 5	−6.991***	−0.719***	−0.024**	−0.075***	−0.029**	−0.046	−0.216	−0.100
	(0.870)	(0.121)	(0.010)	(0.024)	(0.013)	(0.045)	(0.433)	(0.152)
Observations	39,306	39,306	38,093	38,093	35,232	35,232	13,302	13,302
R-squared	0.039	0.014	0.010	0.002	0.017	0.002	0.037	0.045
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes

Table 4 - First Stage

The table reports the first-stage estimation of the instrumental variables analysis. The dependent variable is a dummy that equals to one if a firm completed the IPO filing, and zero otherwise. *NASDAQ returns* variable is constructed differently across specifications. In the *Two Months* specification (columns (1) to (4)), NASDAQ returns are the two-month returns after the IPO filing date. In columns (5) and (6), *All* specification indicates that NASDAQ returns are calculated over the entire book-building period, i.e., from the date of the initial registration statement to the completion or withdrawal dates. Finally, *Binary* in columns (7) and (8) uses a dummy variable and is equal to one if a firm has experienced a NASDAQ drop. A firm is said to have experienced a NASDAQ drop if the two-month NASDAQ returns from the date of the IPO filing are within the bottom 25 percent of all filers in the same year. In columns (3) and (4) the sample is restricted to IPO filings before the year 2000. When control variables are included, the following variables are added to the specification: three-month NASDAQ returns prior to the IPO filing, number of patents in the three years before the IPO filing, VC-backed dummy, Pioneer and Early Follower variables. The variables are defined in the Appendix. The estimated model is Ordinary Least Squares (OLS), and robust standard errors are calculated in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Full	Full	Pre-2000	Pre-2000	Full	Full	Full	Full
Instrument	Two Months	Two Months	Two Months	Two Months	All	All	Binary	Binary
NADSAQ returns	0.704***	0.763***	0.690***	0.723***	0.381***	0.400***	−0.106***	−0.111***
	(0.102)	(0.106)	(0.128)	(0.132)	(0.080)	(0.081)	(0.022)	(0.022)
Observations	1,801	1,801	1,458	1,458	1,801	1,801	1,801	1,801
R-squared	0.138	0.149	0.082	0.089	0.127	0.136	0.124	0.134
Filing year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Control variables	no	yes	no	yes	no	yes	no	yes
F-stat	47.79	52.03	28.9	29.9	22.63	24.13	24.16	25.99

Table 5 - Reduced Form

The table reports differences in the five-year innovative performance following the IPO filing between filers that experienced a NASDAQ drop and other filers in the same year that did not experience a NASDAQ drop. A firm is said to have experienced a NASDAQ drop if the two-month NASDAQ returns after the IPO filing are within the bottom 25 percent of all filers in the same year. This comparison is equivalent to a reduced form estimation when the instrument is binary and equals one if a firm experienced a NASDAQ drop. *IPO* is a dummy variable that is equal to one if a firm completed its IPO filing, and zero otherwise. Variables are described in the Appendix. *, **, and *** indicate that the difference in means is statistically signicant at the 10%, 5%, and 1% levels.

	NASDAQ Drop			No NASDAQ Drop			
	Mean	Median	S.D.	Mean	Median	S.D.	Difference
IPO	0.74	1.00	0.44	0.85	1.00	0.36	−0.111***
Scaled Citations	1.12	0.88	1.21	0.99	0.81	0.86	0.134**
Scaled Number of Patents	5.56	1.91	12.42	5.91	1.49	16.64	−0.351
Scaled Generality	1.10	1.10	0.67	1.10	1.09	0.67	−0.005
Scaled Originality	1.09	1.09	0.39	1.04	1.06	0.43	0.047*
Scaled Best Patent	3.61	2.10	4.66	2.89	1.94	3.13	0.721***

Table 6 - Innovation Novelty

The table reports the effect of an IPO on innovation novelty. The dependent variable is the average scaled citations in the five years after the IPO filing. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. *NASDAQ returns* variable is the two-month NASDAQ returns calculated from the IPO filing date. Control variables included in the regressions are: pre-filing average scaled citations, pre-filing average scaled number of patents per year, Pioneer, Early follower, VC-backed dummy, and the three-month NASDAQ returns before the IPO filing. Variables are described in the Appendix. In columns (1) and (2) the estimated model is Ordinary Least Squares (OLS), and Two-stage Least Squares (2SLS) in column (3). Column (4) estimates the instrumental variables approach using a quasi maximum likelihood Poisson model. In all specifications, marginal effects are reported. The standard errors in column (4) are corrected using the delta method. *Magnitude* is the ratio of the *IPO* coefficient to the pre-filing average of scaled citations. Robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Model	OLS	OLS	2SLS-IV	Poisson-IV
IPO	−0.019		−0.831**	−0.980**
	(0.069)		(0.409)	(0.427)
NASDAQ returns		−0.498**		
		(0.239)		
Magnitude	-1.02%	-	-43.51%	-52.41%
Observations	1,079	1,079	1,079	1,079
R-squared	0.239	0.242	0.128	0.148
Filing year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Control variables	yes	yes	yes	yes

