Does Going Public Affect Innovation?

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Abstract

This paper investigates the effects of going public on innovation. Using a novel data set consisting of innovative firms that filed for an initial public offering (IPO), I compare the long-run innovation of firms that completed their filing and went public with that of firms that withdrew their filing and remained private. I use NASDAQ fluctuations during the book-building period as a source of exogenous variation that affects IPO completion but is unlikely to affect long-run innovation. Using this instrumental variables strategy, I find that going public leads to a 50 percent decline in innovation novelty relative to firms that remained private, measured by standard patent-based metrics. The decline in innovation is driven by both an exodus of skilled inventors and a decline in productivity among remaining inventors. However, access to public equity markets allows firms to partially offset the decline in internally generated innovation by attracting new human capital and purchasing externally generated innovations through mergers and acquisitions. I find suggestive evidence that changes in firm governance and managerial incentives play an important role in explaining the results.

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1. Introduction

Does the transition to public equity markets affect innovation? Although a large body of research examines the performance of firms around their initial public offerings (IPOs), little is known about the effects of going public on innovation. This question is particularly relevant given the reliance of young and entrepreneurial firms on public equity issuances to fund their R&D investments.[1] This paper studies the effects of going public on three important dimensions of firms' innovative activity: internally generated innovation, productivity and mobility of individual inventors, and acquisition of external innovation.

Theoretically, in frictionless financial markets selling public equity 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 enhances 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. For instance, debt financing of R&D may be limited due to associated information problems, skewed and uncertain returns, and the potentially scant collateral value of intangible assets. Equity financing, on the other hand, allows investors to share upside returns and can ease the financing of R&D investments by transferring idiosyncratic innovation risk to diversified investors through public equity markets. Therefore, the financing view suggests that going public will enhance internally generated innovation and may even facilitate technology acquisitions.

In contrast, the "incentives" view suggests that ownership dilution and changes in governance may lead to a decline in the quality of innovation. Following the IPO, inventors may face weaker incentives to pursue novel projects as their claims on subsequent innovations become smaller. Increases in wealth and the ability to cash out may weaken inventors' incentives even further. In addition, since equity markets may fail to correctly evaluate innovation even when outcomes are predictable and persistent (Cohen, Diether, and Malloy, 2011), career concerns and takeover threats may pressure managers to select standard projects that are more easily communicated to stock market investors[3] (Stein, 1989; Ferreira, Manso, and Silva, 2010). Interestingly, the benefits of accessing public markets can be tied to its costs. Managers may prefer to exploit improved access to capital to acquire ready-made technologies rather than innovating internally, as this strategy is more transparent to the stock market and potentially less prone to failure.

To shed light on these two views, I use standard patent-based metrics to study the effects of going public on innovation. Consistent with the incentives view, the main finding of the paper

[1] See Brown, Fazzari and Petersen (2009). In fact, Brown and Petersen (2009) demonstrate that young firms' dependence on public equity markets to finance R&D expenditure has even increased over past decades.

[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 (2009).

[3] Minton and Kaplan (2008) demonstrate that turnover rates in publicly traded firms are high and significantly related to a firm's stock performance. Additionally, Edmans, Goldstein, and Jiang (2011) find that low stock prices strongly affect the likelihood of takeover threats.

illustrates that going public leads to a substantial decline in the novelty of internally generated innovation.

Estimating the effects of going public on innovation is challenging due to an inherent selection bias. A standard approach in the literature uses within-firm variation to study the effects of the transition to public equity markets on firm outcomes.[4] But, as noted by Jain and Kini (1994), this approach is likely to be biased due to the selection of firms to go public at a specific stage in their life cycle. For instance, firms may choose to go public following an innovative breakthrough, as hypothesized by Pastor, Taylor, and Veronesi (2009).[5] In that case, the post-IPO performance may be affected by reversion to the mean, reflecting life cycle, rather than IPO, effects.

To overcome this selection bias, I construct a novel dataset of innovative firms that filed an initial registration statement with the SEC and either completed or withdrew their filing. This sample allows me to compare the innovative activity of firms that went public with private firms at a similar stage in their life cycle, namely, firms that intended to go public at the same time but withdrew their filing. But this does not completely eliminate the selection bias as the decision to withdraw may be related to a firm's R&D policy and innovative opportunities.

I use the two-month NASDAQ fluctuations following the IPO filing date as an instrument for IPO completion. The instrument relies on the sensitivity of filers to stock market movements during the book-building phase (Busaba, Beneveniste, and Guo, 2000; Benveniste et al., 2003; Dunbar, 1998; Dunbar and Foerster, 2008; Edelen and Kadlec, 2005). These fluctuations provide a plausibly exogenous source of variation that affects IPO completion and is unlikely to be related to innovation.

One concern regarding the instrument might be that the exclusion restriction does not hold; i.e., that two-month NASDAQ returns may relate to innovation measures through channels other than the IPO completion (see Section 2.C for a detailed discussion). There are several reasons this may not be the case. First, the analysis compares firms that filed to go public in the same year. I find that the characteristics of filers that experienced a NASDAQ drop during the book-building phase do not differ significantly from other firms that filed to go public during the same year but did not experience such a decline.[6] Second, the analysis uses firm innovation measures that are in relative terms, scaled by the average innovation measures of all patents granted in the same year and in the same technology class.[7] Therefore, even if two-month NASDAQ returns contain information about aggregate changes in innovative opportunities, such a change should affect all firms conducting research in the same area, and is therefore unlikely to affect relative innovation measures.

[4] See, e.g., Degeorge and Zeckhauser (1993), Jain and Kini (1994), Mikkelson, Partch, and Shah (1997), Pagano, Panetta, and Zingales (1998), Pastor, Taylor, and Veronesi (2009), and Chemmanur, He, and Nandy (2009).

[5] Chemmanur, He, and Nandy (2009) find that firms go public following productivity improvements, and experience a decline in productivity following the IPO.

[6] These characteristics include: firm innovation 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 within the IPO wave.

[7] Technology classes are defined by the United States Patent and Trademark Office (USPTO), and capture thechnological essence of an invention.

Using this instrumental variables approach, I find that going public caused a substantial decline of approximately 50 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 projects. Such findings cannot be explained by the financing view which suggests that access to capital may enhance innovative activities.

To uncover the channels driving the decline in innovative activity, I study the effects of going public on individual inventors' productivity and mobility over time. Consistent with the incentives view, I find that the quality of innovation produced by inventors who remained at the firm substantially declines post-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, particularly privately held targets. 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 more than one-fifth of firms' patent portfolio in the five years following the IPO. The acquired patents are more likely to be in technologies that are only weakly related to a firm's previous patents and are higher quality than the patents produced internally. These findings are broadly consistent with the financing and the incentives view.

The results demonstrate that while going public provides financing benefits, these come at the cost of weaker incentives that lead to lower quality internal innovation and the departure of key inventors. To further investigate the underlying causes, I propose two incentives-related explanations. The first explanation suggests that career concerns lead managers to select more incremental projects, while the second explanation suggests that after the IPO inventors are facing weaker incentives to pursue high-quality innovation.

While I cannot rule out the inventors' incentives explanation, I find supportive evidence for the first explanation indicating that changing managerial incentives and public market pressures affect innovation at public firms. If managerial incentives are an important determinant of innovation, firms with more entrenched managers should be less sensitive to market pressures and therefore may invest in more ambitious and novel projects. As a proxy for managerial entrenchment, I use cases in which the CEO also serves as the chairman of the board. This proxy is appealing since it is not likely to directly affect inventors at the firm, allowing to explore managerial incentives explanation presumably separately from the inventors incentives explanation. I find that when managers are more entrenched, the negative effect of going public on innovation novelty is weaker and 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 operating performance measures such as profitability and productivity.[8]

[8] Several papers report a post-IPO decline in 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). Chemmanur, He, and Nandy (2009) reach similar findings regarding firm productivity.

This paper adds to the literature by demonstrating a post-IPO decline in innovation. Perhaps more importantly, the paper establishes that this decline is caused by the IPO, rather than being a symptom of a particular stage of the firm life cycle. This paper is also related to a number of papers studying withdrawn IPOs.[9] By using patent data, this study is the first to investigate the performance consequences of the decision to withdraw an IPO.

The paper reveals a complex trade-off between public and private ownership. While private firms are able to generate higher quality innovation and retain skilled inventors, public firms can acquire technologies externally and attract new human capital. 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, capital structure, and dividend payouts.[10] Additionally, this work contributes to the theoretical and empirical literature that explores the role of governance, capital structure, and ownership concentration on corporate innovation.[11]

The rest of the paper proceeds as follows. Section 2 outlines the main identification strategy. Section 3 explains the various data sources used to construct the sample. Section 4 presents the results about 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. Then, I describe the empirical strategy and the instrumental variables approach 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. I use widely accepted patent-based metrics to measure firm innovative activity (Hall, Jaffe, and Trajtenberg, 2001; Lanjouw, Pakes, and Putnam, 1998). These measures are economically meaningful and have been shown to translate into firm market value (see, e.g., Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2005).

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 (see, e.g., Griliches, 1990). The second metric, therefore, reflects the importance or novelty

[9] 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).

[10] Several aspects of firm behavior are considered in that literature. Asker, Farre-Mensa, and Ljungqvist (2010), and Sheen (2009) focus on investment sensitivity, Saunders and Steffen (2009) and Brav (2009) study debt financing and borrowing costs, Michaely and Roberts (2007) explore dividend payouts, and Gao, Lemmon, and Li (2010) focus on CEO compensation.

