Financial Dependence and Innovation: The Case of Public versus Private Firms

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Abstract

This paper examines the relationship between innovation and firms' dependence on external capital by analyzing the innovation activities of privately-held and publicly-traded firms. We find that public firms in external finance dependent industries generate patents of higher quantity, quality, and novelty compared to their private counterparts, while public firms in internal finance dependent industries do not have a significantly better innovation profile than matched private firms. The results are robust to various empirical strategies that address selection bias. The findings suggest that public listing is beneficial to the innovation of firms in industries with a greater need for external capital.

Key Words: Private Firms, Public Firms, Innovation, R&D, Finance and Growth, Financial Constraints.

JEL Classification: G31, G32, O30, Ol6.

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1 Introduction

While innovation is crucial for businesses to gain strategic advantage over competitors, financing innovation tends to be difficult because of uncertainty and information asymmetry associated with innovative activities. Firms with innovative opportunities often lack capital. Stock markets can provide various benefits as a source of external capital by reducing asymmetric information, lowering the cost of capital, as well as enabling innovation in firms (Rajan (2012)).[1] Given the increasing dependence of young firms on public equity to finance their R&D (Brown et al. (2009)), understanding the relation between innovation and a firm's financial dependence is a vital but under-explored research question. We fill this gap in the literature by investigating how innovation depends on the access to stock market financing and the need for external capital.

We use a firm's public listing status to capture the access to stock markets and investigate its impact on innovation. While firms can gain an access to a large pool of low cost capital by trading on exchanges, they also face the pressure from myopic investors to generate short-term profits (Stein (1989)). Therefore, we expect that the effect of public listing on innovation will depend on the trade-off between the benefits and costs associated with listing on stock markets, which vary across firms with different

[1] Financing research and development is often stated as one of the uses of proceeds in the Securities and Exchange Commission Form S-1. For example, Evergreen Solar Inc. is a manufacturer of solar power products in the semiconductors and related devices industry which is external finance dependent. In the registration statement for its initial public offering on November 2, 2000, Evergreen Solar disclosed that the company would "anticipate using at least $3 million to finance research and development activities". InforMax Inc., a bioinformatics company, also belongs to an industry that relies external capital for investments. It went public on October 3, 2000. In the use of proceeds section of the registration statement, InforMax declared that it would "anticipate that the remaining portion of the offering proceeds would be allocated approximately one-third to expanding research and development".

degrees of dependence on external finance.

By analyzing the innovation activities of a matched sample of private and public firms, we observe that public firms on average have patents of higher quantity, quality, and novelty than their similar private counterparts. After considering the need for external finance, we find that only public firms in *external* finance dependent (EFD) industries have a significantly better innovation profile than private firms, not firms in *internal* finance dependent (IFD) industries. Industries that rely on external (internal) finance for their investments are considered as EFD (IFD) industries.

To understand the differential effects of public listing on innovation of firms in EFD and IFD industries, we explore four factors that may affect the cost-benefit trade-offs associated with being public. First, public listing could relax the financial constraints faced by firms in EFD industries. If this is the case, one would expect that firms with a need for capital will benefit more from obtaining access to stock market financing. Consistent with this conjecture, we find that firms in more innovation intensive industries with more dependence on external capital are more innovative when having access to equity capital compared to firms without such access.

Second, firms vary in the efficiency of converting R&D into patents. Relying on a higher cost of external capital to finance their innovation, public firms in EFD industries may utilize capital raised from stock markets more efficiently than public firms in IFD industries do. To this end, we test whether public and private firms in EFD and IFD industries differ in their innovation efficiency, measured as the natural logarithm of one plus the number of patents per dollar R&D investment. We find a higher innovation efficiency for public firms in EFD industries, but no significant difference for public and private firms in IFD industries.

Third, a part of the literature has argued that public firms are prone to agency problems given the separation of ownership and control. Under the pressure of myopic investors, managers have incentives to pursue short-term performance (Stein (1989), Bolton et al. (2006)).[2] Public firms in EFD industries, with a need for future equity, may select short-term projects that can generate immediate earnings; while public firms in IFD industries, without a need for future equity, may shield from the pressure of market myopia. To explore the influence of stock market short-termism, we investigate public firms' real earnings management activities in relation to their degree of external finance dependence and innovation. We find that public firms in EFD industries engage less in earnings management through their alteration of real activities. Furthermore, real earning management is even lower for more innovative public firms in EFD industries. To the extent that real earnings management represents firms' myopic behavior, innovative firms with a greater need for external capital appear less likely to boost short-term earnings at the expense of innovation investments. The potential reason could be that innovative firms have strong incentives to maintain their reputation as an innovator.