Table 7 - Fundamental Nature of Research

The table reports the effect of an IPO on the fundamental nature of research. In columns (1) to (3) the dependent variable is the average Scaled Originality in the five years after the IPO filing, and in columns (4) to (6) it is average Scaled Generality. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. *NASDAQ returns* variable is the two-month NASDAQ returns calculated from the IPO filing date. In columns (1) to (3) I control for the pre-filing average scaled originality, and in columns (4) to (6) I control for the corresponding generality measure. Additional control variables are: pre-filing average scaled citations, pre-filing average scaled patents per year, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ returns before the IPO filing. Variables are described in the Appendix. The estimated model is OLS, and two-stage least squares in columns (3) and (6). *Magnitude* is the ratio of *IPO* coefficient to the pre-filing average of scaled originality or scaled generality per patent. Robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Scaled Originality	Scaled Originality	Scaled Originality	Scaled Generality	Scaled Generality	Scaled Generality
Model	OLS	OLS	2SLS - IV	OLS	OLS	2SLS - IV
IPO	−0.006		−0.137**	−0.001		−0.087
	(0.010)		(0.068)	(0.016)		(0.092)
NASDAQ returns		−0.081**			−0.050	
		(0.036)			(0.051)	
Magnitude	-0.10%	-	-13%	0%	-	-8%
Observations	1,079	1,079	1,079	1,079	1,079	1,079
R-squared	0.231	0.234	0.102	0.226	0.226	0.206
Filing year FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes

Table 8 - Innovation Scale

The table reports the effect of an IPO on innovation scale. The dependent variable is the average scaled number of patents per year in the five years after the IPO filing. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. *NASDAQ returns* variable is the two-month NASDAQ returns calculated from the IPO filing date. Control variables included in regressions are: pre-filing average scaled citations, pre-filing average scaled number of patents per year, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ returns before the IPO filing. Variables are described in the Appendix. In columns (1) to (4), the pre-filing period is within the range of [-3,0] years around the IPO filing, while the post-IPO corresponds to the years [1,5]. In column (5), the pre-filing period covers the years [-3,1] around the IPO filing while the years [2,5] are used to calculate the post-IPO filing measure. The estimated model is OLS in columns (1) and (2), and two-stage least squares in column (3). Columns (4) and (5) estimate the specification using a quasi maximum likelihood Poisson model. In all specifications, marginal effects are reported. In columns (5)-(6) standard errors are corrected using the delta method. *Magnitude* is equal to the ratio of the *IPO* coefficient, divided by the pre-filing scaled number of patents per year. Robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample	post	post	post	post	post plus
Dependent Variable	Scaled Patents	Scaled Patents	Scaled Patents	Scaled Patents	Scaled Patents
Model	OLS	OLS	2SLS - IV	Poisson IV	Poisson IV
IPO	0.268***		0.200	0.002	−0.003
	(0.066)		(0.474)	(0.662)	(1.067)
NASDAQ returns		0.127			
		(0.305)			
Magnitude	37.75%		28.17%	0.28%	-0.12%
Observations	1,801	1,801	1,801	1,801	1,458
R-squared	0.184	0.178	0.184	0.168	0.174
Filing year FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes	yes

Table 9 - Inventor Summary Statistics

The table reports summary statistics of innovative activity of 16,108 inventors with at least a single patent application before and after the IPO filing date. Inventors are classified into three categories. A *stayer* is an inventor with at least a single patent before and a single patent after the IPO filing at the same sample firm. A *leaver* is an inventor with at least a single patent at a sample firm before the IPO filing, and at least a single patent in a different company after the IPO filing. A *newcomer* is an inventor who has at least a single patent after the IPO filing at a sample firm, but no patents before, and has at least a single patent at a different firm before the IPO filing. Panel A compares the innovative activity of stayers, newcomers and leavers of IPO and withdrawn firms. Panel B compares the innovative activity of stayers, newcomers, and leavers of firms that experienced a NASDAQ drop versus other filers in the same year. A firm is said to experience a NASDAQ drop if the two-month NASDAQ returns from the date of the IPO filing are within the bottom 25 percent of all filers in the same year. Variables are described in the Appendix. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A - Complete vs. Withdrawn IPOs