[11] See Aghion, Van Reenen, and Zingales (2009), Atanassov, Nanda, and Seru (2007), Belenzon, Berkovitz, and Bolton (2009), Bhattacharya and Guriev (2006), Chemmanur and Jiao (2007), Fulgheieri and Sevilir (2009), Fang, Tian, and Tice (2010), Lerner, Sorensen, and Stromberg (2010), and Tian and Wang (2010).

of a patent by counting the number of citations a patent receives following its approval.[12] Hall, Jaffe, and Trajtenberg (2005) illustrate that citations are a good measure of innovative quality and economic importance.[13]

Both citation rates and patent filing propensity vary over time and across technologies. Variations may stem from changes in the importance of technologies over time 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.[14] Specifically, let $Cites_{itk}$ be the number of citations of patent i that was granted in year t and classified in technology class k. The *scaled citations* of patent i, $SCites_{itk}$, is $Cites_{itk}$ divided by $\overline{Cites}_{-itk}$, the average number of citations of all patents granted in the same year and in the same technology class excluding patent i , that is,

$$SCites_{itk} = \frac{Cites_{itk}}{\overline{Cites}_{-itk}}$$

Similarly, to adjust for variations in patent-filing likelihood, each patent is scaled by the average number of patents generated by firms in the same year and in the same technology class. The *scaled patent count* per year is a simple sum of the scaled patents.

The final measures 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.[15] Similarly to patents and citations, I generate *scaled originality* and *scaled generality* by scaling the measures by the corresponding average originality or generality of all patents granted in the same year and technology class.

2.B Empirical Design

The analysis of the effects of going public on firm outcomes is challenging due to inherent selection issues that arise from the decision of firms to go public. A common estimation method

[12] I count citations in the year of patent approval and three subsequent calendar years. I discuss the citation horizon window in Section 2.B.

[13] Specifically, they find that extra citation per patent increases a firm's market value by 3%.

[14] A technological class is a detailed classification defined by the U.S. Patenting and Trademark Office (USPTO) that captures the essence of an invention. Technological classes are often much more refined 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.

[15] 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.

used in the literature[16] is a "within-firm" estimator that compares the performance of the same firm before and after the IPO. This method is attractive as it provides an estimate of the impact of IPOs on innovation that is not affected by a firm's time-invariant characteristics. At the same time, however, this method fails to control for the selection of when firms go public. If firms are more likely to go public following a positive innovative shock,[17] as argued by Pastor, Taylor, and Veronesi (2009), regressions designed to capture the effect of going public may be biased by life cycle effects and reversion to the mean.

To overcome the selection bias associated with firms' decision to go public, 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 filing, firms market equity issue 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 at the same year, but ultimately withdrew their filing and remained private (henceforth 'withdrawn firms'). This setup is attractive as it allows me to compare 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.[18] 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.

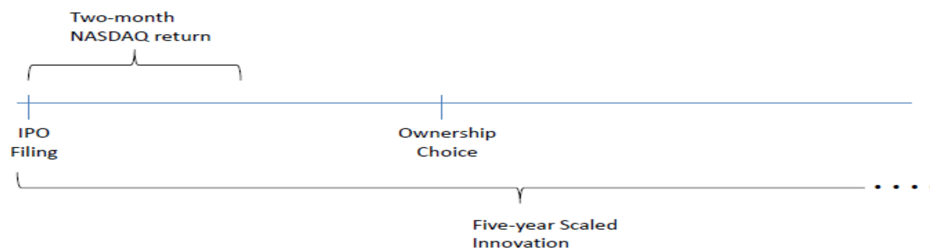
If the decision to withdraw an IPO filing is related to unobserved firm innovation policy or opportunities (captured in the error term), the β_1 estimate may be biased. Therefore, I instrument for the IPO completion choice. Specifically, I use the two-month NASDAQ returns as an instrument, calculated from the IPO filing date (i.e., the first two months of the book-building phase). The figure below illustrates the time line of the IPO filing and the NASDAQ fluctuations during the book-building phase. Firms either choose to complete the IPO or to withdraw their filing. On average, ownership choices are accepted within four months following the IPO filing. The firm-level

[16] Degeorge and Zeckhauser (1993), Jain and Kini (1994), Mikkelson, Partch, and Shah (1997), Pagano, Panetta, and Zingales (1998), Pastor, Taylor, and Veronesi (2009), and Chemmanur, He, and Nandy (2009).

[17] As illustrated in panel D of Table 1, I find that in the three years prior to the IPO, firms produce substantially more novel patents than comparable patents within the same year and technology class.

[18] 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.

innovation is measured over the five-year horizon after the IPO filing:[19]



NASDAQ fluctuations provide a plausibly exogenous source of variation that leads some firms to remain private in spite of their IPO filing. 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 of IPO on firm innovative activity:

$$Y_i^{post} = \alpha_3 + \beta_3 \widehat{IPO}_i + \gamma_3 Y_i^{pre} + X_i' \delta_3 + \nu_k + \mu_t + \varepsilon_{1i} \tag{3}$$

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). This model, which I describe in the Appendix, is the standard estimation method used in the innovation literature and count data analysis more generally.

I use a simple example to illustrate the advantage of using this instrumental variables approach in this setting. Assume that firm innovation following to 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 future innovative projects ($Q = q_H$), will complete the IPO irrespective of market conditions; *Sensitive* firms, with medium-quality innovative projects ($Q = q_M$), will not complete the IPO filing if NASDAQ drops; and *Long Shot* firms, with the poorest innovative

[19] 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.

prospects ($Q = q_L$), will withdraw irrespective of the NASDAQ change.[20] For 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 outcomes in the six cases:

	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:

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

Thus OLS will overestimate the effect of going public in this example because better firms are more likely to complete the IPO filing.[21]

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

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

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

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

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

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

The example illustrates that the IV estimator uses only the *Sensitive* firms whose IPO completion depends on NASDAQ conditions. In fact, any instrumental variables estimator use only

[20] The decision to withdraw or complete the IPO filing is complicated and driven by a long list of observed and unobserved factors. For simplicity in this example I assume that the decision depends only on one factor.

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

the information of the group of firms that respond 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).[22]

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. 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 choices. Additionally, it must not affect the scaled innovation measures through any channel other than the decision to complete the IPO filing. Formally, this means that the two-month NASDAQ returns must be uncorrelated with the residual in equation (1). This residual reflects unobservable characteristics that may influence firm innovation. The latter requirement, the "exclusion restriction", is the focus of the discussion below.

I start by exploring whether firms that experience a NASDAQ drop are significantly different from other firms that filed during the same year. A priori this seems unlikely since it would require high-frequency compositional shifts in IPO filers.

I find no significant differences in observables between firms that experienced a NASDAQ drop and other firms that filed in the same year. As illustrated in Section 3.D, these observables include characteristics at the time of the IPO filing such as firm financial information, age, venture capital backing, IPO filing characteristics, and importantly, innovation performance in the three years before the IPO filing. This suggests that the two-month NASDAQ fluctuations are plausibly exogenous with respect to innovative opportunities within a year. To further address concerns about within-year compositional shifts, I control also for the three-month NASDAQ returns before the IPO filing, and for firms' location within the IPO wave.

The two-month NASDAQ fluctuations may reflect either a change in investor sentiment or in future innovative opportunities. If NASDAQ fluctuations reflect changes in future innovative opportunities, this would raise concerns regarding the exclusion restriction. However, since R&D expenditure is a slow-moving process, firms that file within the same year are likely to respond to similar changes in innovation opportunities (Hall, Griliches, and Hausman 1986; Lach and Schankerman, 1989).

Additionally, since my innovation measures are scaled by average outcomes and therefore

[22] Roughly speaking, the IV estimate is an average of the estimated effect for the firms who would go public if the NASDAQ exceeds some firm specific threshold, weighted by the likelihood of observing that specific NASDAQ returns.

expressed in relative terms within the same year and technology class,[23] changes in aggregate innovative opportunities reflected by the two-month NASDAQ returns should affect all firms conducting research in the same technology. Such changes are not likely to affect the relative innovative performance. For example, consider a firm that submitted an IPO filing in 1995 and was awarded a patent three years later in 1998 in the optical communications technology. The novelty of the patent is scaled by the average novelty of all patents granted in 1998 in the optical communications technology. If the two-month NASDAQ returns following the IPO filing in 1995 reflected a change in innovative opportunities in optical communications in coming years, and thus affected patent novelty, this change should affect the novelty of all patents within this technology class. But, the relative patent novelty is unlikely to be affected.

To further address concerns regarding the exclusion restriction I conduct two additional tests reported in Section 3.E. First, I perform a placebo test. The exclusion restriction requires that the two-month NASDAQ returns affect innovation only through the ownership choice channel. If this is the case, we should expect that two-month NASDAQ returns *after* the IPO completion choice would have no effect on long-run innovation. Indeed, I find that in contrast to the two-month NASDAQ returns immediately after the IPO filing, following the IPO completion choice, the two-month NASDAQ returns have no predictive power. This evidence suggests that the effect of the instrument on the long-run innovation of the firm goes through the IPO completion channel.

Second, I investigate directly whether the instrument can explain changes in innovative trends. I use all patents granted by the U.S. Patent and Trademark Office to calculate changes in innovative trends in core technologies of firms as of the time of their IPO filing. I find no evidence that the instrument can predict changes in these innovative trends. While firms may switch to different technologies subsequent to the IPO filing, 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.

3. Data

I construct a novel dataset that combines IPO filings, patent information, hand-collected financial information and other firm characteristics. In this section I describe the steps I took in constructing the dataset, and provide summary statistics comparing IPO firms and withdrawn firms at the time of the filing.