Fourth, the better innovation profile of public firms in EFD industries may be a result of patent acquisitions outside firm boundaries. Recent studies provide evidence that public firms have incentives to purchase patents and new technologies through

[2] In September 2009, the Aspen Institute along with 28 leaders including John Bogle and Warren Buffett called for an end of value-destroying short-termism in U.S. financial markets and an establishment of public policies that encourage long-term value creation (Aspen Institute (2009)).

mergers and acquisitions (Bena and Li (2013), Seru (2013)). Sevilir and Tian (2013) show that acquiring innovation can enhance the innovative output of the acquirers.[3] To isolate the impact of patent acquisitions, we perform two tests. First, we control for a variable that measures the acquired in-process technology in our models. Second, we conduct our analyses using a sub-sample of firms without acquisitions during the sample period. Our results are robust to these two tests.

Overall, our results suggest that financing benefits coupled with innovation efficiency and innovative firms' lower incentives to behave myopically help to explain the difference in the innovation of public and private firms in EFD industries.

A potential concern regarding our results is that firms in EFD and IFD industries may differ in the importance of technological innovation. Innovation may feature more in EFD industries than IFD industries. We conduct three tests in order to alleviate this concern. First, we investigate the relationship between a industry's external finance dependence and its innovation intensity. Using patents (or R&D) to measure industry innovation intensity, we find the correlation between EFD index and innovation intensity index is 0.08 (or 0.075) and statistically insignificant. Second, we match each matched pair of private and public firms in IFD industries by a matched pair of private and public firms in EFD industries that are same in age, year, and size. Using this sub-sample of age-year-size matched pairs in EFD and IFD industries, we still observe public firms in EFD industries have a better innovation profile than private firms, but no significant

[3]Since the access to stock markets can provide the capital needed for patent purchase, this acquisition-based explanation is actually consistent with the view that public listing provides financing benefits for innovation.

difference in IFD industries. Third, we restrict our analysis to firms with a minimum of one patent and our results remain intact.

Perhaps the biggest challenge of our empirical design is the concern that a firm's decision to gain access to stock markets may be an endogenous choice driven by other observed and unobserved factors. To overcome this selection bias, we adopt several identification strategies enabled by our large panel dataset of U.S. private and public firms. Our fixed effects estimation explicitly controls for observable time-series and cross-sectional variables that are related to innovation and the decision of going public. We then employ an econometric method to directly adjust for selection bias from unobservables. Specifically, we estimate the treatment effect model using an inverse Mills ratio to explicitly correct for selection bias.[4] Furthermore, we adopt several quasi-experimental designs to alleviate the concern about the non-randomness of public and private firms.

The first quasi-experiment applies the propensity score matching method to identify a sample of firms that transition from private to public (treatment group) and a sample of similar firms that remain private (control group). The difference-in-differences approach is then used to isolate the treatment effect by differencing out the influence of cross-sectional heterogeneity or common time trends on the innovation activities of the treated and the controlled groups. Identification of this approach relies on the assumption that the closely matched private firms act as a counterfactual for how the transition firms

[4]We also estimate an instrumental variable model using the percentage of public firms in the industry in a given year as an instrument for being public. A firm is more likely to go public as their peers in the same industry sell their shares publicly (Scharfstein and Stein (1990)), but its innovation activities are unlikely to be affected by the percentage of publicly-traded firms in the same sector other than through the publicly listing channel. The results are reported in the Appendix Table A.1. To address the concern that many firms have no patents, we also estimate poisson models and find similar results.

would have performed without going public. We observe a positive treatment effect in the patent portfolios for firms in EFD industries, while the effect is mostly insignificant for firms in IFD industries.

To ease the concern that a firm may go public at a specific stage of its life cycle, we adopt a second quasi-experiment, which we construct two groups of firms: a treatment group consisting of firms that eventually completed the initial public offering (IPO) after the withdrawal of the initial registration statement with Securities and Exchange Commission (SEC) and a control group of firms that ultimately did not go public after the initial withdrawal.[5] Applying the triple differences approach in a multivariate framework, we find an increase in the quantity and originality of patents for firms that successfully transition from private to public. Furthermore, this improvement in patent portfolios is concentrated in firms in EFD industries.