	IPO Firms					Withdrawn Firms				
	count	mean	count	mean	difference	count	mean	count	mean	difference
Pre-IPO Filing:	*Leavers*		*Stayers*			*Leavers*		*Stayers*		
Scaled Citations	3743	2.37	3806	2.12	0.253***	708	2.36	558	2.74	−0.374**
Scaled Number of Patents	3743	1.1	3806	1.01	0.088***	708	1.21	558	1.29	−0.085
Post-IPO Filing:	*Newcomers*		*Stayers*			*Newcomers*		*Stayers*		
Scaled Citations	6787	1.62	3806	1.41	0.210***	506	1.4	558	3.11	−1.709***
Scaled Number of Patents	6787	0.86	3806	1.28	−0.423***	506	0.86	558	1.14	−0.274***

Panel B - Reduced Form

	No NASDAQ Drop					NASDAQ Drop				
	count	mean	count	mean	difference	count	mean	count	mean	difference
Pre-IPO Filing:	*Leavers*		*Stayers*			*Leavers*		*Stayers*		
Scaled Citations	3351	2.38	3370	2.15	0.224***	1100	2.34	994	2.34	0.001
Scaled Number of Patents	3351	1.10	3370	1.05	0.045	1100	1.17	994	1.02	0.146*
Post-IPO Filing:	*Newcomers*		*Stayers*			*Newcomers*		*Stayers*		
Scaled Citations	5665	1.58	3370	1.58	0.007	1628	1.67	994	1.80	−0.120
Scaled Number of Patents	5665	0.86	3370	1.30	−0.437***	1628	0.84	994	1.13	−0.296***

Table 10 - Inventor Mobility and Changes in Innovative Productivity

The table reports the effects of an IPO on inventors' mobility and innovative activity. Inventors are classified into three categories. A *stayer* is an inventor with at least a single patent before and a single patent after the IPO filing at the same sample firm. A *leaver* is an inventor with at least a single patent at a sample firm before the IPO filing, and at least a single patent in a different company after the IPO filing. Finally, a *newcomer* is an inventor who has at least a single patent after the IPO filing at a sample firm, but no patents before, and has at least a single patent at a different firm before the IPO filing. In columns (1) and (2) the sample is restricted to stayers and the dependent variable is the average scaled citations after the IPO filing. In columns (3) and (4), the sample includes stayers and leavers, and the dependent variable equals to one if inventor left the firm. In columns (5) and (6) the sample includes stayers and newcomers, and the dependent variable equals to one if the inventor joined the firm. *Late Leavers* includes in the sample stayers and leavers who patented in a different firm for the first time three years after the IPO filing. *Late Newcomers* includes in the sample stayers and newcomers that produced their first patent in a sample firm at least three years after the IPO filing. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. The instrument is the two-month NASDAQ returns calculated from the IPO filing date. In all specifications I control for the average scaled citations and scaled number of patents before the IPO filing of the inventor. Additional control variables are: Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ return before the IPO filing. Variables are described in the Appendix. All models, except column (2), are estimated using two-stage least squares. Column (2) estimates the instrumental variable approach using a quasi maximum likelihood Poisson model. *Magnitude* is equal to the *IPO* coefficient, divided by the pre-filing average scaled citations. Robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Citations of Stayers	Citations of Stayers	Likelihood to leave	Likelihood to leave	Likelihood to hire	Likelihood to hire
Description	Full Sample	Full Sample	Full Sample	Late Leavers	Full Sample	Late Newcomers
Model	2SLS - IV	Poisson-IV	2SLS - IV	2SLS - IV	2SLS - IV	2SLS - IV
IPO	−1.094**	−1.169***	0.183***	0.275***	0.388***	0.351***
	(0.457)	(0.397)	(0.062)	(0.070)	(0.078)	(0.069)
Magnitude	-47.94%	-51.23%	-	-	-	-
Observations	6,657	6,657	8,773	5,678	11,678	9,334
R-squared	0.203	0.245	0.017	0.043	0.058	0.084
Filing year FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes	yes	yes

Table 11 - Acquisition of External Technologies

The table reports summary statistics of firm acquisitions in the three years before and five years after the IPO filing. Panel A compares IPO firms and withdrawn firms and their respective M&A activity before and after the IPO filing. Panel B details the ownership status of target firms. Panel C describes the summary statistics of acquisitions of targets with patents. Panel D is a simplified reduced form table, illustrating differences in likelihood to acquire external patents between filers that experienced a NASDAQ drop and other filers in the same year. A firm is said to have experienced a NASDAQ drop if the two-month NASDAQ returns after the IPO filing is within the bottom 25 percent of all filers in a given year. Panel E compares internal patents generated by IPO firms after they went public with the external patents they acquired through mergers and acquisitions. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A - Acquisitions before and after IPO filing

	Complete	Withdrawn	Difference
Three years pre-IPO filing			
Total number of acquisitions	178	46	-
Avg. number of acquisitions per firm	0.12	0.14	-0.022
Likelihood to acquire at least a single firm	0.09	0.10	-0.009
Amount spent on acquisitions	3.94	7.05	-3.113
Five years post-IPO filing			
Total number of acquisitions	4043	428	-
Avg. number of acquisitions per firm	2.27	0.59	1.688***
Likelihood to acquire at least a single firm	0.66	0.24	0.419***
Amount spent on acquisitions	173.47	41.64	131.8***