3.A IPO Filings

To apply for an IPO, a firm is required to submit an initial registration statement to the SEC (usually the S-1 form), which contains the IPO filer's basic business and financial information. Following the submission of S-1 form, issuers market the company to investors (the "book-building"

[23] Technological classes are often much more refined than industry classifications, consisting of about 400 main (3-digit) patent classes, and over 120,000 patent subclasses.

phase) and have the option to withdraw the IPO filing by submitting RW form. The most common stated reason for withdrawing is "weak market conditions".

Filing withdrawals are common in IPO markets, as approximately 20 percent of all IPO filings are ultimately withdrawn. As noted by Busaba et al. (2001), the decision to withdraw is driven by various observed and unobserved considerations that affect the investors' willingness to pay and the issuer's reservation value.[24] As long as the investors' valuation is higher than the issuer's reservation price, the firm will complete the IPO application.

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 due to lags in patent approval and citations, which I discuss below. 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 three 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. 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 Internet and FACTIVA searches to verify matches.

I restrict the sample to firms with at least one successful patent application in the 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. In some cases, firms are acquired, or withdrawn firms may go public in a second attempt.[25] I collect information on firms' patenting activity even after such firm exits, to avoid biases that may arise from truncating firm activity. After all, firm exits are yet another consequence of the IPO effect that influence firms' innovative path. Collecting patent information subsequent to firms' exits is complicated since if a firm is acquired its patents may be assigned to the acquiring firm. Nevertheless, I find that in most cases patents are still assigned to the acquired company after its

[24] The investors' valuation may be affected by the issuer's financials, innovative activity, sentiment, and other unobserved factors. Similarly, the issuer's reservation value is influenced by future investment opportunities, cash reserves, alternative funding options, and other unobserved elements such as entrepreneur's benefits from diversification and loss of private benefits of control.

[25] See Panel F in Table 1 for a description of the acquisition statistics of IPO and withdrawn firms.

acquisition. This allows me to capture the patenting activity in more than 90 percent of firm-year observations, irrespective of whether a firm was acquired. In the remaining firm-years, no patent was assigned to the acquired firm. This could be either because the acquired firm did not generate additional patents, or because any patents generated were assigned to the acquiring company. To identify missing patents, I use inventor identifiers and geographic location to isolate patents that were produced by the acquired rather than the acquiring company.[26]

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 patent's approval and the considerable serial correlation in citation rates (Akcigit and Kerr, 2011), three years is reasonably sufficient to capture the patent's importance.[27]

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. 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 the industries that rely on intellectual property, such as computer, drugs, and electronics industries.

Panel D compares the patenting measures 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 are substantially more frequently cited than comparable average patents (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

[26] Specifically, I start by collecting inventor identifiers of patents produced by the acquired firm before the acquisition. These unique inventor identifiers are available through the Harvard Business School patent database. Then, I go over the patents produced by the acquiring firm in the post-acquisition years, to identify all patents produced by the same inventors.

[27] I verify that the results are not sensitive to the selected citation horizon.

of post-IPO reversion to the mean.

3.C Financial Information and Firm Characteristics

The analysis of private firms is complicated by 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 when using standard financial databases. To partially overcome this constraint, I collect withdrawn firms' financial information from initial registration statements. I download 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.

I collect additional information on firm characteristics 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), R&D spending and profitability (both normalized by firm size). However, withdrawn firms have a higher Cash-to-Assets ratio.

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.[28] 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.[29] However, I find that withdrawn firms are slightly more likely to be backed by VC funds (51 percent relative to 46 percent of IPO firms). This difference is significant at the 10 percent threshold. Finally, there are no significant differences in the location within the IPO wave.[30]

There are stark differences, however, in the NASDAQ fluctuations that firms experience as

[28] 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.

[29] 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.

[30] Beneveniste et al. (2003) demonstrate that differences in the location within the IPO wave may be associated with the probability of IPO completion. I follow their methodology and define a firm 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.

they choose whether to complete 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). Given the importance of NASDAQ fluctuations around the time of the IPO filing in this analysis, I discuss these differences separately in the next section.

3.D IPO Filings and NASDAQ Fluctuations

Issuers are highly sensitive to stock market fluctuations during the book-building phase (Busaba, Benveniste, and Guo, 2001; Benveniste et al., 2003; Dunbar, 1998; Dunbar and Foerster, 2008; Edelen and Kadlec, 2005). Stock market fluctuations shift both investors' willingness to pay and issuers' reservation value. If a firm only partially adjusts its reservation value, stock market declines may lead to an issuer's withdrawal.[31]

However, if NASDAQ fluctuations change investors' willingness to pay, why wouldn't firms simply wait for more favorable market conditions rather than withdraw the filing? 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. Any new information disclosed must be incorporated into the public registration statement. In fact, firms are required to update the registration statement periodically to reflect the current affairs of the company irrespective of raising alternative means of capital. These considerations lead firms to withdraw at an even earlier date prior to the automatic expiration of the IPO filing.

Figure 1 illustrates the sensitivity of issuers to market movements over the time period of the sample. I plot the fraction of filings that ultimately withdrew in each month 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. The figure demonstrates a strong and negative correlation between NASDAQ movements and IPO withdrawals, even when focusing on the pre-2000 period.[32]

In light of the costs associated with preparing for an IPO filing, this sensitivity might be surprising. However, Ritter and Welch (2002) argue that "market conditions are the most important factor in the decision to go public"; therefore, firms are likely to withdraw following a deterioration in market conditions. Indeed, a survey by Brau and Fawcett (2006) finds that CFOs that withdrew an IPO registration recognized that market conditions "played a decisive role in their decision."

[31] The summer of 2011 illustrates the sensitivity of issuers to market fluctuations. For example, in the week of August 8th, U.S. stocks plummeted following the downgrade of U.S. treasuries and the debate over the U.S. debt ceiling. During the same week, 12 IPOs were planned but only one completed the process.

[32] 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.

Welch (1992) argues that "information cascades" can induce later investors to rely on earlier investors' choices, which may lead to rapid failure of the issue offerings in cases of market declines during the initial period of the book-building phase.

Panel F describes firm exit events in the five years following the IPO filing. These include acquisitions, bankruptcies, or IPOs of withdrawn firms. As discussed earlier, I am able to capture the patenting activity of firms in the five years following their IPO filing, even after either acquisitions or second 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 acquired over this period.

The resulting low rate of return to public equity markets was highlighted in the literature (Dunbar and Foerster, 2008; Busaba, Beneviste, and Guo, 2001). However, when incorporating alternative exit options of withdrawn firms, approximately 50 percent of them exit in the five years following the event. There are several explanations for the low rate of return to the public equity markets. 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) find additionally 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 re-generate 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.E Instrumental Variable Related Tests

Having introduced the data, I present the results briefly discussed in Section 2.D to explore the validity of the instrumental variables approach. The first set of results is provided in Table 2. I explore whether firms experiencing NASDAQ drops are significantly different from other firms filing 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 of filers in a given year. I repeat the same exercise with the bottom 25 percent, and median as alternative cutoff thresholds. I explore whether firms that experienced NASDAQ drops are significantly different across various observables such as firm financial information at the time of filing, age, VC backing, IPO filing characteristics, and pre-filing innovation measures. I find no differences between the two groups when thresholds reflect a substantial drop in NASDAQ conditions, i.e., at the bottom 10 percent or 25 percent threshold. When using medians as a cutoff, I find weak differences in the profitability and VC backing variables.

For a second set of results, I conduct a placebo test. The exclusion restriction requires that the two-month NASDAQ returns affect innovation only through the ownership choice channel. If this is the case, we should expect that two-month NASDAQ returns *after* the IPO completion choice would have no effect on long-run innovation. In Table 1 of the Appendix, I explore whether the two-month NASDAQ returns can predict future innovation once the ownership structure is fixed, i.e., immediately after the decision to either issue equity or withdraw filing. I find that once ownership is determined, NASDAQ fluctuations do not significantly predict long-run innovative performance, in contrast to the two-month returns immediately after the IPO filing.

Finally, I investigate directly whether the instrument can explain changes in innovative trends in the core technologies of firms at the time of IPO filing.[33] I use all patents granted by the USPTO to calculate changes in innovative trends in these technologies.[34] In Table 2 of the Appendix, I find that the instrument cannot predict changes in these innovative trends. 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.

4. Results

4.A Suggestive Evidence

In this section I briefly explore the within-firm innovative dynamics of firms that successfully completed their 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 applied 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.[35]

The unit of observation in columns (1) to (6) of Table 3 is at the patent level. The dependent variable in column (1) is a simple 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 citations vary over time and between technology classes, in column (2) I use the *scaled citations* measure. Coefficients represent 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 1. The magnitude of the effect is substantial. For example, the coefficient of the year dummy three years

[33] I define a technology class as a core technology if the share of patents in that class, in the pre-IPO filing period, is above the pre-IPO filing median share of the firm's patent portfolio.

[34] Specifically, I calculate the change in average quality per patent within each core technology in the five years after the IPO filing, divided by the average quality in the three years prior to the IPO filing. 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 number of patents a firm produced in each core technology class.

[35] 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. The model is discussed in the Appendix.

after the IPO equals -0.597, implying a decline of 31.64 percent in innovation quality relative to the pre-IPO filing period (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. 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 patents 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, note that these results do not have a causal interpretation, as it could be driven by life cycle effects and mean reversion that coincide with the selection to go public that would have happened irrespective of the IPO filing.