The triple differences approach relies on the assumption that the average outcome variables follow a parallel trend over the pre-treatment period. The validation of this parallel trend assumption is verified in our graphical test. Figure 3 shows that the trends in patents for both treatment and control groups are similar during the pre-withdrawn and pre-IPO eras, while the number of patents in the treatment group increases significantly after an IPO. Our multivariate test also confirms that there is no systematic difference in the trend of patents between the treatment and control group during the pre-treatment era.

[5]The process of going public in the U.S. requires filing security registration documents with the SEC. After the registration, the filers still have the option to withdraw their offering before issue. Withdrawals of registered IPOs are not uncommon. Dunbar and Foerster (2008) examine the 1985-2000 period and document that about 20% of firms withdrew their IPO filings and 9% of the withdrawn firms successfully complete the process later.

The third quasi-experiment involves a fuzzy regression discontinuity design exploiting the discontinuous nature of NASDAQ listing requirements for assets. The NASDAQ requires that a listed firm have a minimum number of net tangible assets.[6] Identification of this design relies on the assumption that observations close to the discontinuity threshold are similar. We first conduct a graphic analysis of the relationship between patent portfolios and the forcing variable (normalized net tangible assets in the IPO year) around the threshold. Figure 4 shows that firms with net tangible assets above the cutoff have a better patent portfolio than firms with net tangible assets below the cutoff. Moreover, the placebo analysis that uses normalized net tangible assets in a random year as the forcing variable exhibits no jump in patent portfolios at the threshold (Figure 5). Our formal fuzzy regression discontinuity estimations indicate that IPO firms listed on the NASDAQ have a relatively stronger innovation profile compared to private firms with net tangible assets very close to the minimum listing requirements of the NASDAQ.

Our study contributes to the nascent literature on identifying various economic factors driving firm innovation. The literature shows that innovation is affected by the development of financial markets (Amore et al. (2013), Chava et al. (2013), Hsu et al. (2013)), legal system (Brown et al. (2013)), bankruptcy laws (Acharya and Subramanian (2009)), labor laws (Acharya et al. (2013)), competition (Aghion et al. (2005)), investors' tolerance for failure (Tian and Wang (2012)), institutional ownership (Aghion et al. (2013)), and private equity (Lerner et al. (2011))[7]. Differing from previous work

[6] See Section 5.4 for details of the requirement.

[7] Lerner et al. (2011) find no evidence that private equity sacrifices innovation to boost short-term

focusing on public firms, we analyze a large sample of private and public firms and find that the innovation capacity of firms in EFD industries is influenced by access to stock market financing.

This paper adds new evidence to the recent surge of debate on the trade-off between public listing and staying private and its influence on firms' real activities. On the one hand, the benefits of an easier access to cheaper capital allow public firms to conduct more mergers and acquisitions (Maksimovic et al. (2012)), to raise more equity capital (Brav (2009)), and to pay more dividends (Michaely and Roberts (2012)) than private firms. Public firms can take better advantage of growth opportunities and are more responsive to changes in investment opportunities than their private counterparts (Mortal and Reisel (2012)). On the other hand, the agency conflicts resulting from divergent interests between managers and investors at public firms distort their cash holdings (Gao et al. (2013)), investments (Asker et al. (2011)). Our findings suggest that the lower cost of capital associated with public listing is important for innovation of firms with large capital needs, while the financing benefits of stock markets are weaker for innovation of firms in IFD industries.

Our paper is also related to Bernstein (2012) that finds a change in quantity and quality of innovation produced internally and acquired externally by IPO firms. Unlike his study that focuses on innovation activities of IPO firms, we investigate innovation

performance using a sample of 472 leveraged buyout (LBO) transactions during 1980-2005. In a similar spirit, we identify firms that experienced LBOs based on our sample (1994-2004) and explore changes in innovation of these firms in comparison with the matched public firms based on firm characteristics. Our unreported results from propensity score matching coupled with difference-in-differences estimations show no significant difference in changes in innovation during the transition between the LBO firms and the controlled public firms.

of similar public and private firms in general and adopt several quasi-experiments to gauge the effect of public listing on innovation. Our results highlight the importance of considering a firm's external financing need when evaluating the role of stock markets in innovation.