Panel B - Target ownership status

Ownership Status		
Public	324	7.98%
Public Sub.	604	14.88%
Private Sub.	585	14.41%
Private	2,547	62.73%
Total Public	928	22.86%
Total Private	3,132	77.14%

Panel C - Acquisitions of external patents

Three years pre-IPO filing	Complete	Withdrawn	difference
Avg. number of external patents per firm	0.08	0.14	-0.057
Likelihood to buy an external patent	0.01	0.02	-0.006
Fraction of external patents in portfolio	0.01	0.03	-0.013

Five years post-IPO filing	Complete	Withdrawn	difference
Avg. number of external patents per firm	4.91	0.84	4.066**
Likelihood to buy an external patent	0.16	0.06	0.097***
Fraction of external patents in portfolio	0.31	0.08	0.229***

Panel D - Reduced form

Pre IPO-filing	No NASDAQ Drop	NASDAQ Drop	difference
Number external patents per firm	0.09	0.04	-0.046
Likelihood to buy an external patent	0.01	0.01	-0.000
Fraction of external patents in portfolio	0.02	0.01	-0.004

Post IPO-filing	No NASDAQ Drop	NASDAQ Drop	difference
Number of external patents per firm	4.70	1.27	3.424***
Likelihood to buy an external patent	0.15	0.07	0.083***
Fraction of external patents in portfolio	0.28	0.12	0.153***

Panel E - Comparing external and internal patents of IPO firms

	Internal	External	difference
Citations	7.563	10.709	-3.145***
Scaled citations	1.45	1.65	-0.196**
Core technology	0.659	0.501	0.157***
New technology	0.271	0.456	-0.185***

Table 12 - Suggestive Evidence of Underlying Channel

The dependent variables are listed separately in each column. In columns (1)-(2), the unit of observation is at the firm level and the dependent variable is the average scaled citations in the five years after the IPO filing. In columns (3)-(4), the unit of observation is at the individual level, inventors are included in the sample only if they are either a *stayer* or *leaver*, and the dependent variable is a dummy indicating whether an individual is a leaver. Stayer and leaver classifications are defined in Table 8 and in the text. In sub-sample *Chair*, the sample includes all withdrawn firms and only IPO firms that at the time of the IPO filing the CEO acts as the chairman of the board. The *No Chair* sub-sample includes all withdrawn firms and only IPO firms that at the time of the IPO filing the CEO is not the chairman of the board. Information about CEO position is collected from initial registration statements which are available from 1996. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. The instrument is the two-month NASDAQ returns calculated from the IPO filing date. All specifications include the following control variables: average scaled citations before the IPO filing, pre-filing average scaled number of patents, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ return before the IPO filing. Variables are described in the Appendix. All models are estimated using two-stage least squares. *Magnitude* equals to the *IPO* coefficient divided by the pre-filing average scaled citations of the firms in the respective sample. Robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	Scaled Citations	Scaled Citations	Likelihood to Leave	Likelihood to Leave
Sub-sample	Chair	Not Chair	Chair	Not Chair
IPO	−0.359	−1.193**	−0.140	0.108*
	(0.529)	(0.558)	(0.086)	(0.065)
Magnitude	-20.17%	-64.14%	-	-
Observations	325	428	2,626	4,292
R-squared	0.207	0.247	0.049	0.032
Filing year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Control variables	yes	yes	yes	yes

Figure 1 - NASDAQ Fluctuations and IPO Withdrawals

The figure illustrates the sensitivity of IPO filings to NASDAQ fluctuations. The sample includes all IPO filings from 1985 through 2003 in the United States, after excluding unit investment trusts, Closed-end funds, REITs, Limited partnerships, and financial companies. Overall there are 8563 IPO filings, with 6958 complete registrations and 1605 withdrawn registrations. The dashed line is the fraction of monthly filings that ultimately withdrew their registration. The solid line is the two-month NASDAQ returns calculated from the middle of each month. The correlation of the two plots is -0.44, and -0.34 before 2000. Both correlations are significantly different from zero at 0.01% level.