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 the two-month NASDAQ returns on IPO completion. The dependent variable is equal to one if a filer completed the IPO, and zero otherwise. All specifications include filing year and industry fixed effects using OLS.[36] In column (1), I find that the coefficient on the two-month NASDAQ returns equals 0.704 and is significant at 1 percent. A change 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 $F = 10$ which suggests that the instrument is strong and unlikely to be biased toward 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. 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

[36] When I used a probit model to estimate these specifications, the results remain unchanged.

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.

In columns (3) and (4) I verify that the variation of the instrument is not driven only by the year 2000. I repeat the specification above, but limit the sample to pre-2000 years. The sensitivity of IPO completion to market fluctuations remains strongly significant at 1 percent, with only a slight change in magnitude (0.690 relative to 0.704 estimated in column (1)).

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.[37] Although the coefficient is still significant at 1 percent, and the F-statistic is sufficiently high, the magnitude of the coefficient declines, and one standard deviation change reflects a 6.17 percent change in the likelihood that the firm will complete the IPO filing. The weaker effect reflects 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.

Finally, 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 variable is highly significant, reflecting a 10.6 percent decline in the likelihood that a firm will complete the IPO filing.

Overall, the first-stage results indicate that NASDAQ fluctuations have a strong effect on IPO completion. Moreover, the two-month NASDAQ effect seem to be orthogonal to the added control variable.

4.B.2 Reduced Form Results using a Binary Instrument

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. 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 scaled measures of innovation, differences in averages illustrate the effects of going public on innovative activity.

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 (2) 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.

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

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 (the difference is significant at a 1 percent level) 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.

Reduced-form results demonstrate that going public affects firms' innovative activity, as it leads to more incremental innovation. The rest 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 of patents in the five years following the IPO filing. I control for the 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 Pioneer and Early Follower indicators that capture the location within the IPO wave. Robust standard errors are reported in parentheses.[38]

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. This strong correlation is plausibly generated through the effect of the two-month NASDAQ fluctuations on the decision of firms whether to complete the IPO filing or not. 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 per patent 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): the coefficient of interest is significant, negative, and of a similar magnitude.

[38] It may be natural to cluster standard errors at the level of the quarter 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 in fact clustered standard errors decline 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.

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 on average, more innovative firms are more likely to complete the IPO filing

4.B.4 The Fundamental Nature of Research

In this part 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 for the instrument, shows that the instrument is significant at -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 after the IPO filing. I control for the pre-IPO filing corresponding measure. The specification is identical to the estimation in the previous sections. When studying number of patents generated by firms, it is necessary to consider the attrition problem that may arise due to patent approval lags, particularly toward the end of the sample. In that regard, scaling patent counts is important not only to account for variations in patent filings but also because it alleviates the attrition problem. The attrition problem is further mitigated by the fact that patent approval lags affect both IPO firms and withdrawn firms.

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 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 Patent Portfolio

Since the change in patent quality is not driven by changes in the number of patent filings, it is natural to further investigate the nature of the change in firms' research following the IPO. In this part, I study the structure of the patent portfolio.

In the first analysis I investigate the dispersion of patents across different technology classes, using the Herfindahl index. The lower the Herfindahl measure, the higher the concentration of patents in a specific set of technologies. To allow a meaningful calculation of the Herfindahl measure, I restrict the analysis to firms that have at least two patents before and two patents after the IPO filing.[39] The dependent variable is the Herfindahl measure of all patents applied in the five years subsequent the IPO filing. I control for the pre-IPO filing corresponding measure, and the other standard control variables described in previous sections. In column (1) of Table 9 I estimate the 2SLS-IV specification. The coefficient of the IPO variable is significant and equals to -0.287, which is equivalent to a 58 percent decline in the dispersion of patents across technology classes relative to the pre-IPO filing period. This finding suggests that following the IPO, firms' patent portfolio becomes more focused on a narrower set of technologies.

I obtain further insights into firm patenting activity by exploring changes in the quality of patents in core technologies and in expanded technology classes. I divide patents in two ways. First, I divide patents into those in core technologies versus those in non-core technologies. I define a technology as a *(non-) core technology* if the share of patents in a certain technology before the IPO filing is above (below) the median share of patents across classes in the firm. Second, I divide patents that belong to expanded technology classes versus non-expanded classes. I consider a technology class as an *expanded class* if the share of patents in a class increases following the IPO relative to its share before the IPO.

The results of this analysis are presented in the remaining columns of Table 9. The dependent variable in column (2) is the average scaled citations of patents within core technologies in the five years following the IPO filing. I control for the pre-IPO filing patent quality within the same technologies. Estimating the 2SLS model, I find that the IPO coefficient equals -0.910 and is

[39] Similar results are obtained even when the sample is restricted to firms with at least four patents before and four after the IPO filing in order to get a more precise Herfindahl measure, although the results are noisier due to the smaller sample size.

significant at a 5 percent level. This estimation reveals large differences in the post-IPO quality of patents within the core technologies, as the quality of patents of IPO firms is lower by 48.6 percent relative to the pre-IPO filing average quality of patents at core technologies. I re-estimate this model in column (3), but focus on innovation novelty in non-core technologies. While the IPO coefficient is negative, I don't find significant differences between IPO firms and withdrawn firms. Similarly, I repeat the analysis for expanded and non-expanded classes in columns (6) and (7). I find that the decline in the quality of the patents of IPO firms is concentrated in expanded technology classes.

The results suggest that IPO firms focus on a narrower set of technologies, while those that remained private are more likely to experiment in a broader set of technologies. Moreover, IPO firms produce lower quality patents particularly in core technology classes and technology classes that were expanded following the IPO.

4.B.7 Robustness Checks

In the following section I summarize the results of several unreported supplemental analyses that test the robustness of the findings and explore alternative explanations. I start by considering more carefully the hypothesis that IPO firms have a lower threshold of filing patent applications, which leads to the addition of low-quality patents and hence the decline in average quality. However, the best (most-cited) patent is unlikely to be affected by such addition of low-quality patent filings. Studying changes in the best patent, I find that the quality of the best patent declines following the IPO, with comparable magnitude to the decline in the average innovation quality reported in Table 6. This evidence, which adds up to the finding of the overall number of patents, 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.

Third, 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 of 1999 – 2000. Naturally, standard errors increase due to the decline in sample size, but the results remain significant and qualitatively the same.

Fourth, I 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.

Finally, a common caveat in interpreting instrumental variables results is that the estimates apply only to a subset of firms who respond to variations in the instrument. Since firms highly capital-dependent firms are likely to complete the IPO irrespective of NASDAQ fluctuations, the IV estimate may underestimate the average treatment effects of IPO on innovation.

To explore this caveat in detail, it is useful first to recognize that the fraction of sensitive firms varies with NASDAQ fluctuations. The larger the NASDAQ drops are, the larger the fraction of firms that are likely to withdraw (i.e., the larger the sensitive group). In fact, at the limit, all firms are likely to be sensitive. Therefore, I repeat the IV analysis, using extreme fluctuations in the NASDAQ (using the tails in the of the NASDAQ returns distribution). While this decreases the size of the sample, it increases the external validity of the results, since the fraction of sensitive firms is larger. As expected, I find that the fraction of firms that respond to such variations increases. Importantly, when using the extreme values of NASDAQ as an instrument, the effect of IPO on innovation novelty remain similar to previous findings. This evidence suggests that the results are not driven by a unique unrepresentative set of firms, but rather relevant to a broad set of firms in the population.

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. Their efforts generate intangible assets, which encompass the firm's knowledge. To the extent that this knowledge is "tacit," it is embedded in the firm's human capital, and departure of inventors may lead to knowledge loss. Therefore, firms tend to smooth their R&D spending over time in an effort to reduce the risk of human capital loss (Hall, Griliches, and Hausman, 1986; Lach and Schankerman, 1989). Changes associated with 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, and disparities in wealth between employees may affect their incentives. Additionally, dilution in ownership and changes in firm governance may affect employees as well. Given the decline in innovation novelty and the importance of inventors, it is natural to explore the human capital channel. 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, in 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). I attribute a patent equally to each inventor of a patent. 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 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.[40]
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 classify 13,300 inventors by the above categories. These inventors account for approximately 65 percent of the patents in the sample.

In Panel A of Table 10, I compare the patenting activity of stayers and leavers in the three years before the IPO filing.[41] I first consider only IPO firms, and find that leavers produced more novel patents, measured by either raw or scaled citations. These differences are significant at a 1 percent level. Additionally, leavers generate slightly more patents, when accounting for variations in propensity to patent across technologies and over time. Interestingly, these patterns are reversed for withdrawn firms. Those who remained at the firm produced higher-quality patents measured by scaled citations, while no significant differences arise 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, and differences are significant at 1 percent when I compare either raw or scaled citations. Additionally, newcomers produce fewer patents than stayers, although this may result mechanically from the shorter time period they stayed at the firm following the IPO. Again, I find opposite results when considering withdrawn firms. The quality of patents produced by newcomers is lower than those who remained at the firm, when considering either raw or scaled citations. These differences are strong and significant at a 1 percent level.

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

[41] If an inventor's status corresponds to the definitions of both a stayer and a leaver, I classify her as a leaver. The results do not change in a meaningful way if I classify her as a stayer instead.

Interestingly, the quality of patents generated by leavers is significantly higher than the quality of patents generated by newcomers for both IPO firms and withdrawn firms.

4.C.2 Inventor Level Analysis

I explore the 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.

I report the results in Table 11, 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 per patent produced by inventors in the five years after the IPO filing. Similar to previous specifications, I control for the 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. I cluster standard errors 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 is significant at a 1 percent level. The magnitude of this coefficient is large, corresponding to a 48 percent decline in inventor's 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.