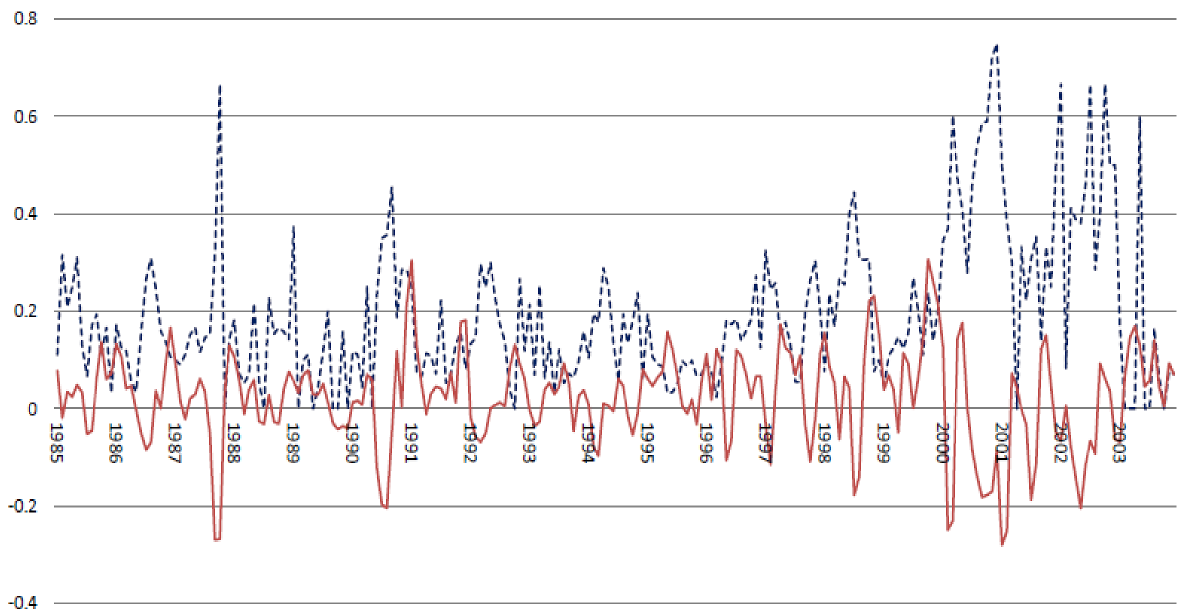


Figure 2 - Quality of Innovation around the IPO Event

The figure presents changes in patent quality, measured by scaled citations, in the years around the IPO (year zero is the year of the IPO event). The chart estimates and confidence intervals are taken from the year dummy variables in the second column of Table 3.

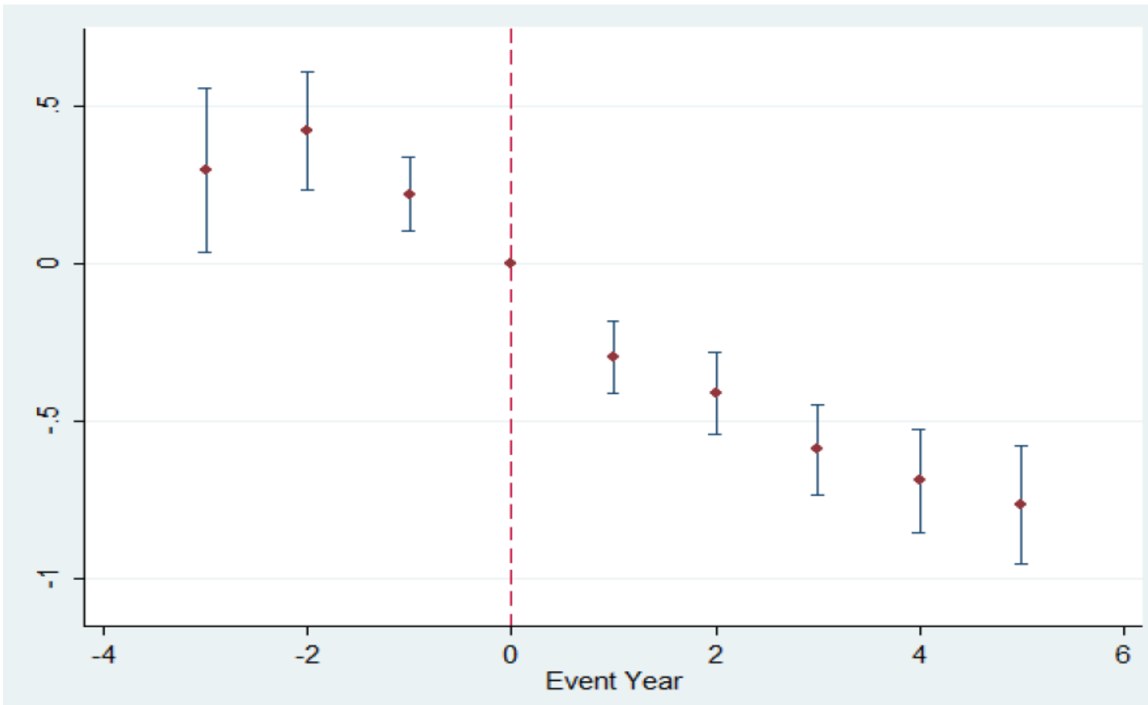


Figure 3 - Two-month NASDAQ fluctuations and IPO completion likelihood

The figure presents the non-parametric association of the two-month post-IPO filing NASDAQ returns and the likelihood to complete the IPO filing of firms in the sample.

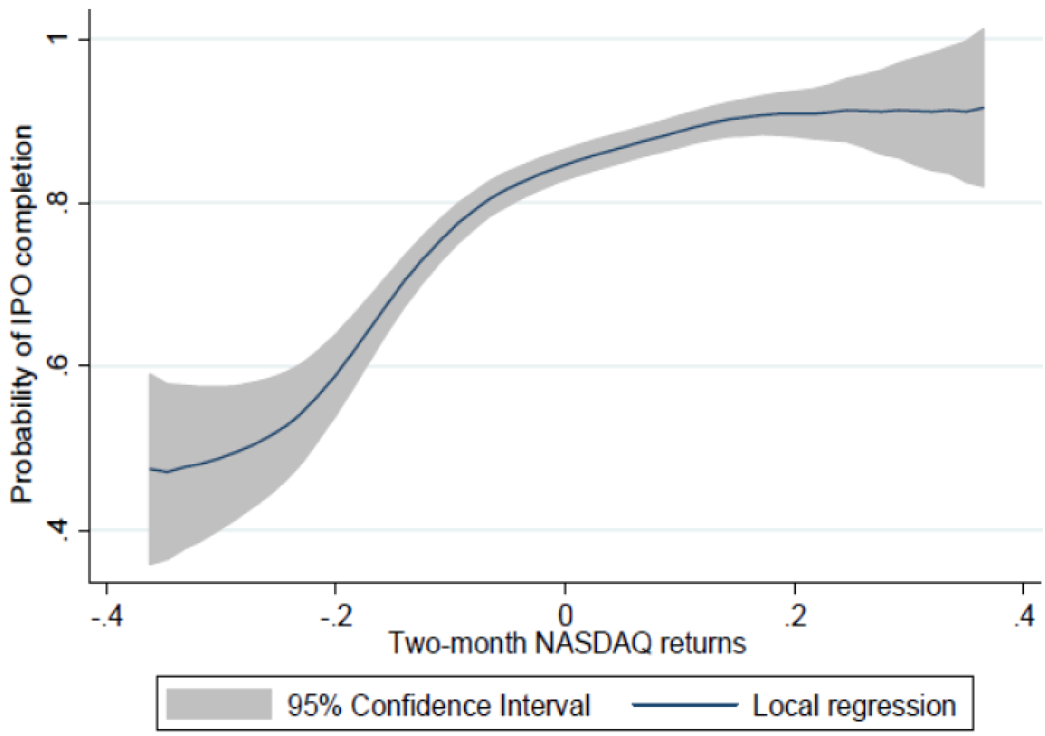


Figure 4 - Acquisition Likelihood

The figure presents the annual probability to acquire at least a single firm in the three years before and five years after the IPO filing. The solid line describes filers that completed the IPO filing, and the dashed line corresponds to withdrawn filers.