In column (3) I focus on stayers and leavers, and estimate whether inventors are more or less likely to leave the firm after the IPO filing. The dependent variable equals one if the inventor left the firm in the five years following the IPO filing. 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 the 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 coefficient is significant at 1 percent.

A natural concern regarding the validity of the instrument in this setup is that NASDAQ returns may affect 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 at 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 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 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. 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, I restrict the analysis to stayers and newcomers. The dependent variable in column (5) is a dummy variable indicating 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 late newcomers who produce their first patent at least three years after the IPO filing. I find that the coefficient slightly decreases, but is still highly significant, corresponding to a 35 percent increase in the likelihood to hire 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. Additionally, going public affects the productivity of the inventors who remained at the firm. 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. Moreover, the average quality of patents produced by stayers decline substantially at IPO firms. These two effects can explain the decline in the innovative quality of 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 firm.

4.D Acquisition of External Technology

The transition to public equity markets allows firms to acquire companies more easily by exploiting access to capital and the potentially overvalued stock (Shleifer and Vishny 2003). Acquisition of ready-made technologies is attractive since it is easier to communicate to shareholders, quicker to implement, and less prone to failures relative to a long process of internal innovation. This section shows that following the IPO, firms are more likely to rely on external technologies.

Figure 4 illustrates the annual acquisition likelihood of at least a single target in the years around the IPO filing. IPO firms exhibit a sharp increase in likelihood following the IPO, while there is no meaningful effect for withdrawn firms. In Panel A of Table 12, I find that the acquisition likelihood of IPO firms increases from 9 percent in the three years prior to the IPO, to 66 percent following the event. The comparable change for withdrawn firms is from 10 percent to 24 percent following the IPO filing, and this change is not significant. These findings confirm the results of Celikyurt, Sevilir, and Shivdasani (2010) who find that IPO firms are more prolific acquirers even than mature public firms within their industry, and their average expenditure on acquisitions is substantially greater than either capital expenditures or R&D.

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. A complication arises since, as demonstrated in Panel B, approximately 30 percent of the acquisition targets are firm subsidiaries. In these cases, it is difficult to distinguish whether assigned patents are generated by the parent firm or by the subsidiary. Therefore, I collect patent information about independent firms only (approximately 90 percent of these are privately owned). Given that almost all of the subsidiaries are acquired by IPO firms, the result underestimates the true contribution of acquisitions to the IPO firms' innovation and provide only a lower bound.

The number of external patents acquired by public firms in the five years following the IPO is substantial. As illustrated in panel C, approximately 7500 patents were acquired through mergers and acquisitions, relative to approximately 30,000 patents produced. Before the IPO filing, both withdrawn and IPO firms rarely acquire external patents through M&A (likelihood averages 3 percent and 1 percent for withdrawn and IPO firms respectively). However, in the years following the IPO filing there is a drastic change. The likelihood to acquire an external patent increases to 31 percent for IPO firms while it remains small for withdrawn firms (8 percent). This pattern is illustrated in Figure 5, demonstrating the annual likelihood to acquire external patents.

The patterns described so far demonstrate a sharp increase in dependence on external technologies following the IPO. Similar patterns arise when using the instrumental variable approach. For example, panel D shows that firms that experienced two-month NASDAQ returns within the bottom 25 percent of all filers in the same year acquire significantly fewer external patents relative to the rest of filers in the same year (1.27 versus 4.70 patents in the subsequent five years). Similar results arise when using the multivariate IV analysis, even when I control for industry acquisition propensities.

Given the substantial reliance on external patents, it is interesting to compare the external and internal patents of IPO firms. Panel E details these differences. On average, external patents constitute more than 20 percent of the overall patent portfolio of IPO firms in the five years following the event. Additionally, external patents exhibit higher quality than patents generated internally and are more likely to be in new technology classes (less likely to be in core technology classes) relative to the patents generated within the firm.

5. Discussion

The empirical findings illustrate that going public has substantial effects on the manner in which firms pursue innovation. The financing view suggests that the improved access to capital may allow firms to enhance their innovative activities. While I find that the transition to public equity markets enables firms to acquire external technologies, the financing view by itself cannot explain the decline in the quality of internal innovation following the IPO, nor the departure of key inventors from the firm.

The incentives view, however, is consistent with the main empirical findings. This view suggests that in addition to the improved access to capital, the transition to public equity market affects managers' and inventors' incentives. This translates into a selection of less novel projects and reliance on a narrower set of technologies. In this section, I explore two incentives-related explanations of the post-IPO decline in innovation.

5.A Managerial Incentives

Going public may affect managerial incentives and consequently the type of projects they select. Evidence shows that stock markets misvalue innovation, even when outcomes are persistent and predictable (Cohen, Diether, and Malloy, 2011). As argued by Aghion, Van Reenen, and Zingales (2009), this may be driven by the weaker incentives of dispersed shareholders to fully understand complex projects pursued by the firm relative to more concentrated ownership structures. Career concerns and takeover threats may pressure managers to select more conventional projects which can be more easily communicated to the stock market (Stein, 1989; Ferreira, Manso, and Silva, 2010). Concerns regarding such adverse effects of market pressures are often raised by CEOs and entrepreneurs. For example, when explaining the delay in Facebook's IPO, Mark Zuckerberg, CEO and founder, 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."[42]

The difficulty in conveying complex projects to the stock market may lead managers to exploit the improved access to capital and potentially overvalued stock in order 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 and the greater reliance on external technologies may lead to the departure of skilled entrepreneurial inventors.

Overall, a change in managerial incentives can explain the three main findings in the paper: decline in innovation novelty, departure of inventors and the increased reliance on external technologies.

5.B Inventor Incentives

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 may lead inventors to leave the firm to implement their ideas in a private firm setting in which they can capture a larger fraction of the returns for their innovation.

Another difficulty in retaining inventors following the IPO arises in cases where key inventors become wealthy enough through their stock options not to have to work. Google's prospectus provides some anecdotal evidence. As claimed in the risk factors section in 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."[43] This naturally raises the question why couldn't Google provide even stronger financial incentives to prevent the

[42] Facebook Blog, September 2010.
[43] Google's prospectus, p. 13

departure of key employees. While Google provides some additional grants, these are relatively mild to avoid generating substantial gaps in pay between employees. Specifically, the filing states that "this offering may create disparities in wealth among Google employees, which may adversely impact relations among employees and our corporate culture in general."[44] This anecdotal evidence is consistent with broader evidence suggesting that firms' wage setting is constrained by workers' views about what constitutes a fair wage (Blinder and Choi, 1990; Agell and Lundborg, 1995; Campbell and Kamlani, 1997).

Inventors' incentives may also be affected by the improved ability of firms to acquire external technologies following the IPO. Rotemberg and Saloner (1994) discuss the incentives benefits from having a narrow business, which increases the likelihood of implementation ideas generated by employees and therefore increases their ex-ante incentives. Acquisitions may adversely affect the likelihood of implementing inventors' innovative projects and weaken their incentives to pursue ambitious and novel projects.

This discussion 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. 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 inventors' incentives, associated with the transition to public equity markets, can be similarly consistent with the findings of a decline in novelty of innovation, departure of skilled inventors, and the greater reliance on acquisitions.

5.C Suggestive Evidence of Theories

While both theories can explain the empirical findings, they have different implications. The managerial incentives explanation suggests that firms can pursue high-quality innovation, but corporate governance considerations translate into managerial career concerns and prevent managers from doing so. The inventor's incentives theory suggests that providing appropriate incentives to inventors is difficult in a public firm setup and therefore, irrespective of managerial preferences, this setting is less productive for innovation. I perform several cuts of the data in an attempt to shed some light on the underlying channels leading to the decline in innovative novelty following the IPO.

I start by considering 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 responding to takeover threats. Inventors' incentives, however, are plausibly not affected directly by whether the CEO is also the chairman of the board. Thus, if CEO entrenchment is correlated with a higher quality of innovation, this may provide evidence for the importance of managerial incentives and stock market pressures.

[44] Google's prospectus, p. 9

I collect information on board characteristics from S-1 filings, to determine whether the CEO is also the chairman at the time of the IPO.[45] Since S-1 filings are available through the SEC Edgar system from 1996, the number of observations in this analysis is smaller. In Table 13, 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.[46] 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 to leave the firm is in fact 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 effect on inventors turnover.

In order to test whether dilution of ownership claims on innovation and cashing out affect inventors incentives and departure choices, it is necessary to have information on their compensation within the firm. In the absence of this type of data, I consider whether acquisitions adversely affect inventors. If acquisitions reduce the likelihood of implementation of internal projects, and adversely affect inventors, I expect to find a substitution effect between acquisitions and internal innovation.

I distinguish between firms that acquired external technologies in the five years following the IPO and firms that did not engage in such acquisitions, and run the IV estimation separately for each group, using innovation novelty as a dependent variable. In column (5) I find no significant decline in innovation quality for firms that acquired external technologies (although the coefficient is negative), while in column (6) I find a significant decline in the innovation quality of firms that did not engage in such acquisitions. Additionally, in columns (7) and (8) I study the likelihood of inventors leaving the firm, and find that inventors are more likely to leave firms that did not acquire external technologies. These findings are consistent with Sevilir and Tian (2011) who find that acquisitions complement innovation and improve the acquiring company's innovation. Hence, I find no direct evidence of an adverse effect of acquisitions on internal innovation. However, these findings should be interpreted lightly as they merely reflect correlations and do not test for alternative channels through which inventors' incentives might be affected following the IPO.