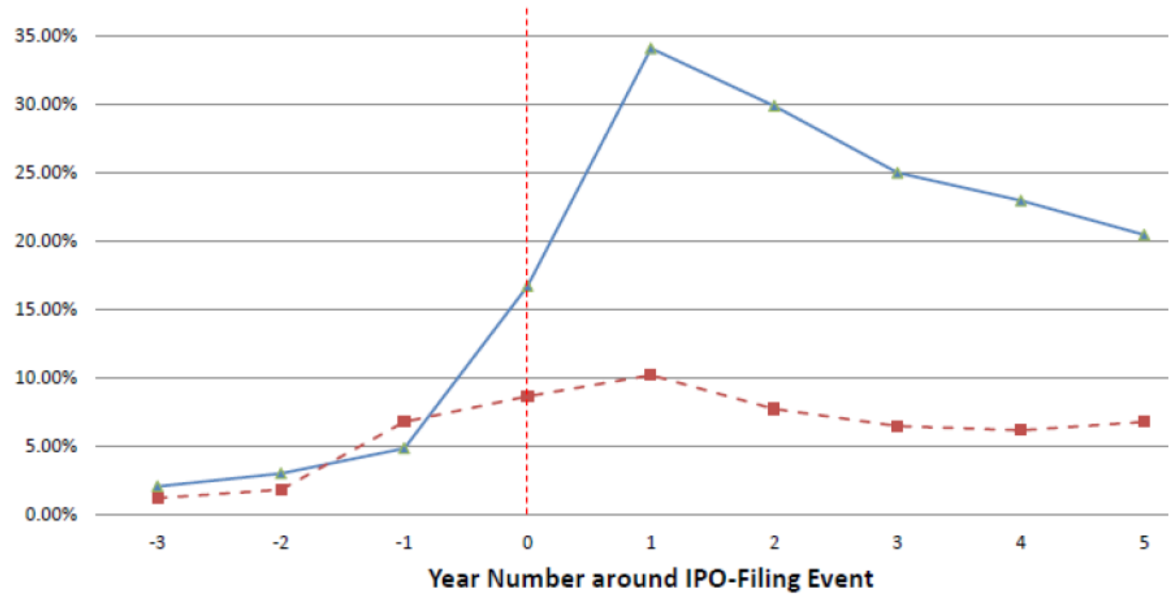
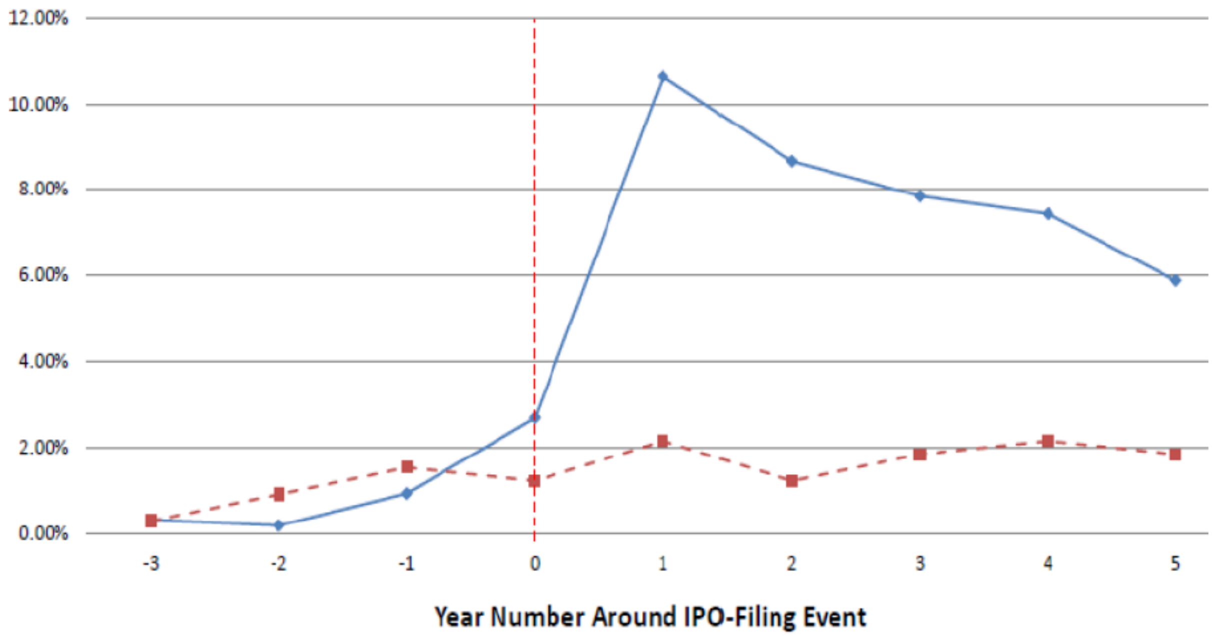


Figure 5 - Acquisition Likelihood of External Patents

The figure presents the annual probability to acquire at least a single external patent through M&A in the three years before and five years after the IPO filing. The solid line describes firms that completed the IPO filing, and the dashed line corresponds to withdrawn filers.



Appendix

Variable Definitions

Innovation Measures

1. *Citations* - Number of citations a patent receives in its grant year and the following three calendar years.

2. *Generality* - A patent that is being cited by a broader array of technology classes is viewed as having greater generality. Generality is calculated as the Herfindahl index of *citing* patents, used to capture the dispersion across technology classes of patents using the patent. To account for cases with a small number of patents within technology classes, I use the bias correction described in Jaffe and Trajtenberg (2002).

3. *Originality* - A patent that cites a broader array of technology classes is viewed as having greater originality. Originality is calculated as the Herfindahl index of *cited* patents, used to capture dispersion of the patent citations across technology classes. To account for cases with a small number of patents within technology classes, I use the bias correction described in Jaffe and Trajtenberg (2002).

4. *Scaled Citations* - Number of citations a patent receives divided by the average number of citations received by all patents granted in the same year and technology class.

5. *Scaled Generality* - Generality measure of a patent divided by the average generality of all patents granted in the same year and technology class.

6. *Scaled Originality* - Originality measure of a patent divided by the average originality of all patents granted in the same year and technology class.

7. *Scaled Number of Patents* - Each patent is adjusted for variations in patent filings likelihood and for truncation bias. The truncation bias in patent grants stems from the lag in patent approval (of about two years). Thus, towards the end of the sample, patents under report the actual patenting since many patents, although applied for, might not have been granted. Following Hall, Jaffe, and Trajtenberg (2001), the bias is corrected by dividing each patent by the average number of patents of all firms in the same year and technology class.