Overall, this section provides suggestive evidence regarding the underlying mechanisms that generate the decline in firm-level innovation. More precisely, I find that managerial incentives play

[45] Execucomp database collects information about executives from S&P 1000 firms only.

[46] I estimate columns (1) and (2) separately, instead of using an interaction term of IPO variable and CEO entrenchment dummy. An interaction term will require using an additional instrumental variable. While it is possible to use the interaction of NASDAQ returns and entrenched CEO dummy as an instrument, this has limited power, and is particularly problematic given the small number of observations.

an important role in leading to a decline in quality of innovation and departure of skilled inventors.

6. Conclusion

In this paper, I investigate an important but understudied aspect of initial public offerings, namely, the effect on firm innovation. I find that the transition to public equity markets has a substantial effect on firms' innovative activities along three dimensions. First, the projects selected within the firm are less novel, and rely on a narrower set of technologies. Second, key inventors are likely to leave the firm, and the productivity of remaining inventors declines. Third, firms rely more heavily on acquisition of external technologies.

I consider two views in which going public may matter for innovation. On the one hand, the financing view suggests that improved access to capital may enhance innovation. On the other hand, the incentives view suggests that, in addition to access to capital, going public affects managers' and inventors' incentives. This may lead to a selection of more conventional projects. I find that although the financing view is consistent with some aspects of the empirical findings (the increased reliance on external technologies), it cannot explain the decline in the novelty of internal innovation and the departure of key inventors following the IPO. In contrast, the incentives view explains the effects of going public along all three dimensions of the empirical findings.

Estimating the effects of going public on innovation is challenging due to its inherent selection bias. My empirical strategy compares firms that went public with firms that intended to go public, but ultimately withdrew their IPO filing and remained private. I use NASDAQ fluctuations during the book-building phase as an instrument for the decision to complete the IPO filing. Additionally, this may

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 in its life cycle.

The results 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 (2010) 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.[47] 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 IPOs affect innovation, but that their effects may be indirect. While 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.

[47] 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 sample. 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. Both innovative measures and firm characteristics are defined in Section A of the Appendix. Finally, Panel F includes firm exit characteristics in the five years after the IPO filing, where firm exits are corporate events such as acquisition, bankruptcy, or an IPO of 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 - Patent portfolio characteristics before the IPO filing

	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 patet	4.30	2.89	5.71	4.00	2.49	4.92	0.31

Panel E - Firm characteristics and market conditions

	Complete			Withdrawn			
	Mean	Median	S.D.	Mean	Median	S.D.	Difference
Pre-Filing Financial Information (from 1996)							
Log Total Assets	3.07	2.91	0.056	2.97	2.93	0.11	−0.09
R&D / Assets	0.35	0.23	0.46	0.33	0.19	0.54	0.01
Net Income / Assets	−0.53	−0.31	0.95	−0.61	−0.41	1.10	0.08
Cash / Assets	0.32	0.26	0.27	0.37	0.32	0.31	−0.05**
IPO Characteristics							
Lead Underwriter Ranking	8.16	9.00	1.27	8.17	9.00	1.33	−0.01
Firm age	15.31	8.00	20.48	13.76	7.00	18.70	1.55
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 following 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 are Not Correlated with Firm Characteristics

The table reports differences in firm characteristics between IPO filers that experienced a NASDAQ drop and other filers in the same year. In column (1), 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 of all filers in the same year. In column (2) a NASDAQ drop is defined if the two-month NASDAQ returns after the IPO filing are within the bottom 25 percent of all filers in the same year. In column (3) a NASDAQ drop is defined if the two-month NASDAQ returns after the IPO filing are within the bottom 50 percent of all filers in the same year. Innovative measures are defined in Section A of the Appendix, and are based on the three years up to (and through) the IPO filing year. *, **, and *** indicate that differences in means are statistically significant at the 10%, 5%, and 1% levels.

NASDAQ Drop Threshold (annual):	Bottom 10%	Bottom 25%	Bottom 50%
Pre-Filing Financials Information			
Log Total Assets	0.215	0.078	0.107
R&D / Assets	−0.055	−0.042	−0.047
Net Income / Assets	0.064	0.068	0.089*
Cash / Assets	0.036	0.013	0.015
IPO Characteristics			
Lead Underwriter Ranking	0.124	0.110	0.067
Firm age at filing	0.348	−1.521	−0.653
VC-backed	0.061	0.053	0.053*
Pre-Filing Patents Characteristics:			
Citations	0.905	0.064	0.262
Scaled Citations	−0.071	0.072	0.101
Number of Patents	0.603	−1.354	−2.204
Scaled Number of Patents	0.330	−0.326	−0.530
Generality	−0.009	0.004	0.013
Originality	−0.021	−0.007	0.005
Scaled Best patent	−0.197	0.277	0.158

Table 3 - Dynamics of Innovative Activity around IPO Events

The reported regressions illustrate the changes in innovative activity of firms that went public in the three years before and five years after an IPO event. The dependent variables are stated at the top of each column and defined in section A of the Appendix. In columns (1) to (6), a patent is the unit of observation, while in columns (7) and (8) the unit of observation is at the firm-year level. *Event Year* are dummy variables indicating the relative year around the IPO event (the omitted category is the year of the IPO). The estimated model is Ordinary Least Squares (OLS), and standard errors, clustered at the level of the firm, 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 and equals to one if a firm completed the IPO filing, and zero otherwise. The *NASDAQ returns* variable is constructed differently across specifications. In the *Two Months* type (columns (1) to (4)), NASDAQ returns are the two-month NASDAQ returns after the IPO filing date. In columns (5) and (6), *All* 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 leading to the IPO filing, VC-backed dummy, Pioneer and Early Follower variables. The variables are defined in Section A of 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 with Binary Instrument

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. 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 equal to one if a firm completed its IPO filing. Variables are described in section A of the Appendix. *, **, and *** indicate that the difference in means is statistically signicant at the 10%, 5%, and 1% levels.

	Below (25%)			Above (25%)			
	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	1.59	1.19	2.05	1.34	1.09	1.15	0.247***
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	5.36	3.14	7.92	4.14	2.69	4.99	1.215***

Table 6 - Innovation Novelty

The table reports the effect of an IPO on the average scaled citations per patent in the five years after the IPO filing. Innovation measures are detailed in Section A of the Appendix. *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 number of patents, Pioneer, Early follower, VC-backed dummy, and the three-month NASDAQ returns leading to the IPO filing. 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, which is discussed in Section B of the Appendix. 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 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)
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 average scaled originality and generality per patent in the five years following the IPO filing. The dependent variable is average Scaled Originality in columns (1) to (3) and average Scaled Generality in columns (4) to (6). Innovation measures are detailed in Section A of the Appendix. *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 number of patents, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ returns before the IPO filing. 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 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)
	Originality	Originality	Originality	Generality	Generality	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, measured by the average scaled number of patents per year in the five years following the IPO filing. Innovation measures are detailed in Section A of the Appendix. *IPO* is a dummy variable equal 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. 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] while the years [2,5] 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 discussed in Section B of the Appendix. 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
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 - Patent Portfolio

The table reports the effect of an IPO on patent portfolio composition in the five years following the IPO filing. In column (1), the dependent variable is the Herfindahl of patent distribution across technology classes. I control for the pre-IPO filing Herfindahl of patents generated in the three years before the IPO filing. In columns (2) to (5) the dependent variable is the average scaled citations of patents within the (non-) core technologies or (non) expanded classes. I define a technology class as a (non-) core technology if the share of patents in a certain technology class before the IPO filing is above (below) the median share of patents across technology classes in a firm. Additionally, a technology class is considered (non-) expanded if the share of patents in a class (did not) increase following the IPO relative to the share of patents before the IPO filing. In all specifications I control for the average scaled citations before the IPO filing in the correponding partition. Innovation measures are detailed in Section A of the Appendix. *IPO* is a dummy variable equals to one if a firm completed the IPO filing, and zero otherwise. The instrumental variable is the two-month NASDAQ returns calculated from the IPO filing date. Additional control variables included in all regressions are: pre-filing average scaled number of patents, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ returns before the IPO filing. The models are estimated using two-stage least squares. *Magnitude* is equal to the *IPO* coefficient, divided by the pre-filing average scaled citations in the respective partition. 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)
Dependent Variable	Herfindahl	Core Tech	Non-Core Tech	Expanded Classes	Non-Expanded Classes
Model	2SLS - IV	2SLS - IV	2SLS - IV	2SLS - IV	2SLS - IV
IPO	−0.287**	−0.910**	−0.383	−0.846*	−0.095
	(0.142)	(0.458)	(0.450)	(0.464)	(0.377)
Magnitude	-58.37%	-48.66%	-22.31%	-50.66%	-6.51%
Observations	792	1,079	898	1,079	670
R-squared	0.158	0.171	0.141	0.078	0.248
Filing year FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes	yes

Table 10 - Inventor Summary Statistics

The table reports summary statistics of innovative activity of 16,108 inventors in the sample with at least a single patent application before and after the IPO filing date. Panel A compares the pre-IPO filing patents of inventors who either remained at the firm or left after the IPO filing. Panel B compares the post IPO-filing innovative activity of inventors that remained at the firm relative to newcomers,i.e., inventors that joined the firm following the IPO filing. I define Stayers, Leavers, and Newcomers as follows. 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. Innovation measures are defined in Section A of the Appendix. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A - Pre IPO Filing

	IPO Firms					Withdrawn Firms				
	Leavers		Stayers			Leavers		Stayers		
	count	mean	count	mean	difference	count	mean	count	mean	difference
Citations	3743	14.44	3806	11.71	2.731***	708	11.49	558	11.85	−0.354
Scaled Citations	3743	2.37	3806	2.12	0.253***	708	2.36	558	2.74	−0.374**
Number of patents	3743	2.96	3806	2.86	0.107	708	3.35	558	3.36	−0.009
Scaled Number of patents	3743	1.1	3806	1.01	0.088***	708	1.21	558	1.29	−0.085

Panel B - Post IPO Filing

	IPO Firms					Withdrawn Firms				
	Newcomers		Stayers			Newcomers		Stayers		
	count	mean	count	mean	difference	count	mean	count	mean	difference
Citations	6787	7.58	3806	5.61	1.968***	506	4.61	558	7.08	-2.466***
Scaled Citations	6787	1.62	3806	1.41	0.210***	506	1.4	558	3.11	-1.709***
Number of patents	6787	2.49	3806	3.52	−1.033***	506	2.37	558	3.17	-0.803***
Scaled Number of patents	6787	0.86	3806	1.28	−0.423***	506	0.86	558	1.14	-0.274***

Table 11 - Inventor Mobility and Changes in Innovative Productivity

The table reports the effect of an IPO on inventor mobility and innovative activity of inventors who remained at the firm. Innovation measures are detailed in Section A of the Appendix and inventor classifications are defined in Table 10. *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 columns (1) and (2) the sample is restricted to stayers and the dependent variable is the average scaled citations after the IPO filing of stayers. In columns (3) and (4), the sample includes inventors who are either stayers or leavers, and the dependent variable equals to one if inventor left the firm. In columns (5) and (6) the sample includes inventors who are either stayers or newcomers, and the dependent variable equals to one if the inventor joined the firm. *Late Leavers* includes in the sample only leavers who patented in a different firm for the first time three years after the IPO filing. *Late Newcomers* includes in the sample only newcomers that produced their first patent in a sample firm at least three years after the IPO filing. In all specifications I control for the average scaled citations before the IPO filing of the inventor. Additional control variables are: pre-filing average scaled number of patents, Pioneer, Early follower, VC-backed variable, and the three-month NASDAQ return before the IPO filing. 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 which is discussed in Section B of the Appendix. *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 12 - Acquisition of External Technologies

The table reports summary statistics of firm acquisitions before and after the IPO filing. Panel A compares IPO firms and withdrawn firms and their respective likelihood to engage in acquisitions. 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
Pre-filing year			
# acquisitions	178	46	-
avg. # acquisitions per firm	0.12	0.14	-0.022
prob. to have at least 1 acquisition.	0.09	0.10	-0.009
amount spent on acquisitions	3.94	7.05	-3.113
Post-filing year			
# acquisitions	4043	428	-
avg. # acquisitions per firm	2.27	0.59	1.688***
prob. to have at least 1 acquisition.	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

Pre IPO-filing	Complete	Withdrawn	difference
Number of external patents	0.08	0.14	-0.057
Likelihood to buy external patents	0.01	0.02	-0.006
Fraction of external patents	0.01	0.03	-0.013

Post IPO-filing	Complete	Withdrawn	difference
Number of external patents	4.91	0.84	4.066**
Likelihood to buy external patents	0.16	0.06	0.097***
Fraction of external patents	0.31	0.08	0.229***

Panel D - Reduced form - an increase in acquisitions of external patents after the IPO

Pre IPO-filing	Top 75%	Bottom 25%	difference
Number external patents	0.09	0.04	-0.046
Likelihood to buy external patent	0.01	0.01	-0.000
Fraction of external patents	0.02	0.01	-0.004

Post IPO-filing	Top 75%	Bottom 25%	difference
Number of external patents	4.70	1.27	3.424***
Likelihood to buy external patents	0.15	0.07	0.083***
Fraction of external patents	0.28	0.12	0.153***

Panel E - Comparing external and internal patents of IPO firms

	Internal	External	difference
Number of patents	18.35	4.91	13.44***
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 13 - Empirical Evidence of Alternative Theories

The dependent variables are listed separately in each column. Innovation measures are detailed in Section A of the Appendix. *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 the sub-sample *Chair*, the estimation includes all the 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 the 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. The sub-sample *M&A* includes all withdrawn firms and only IPO firms that acquired at least one firm in the five years following the IPO filing. *No M&A* is constructed similarly, but includes only IPO firms that did not acquire target firms. When the dependent variable is *Scaled Citations*, the unit of observation is at the level of the firm, When the dependent variable is *Likelihood to Leave*, the unit of observation is at the inventor level, and includes either stayers or leavers. The dependent variable is a dummy indicating whether an inventor left the firm. All specifications add 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. 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)	(5)	(6)	(7)	(8)
Dependent Variable	Scaled Citations	Scaled Citations	Likelihood to Leave	Likelihood to Leave	Scaled Citations	Scaled Citations	Likelihood to Leave	Likelihood to Leave
Sub-sample	Chair	Not Chair	Chair	Not Chair	M&A	No M&A	M&A	No M&A
IPO	−0.359	−1.193**	−0.140	0.108*	−0.555	−0.898**	0.031	0.164**
	(0.529)	(0.558)	(0.086)	(0.065)	(0.405)	(0.416)	(0.059)	(0.070)
Magnitude	-20.17%	-64.14%	-	-	-28.46%	-50.17%	-	-
Observations	325	428	2,626	4,292	759	490	6,232	3,803
R-squared	0.207	0.247	0.049	0.032	0.145	0.135	0.039	0.029
Filing year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes	yes	yes

Figure 1 - NASDAQ Fluctuations and IPO Withdrawals

The chart 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 are excluded from the sample. 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%.

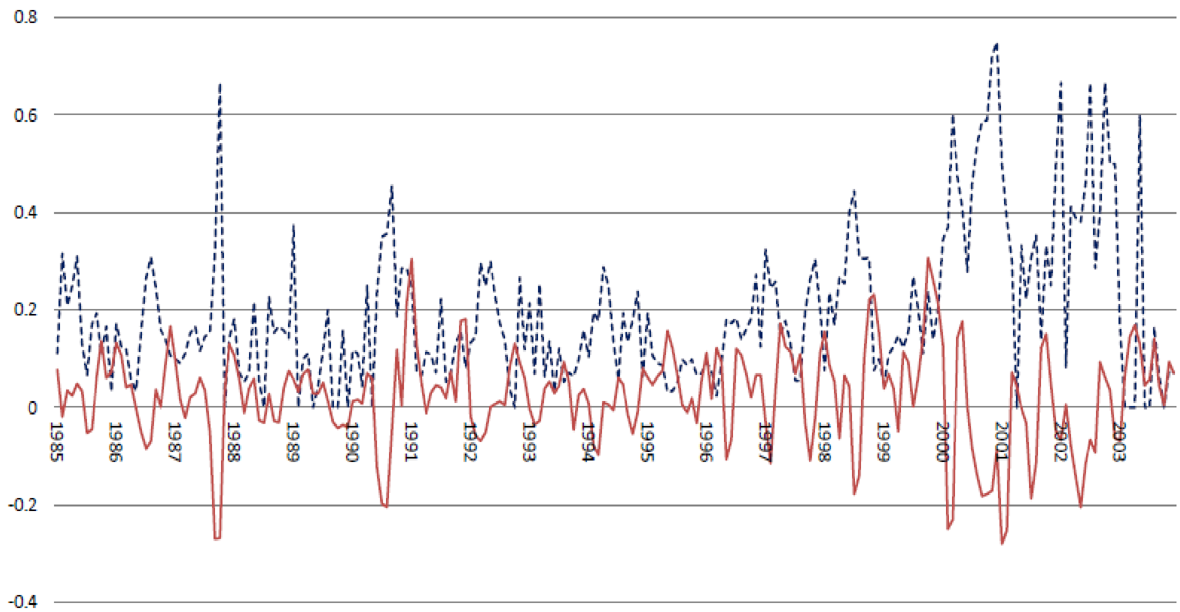


Figure 2 - Quality of Innovation around the IPO Event

The chart presents the 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.

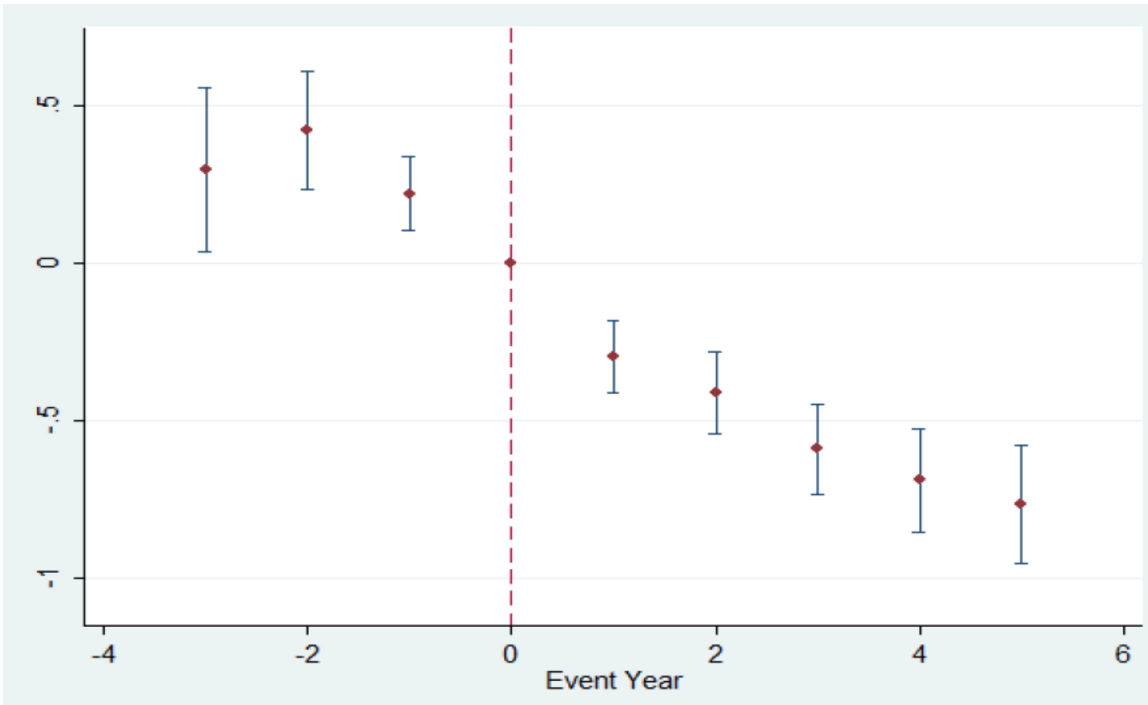


Figure 3 - Acquisition Likelihood

The chart 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.