8. *Technology Class* - A technology class is a detailed classification of the U.S. Patenting and Trademark Office (USPTO) which clusters patents based on similarity in the essence of their technological innovation. Technological classes are often more detailed than industry classifications, consisting of about 400 main (3-digit) patent classes, and over 120,000 patent subclasses. For example, within the communications category, there are various technology classes such as: wave transmission lines and networks, electrical communications, directive radio wave systems and devices, radio wave antennas, multiplex communications, optical wave guides, etc.

IPO Characteristics

9. *Firm Age* - Firm age at the year of the IPO filing, calculated from the founding date.

10. *Early Follower* - An indicator variable that captures the location of a filer within the IPO wave. Following Beneveniste et al. (2003), a filer is considered an early follower if filed within 180 days of a pioneer in the same Fama-French 48 industry.

11. *Pioneer* - An indicator variable that captures the location of a filer within the IPO wave. Following Beneveniste et al. (2003), a filer is considered a pioneer if its filing is not preceded by an IPO filing in the same Fama-French 48 industry in the previous 180 days.

12. *Lead Underwriter Ranking* - A ranking of the lead underwriter on a scale of 0 to 9, where 9 is the highest underwriter prestige. The ranking is compiled by Carter and Manaster (1990), Carter, Dark, and Singh (1998), and Loughran and Ritter (2004).

13. *VC-Backed* - An indicator is equal to one if the firm was funded by a venture capital firm at the time of the IPO filing.

14. *Post-filing NASDAQ returns* - The two-month NASDAQ returns calculated from the day of the IPO filing.

15. *Pre-filing NASDAQ returns* - The three-month NASDAQ returns leading to the IPO filing date.

    Financial Characteristics at IPO filing

16. *Log Total Assets* - the natural logarithm of the total book value of assets.

17. *R&D / Assets* - the ratio of R&D expenditure to book value of assets.

18. *Net Income / Assets* - the ratio of net income to book value of assets.

19. *Cash / Assets* - the ratio of cash holdings to book value of assets.

Table A.1 - Placebo Test

The dependent variable is the average scaled citations in the five years after the IPO filing. *Returns following IPO-filing* are the two-month NASDAQ returns calculated from the IPO filing date. *Returns following IPO outcome* are the two-month NASDAQ returns calculated from either the date of the equity issuance or the date of the IPO filing withdrawal. When the date of IPO filing withdrawal is not available, I use the date of 270 days subsequent to the last amendment of the IPO filing (Lerner 1994). *Returns in year before IPO-filing* are the two-month NASDAQ returns calculated from a year before the IPO filing. *Returns in year after IPO-filing* are the two-month NASDAQ returns calculated from a year after the IPO filing. The variables included in the regressions are pre-filing average scaled citations, pre-filing number of patents, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ returns before the IPO filing. Variables are defined in the Appendix. The estimated model is Ordinary Least Squares (OLS), and robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Returns following IPO-filing	−0.498**				−0.482**	−0.495**	−0.509**
	(0.239)				(0.237)	(0.237)	(0.241)
Returns following IPO outcome		0.207			0.162		
		(0.251)			(0.248)		
Returns in year before IPO-filing			0.201			0.193	
			(0.254)			(0.252)	
Returns in year after IPO-filing				0.006			0.037
				(0.096)			(0.094)
Observations	1079	1079	1079	1079	1079	1079	1079
R-squared	0.242	0.240	0.239	0.239	0.242	0.242	0.242
Filing year FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes	yes

Table A.2 - NASDAQ Returns and Long-run Aggregate Innovation Trends

The table reports the association of the two-month NASDAQ returns after the IPO filing date with changes in innovation trends in the core technologies of filing firms. Firm's technology class is defined as a core technology if the share of patents in that class, in the three years before the IPO filing, is above the median share of patents across all the technology classes of the firm. Innovation trends in core technologies are calculated using all patents granted by the USPTO in the respective technology classes. The unit of observation is at the level of the firm. Since firms may have multiple core technologies, measures are weighted by the share of patents a firm produced in each core technology class. The dependent variable in column (1) is the change in average patent quality calculated by the average scaled citations of all patents approved in each filer's core technology in the five years after the IPO filing, divided by the average scaled citations in the three years prior to the IPO filing. In column (2), the dependent variable is the change in the total number of patents in the core technologies. In column (3), the dependent variable is the weighted change in the number of patents, when patents are weighted by number of citations. The estimated model is Ordinary Least Squares (OLS) and robust Standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent Variable	Patent Novelty	Patent Counts	Weighted Patent Counts
Post-IPO filing NASDAQ returns	−0.007	−0.055	0.001
	(0.053)	(0.142)	(0.171)
Observations	1,372	1,372	1,372
R-squared	0.789	0.275	0.429
Industry FE	yes	yes	yes
Filing Year FE	yes	yes	yes
Control Variables	yes	yes	yes