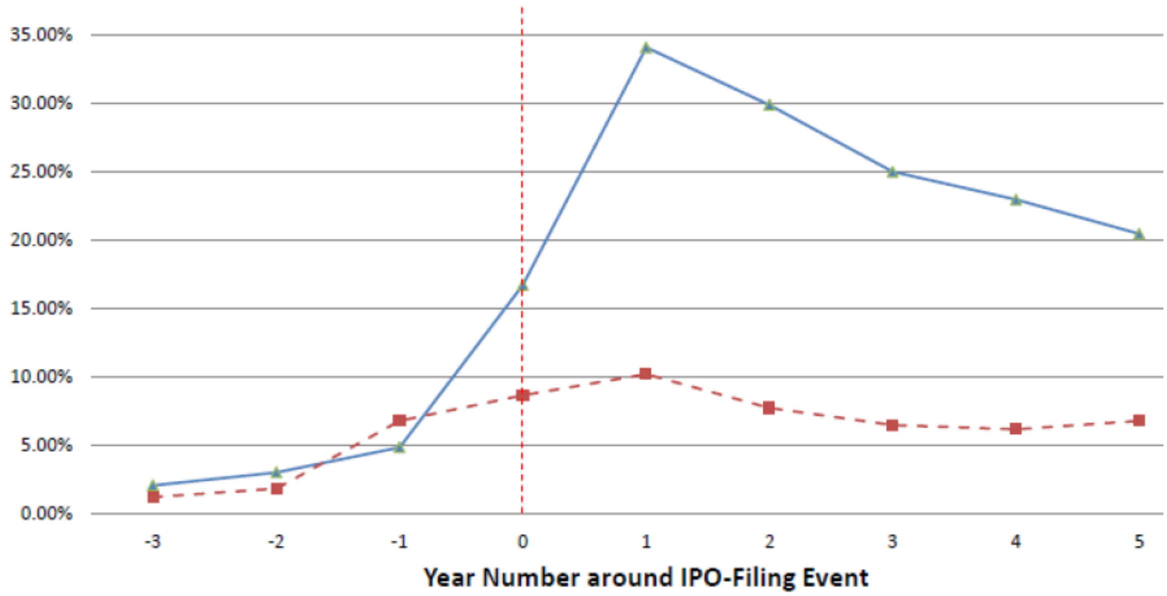
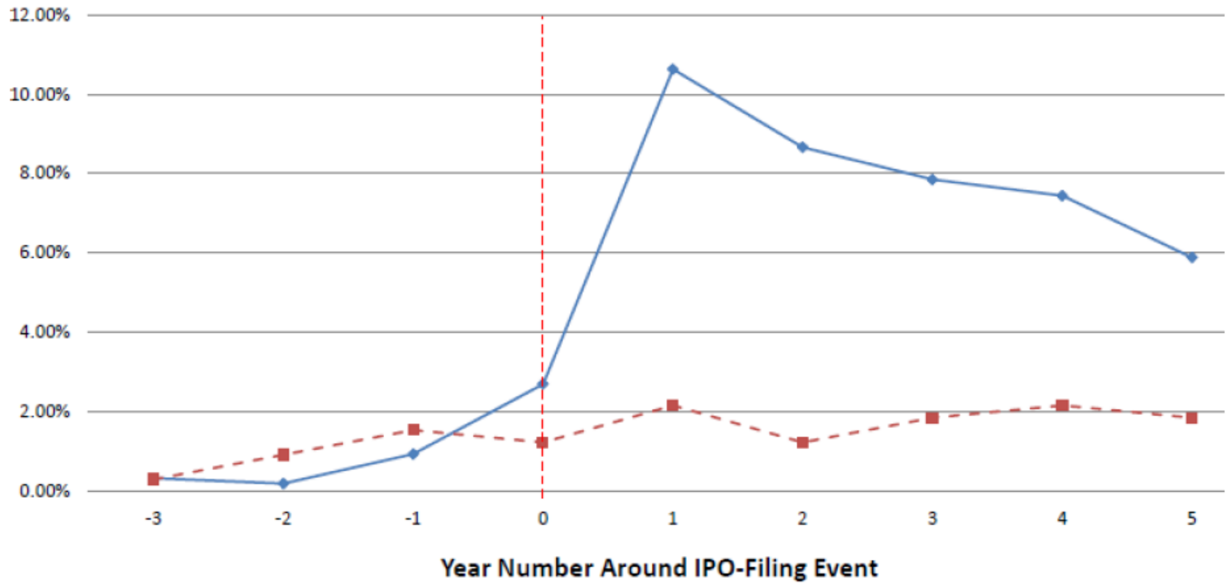


Figure 4 - Acquisition Likelihood of External Patents

The chart 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

A. Variable Definitions

1. *Citations* - Number of citations a patent receives from 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 dispersion across technology classes 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 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).

4. *Scaled Citations* - Number of citations a patent receives divided by the average number of citations received by 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 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 propensity 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. 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.

9. *Firm Age* - Firm age in the year of the IPO filing, calculated from the founding date. Firm age of firms that went public is kindly available at Jay Ritter's webpage. I collected the firm age of firms that remained private from registration statements.

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.

B. Quasi-Maximum Likelihood Poisson Model

A standard approach in the technological innovation literature is to estimate count-data, such as patents and citations, using quasi-maximum likelihood (QML) method. This implies assuming that the conditional mean has the following structure:

$$E\left(Y_i^{post}|X_i\right) = \exp(\alpha + \beta IPO_i + \gamma X_i) \tag{4}$$

An important property of the QML is that the standard errors are consistent under fairly general conditions, even if the underlying data-generating process is not Poisson. In addition, the estimator can be used for any non-negative dependent variables, whether integer or continuous (Santos Silva and Tenreyro, 2006) and QML standard errors are robust to arbitrary patterns of serial correlation (Wooldridge, 1997). The QML Poisson reported coefficients reflect marginal effects (derivative of dependent variable with respect to covariates) to allow easy comparison to the OLS estimates.[48]

The instrumental variable Poisson estimate uses a control-function approach (Blundell and Powell, 2004). To illustrate this approach, consider first the exogenous case, in which IPO_i is not correlated with the error term that satisfies:

$$E(v_i|IPO_i, X_i) = 1$$

when v_i denotes the error term in equation (4). This will not hold if IPO_i is correlated with the error term. Assume that $NSDQ_i$ (two-month NASDAQ fluctuations) satisfy:

$$IPO_i = \alpha^o + \delta NSDQ_i + \beta^o X_i^o + v_i^o$$

with

$$E(v_i^o|X_i^o) = 1$$

then controlling for v_i^o in the conditional mean equation is sufficient to remove the endogeneity bias. In the estimation, I use the extended moment condition

$$E\left(Y_i^{post}|X_i\right) = \exp(\alpha + \beta IPO_i + \gamma X_i + v_i^o)$$

Intuitively, the residual v_i^o captures the endogenous variation within the variable IPO_i; adding it as a control variable in the second-stage estimation allows identifying β consistently.

[48] Standard errors are adjusted appropriately using the delta-method.

Table A.1 - Placebo Test of Reduced Form Results

The dependent variable is the average scaled citations per patent over the five years after the IPO filing. *Post-IPO Filing NASDAQ returns* are the two-month NASDAQ returns calculated after the IPO filing date. *Post-Ownership choice NASDAQ returns* are the two-month NASDAQ returns calculated after 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). 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. 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)
	OLS	OLS	OLS
Post-IPO filing NASDAQ returns	−0.498**		−0.482**
	(0.239)		(0.237)
Post-Ownership choice NASDAQ returns		0.150	0.162
		(0.254)	(0.248)
Observations	1,079	1,079	1,079
R-squared	0.242	0.240	0.242
Filing year FE	yes	yes	yes
Industry FE	yes	yes	yes
Control variables	yes	yes	yes

Table A.2 - NASDAQ Drops are Not Correlated with Long-run Innovation Trends

The table reports the association of the two-month NASDAQ returns after the IPO filing date with changes in innovation trends within core technologies of filing firms. I define a technology class as a core technology if the share of patents in a certain technology class before the IPO filing is above the median share of patents across technology classes in a firm. Innovation trends in core technologies are calculated using all patents granted by the USPTO in the respectivce core technologies. The dependent variable in column (1) is the change in average quality per patent within each filer's core technology in the five years after the IPO filing, relative to the average quality 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)
	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