The rest of the paper is organized as follows. We develop hypotheses in Section 2. In Section 3, we describe the data, innovation, and external finance dependence measures. Section 4 presents differences in innovation of private and public firms. In Section 4.5, we exploit several quasi-experimental designs to isolate the treatment effects. Section 6 discusses the potential explanations for the observed difference in innovation of private and public firms. We conclude in Section 7.

2 Theoretical Motivation and Empirical Hypothesis

The theoretical literature presents two opposing views on the impact of stock markets on innovation. One view focuses on the myopic nature of stock markets and/or managers. These models of short-termism argue that stock markets tend to be obsessed with short-term earnings and such myopia could induce public firms to invest sub-optimally (Stein (1989); Bebchuk and Stole (1993)). With their compensation linked to stock performance, managers of public firms have incentives to sacrifice long-term investments in order to boost short-term stock returns. Innovation typically requires a substantial amount of investments for a long period of time and the probability of success is highly uncertain. Holmstrom (1989) and Acharya et al. (2013) suggests that managers, under the pressure to establish a good performance record in capital markets, have few incentives to undertake long-term investments such as innovation. Moreover, with the assumption of observable cash flows and no tolerance for failures in public companies, Ferreira et al. (2012) develop a model to demonstrate that managers of public companies are rationally biased against innovative projects, which usually have a higher failure rate. An implication of these models is that stock markets hinder managers from investing in innovation.

The other view focuses on the financing advantages of stock markets for innovation. First, stock markets are an important source of financing for innovation. Allen and Gale (1999) model indicates that public equity markets, which allow investors with diversified opinions to participate, enable the financing of innovative projects with uncertain probabilities of success. As illustrated in the model of Rajan (2012), the ability to secure capital alters the innovative nature of firms. Equity markets play an essential role in providing the capital and incentives that an entrepreneur needs to innovate, transform, create enterprise, and generate profits. He argues that firms with an easier access to equity capital are more likely to conduct capital-intensive fundamental innovation.

Second, the literature suggests that equity is preferable to debt in financing innovative projects. Hall and Lerner (2010) suggest that intangible assets and knowledge created by innovation are difficult to quantify as collateral for debt financing. The uncertainty and volatile return of innovative projects also make them unattractive to many creditors (Stigliz (1985)). Moreover, Rajan (2012) points out that the possibility of losing the critical asset to creditors in the event of project failure discourages entrepreneurs to innovate. In contrast, equity capital is a favorable way to finance innovation since it allows investors to share upside returns and does not require collateral.

Third, the listing in a stock market lowers the cost of capital as investors' portfolios become more liquid and diversified (Pagano et al. (1998); Benninga et al. (2005)). It also helps to lower borrowing costs because of the reduced asymmetry of information (Schenone (2010)) and increased lender competition (Saunders and Steffen (2011)).

Given the contrasting predictions of the two streams of research, it becomes an empirical question as to how stock markets actually affect innovation. Moreover, the impact may vary based on reliance on external financing. Rajan and Zingales (1998) argue that industries differ in their demand for external financing due to the differences in the scale of the initial and continuing investments, the incubation period, and the payback period. With the differential needs for external capital, firms face different trade-offs between the costs and benefits associated with public listing.

For firms with insufficient internal cash flows for their investments, the infusion of public equity could relax their financial constraints and therefore facilitate innovation. Additionally, bearing a higher cost of funding, they would utilize their capital more efficiently. However, with a need to raise equity in the future, they may face the pressure to choose short-term projects that will satisfy quarterly earnings growth.

For firms with excess cash flows over their investment needs, the additional capital raised from stock markets may enable them to acquire innovation externally. However, ample capital may give rise to agency problems, which will reduce innovation efficiency. In addition, the exposure to stock market short-termism might potentially stifle the innovative activities of these firms, although may be to a lesser degree due to their lower need for future equity. With the implications of theoretical models in mind, we conjecture that *the impact of listing in stock markets on innovation varies with the degrees of external finance dependence.*

3 Data and Measures

3.1 Data

To measure innovation activities, we collect firm-year patent counts and patent citations data from the latest edition of the National Bureau of Economic Research (NBER) Patent Citation database. The database contains information on every patent granted by the United States Patent and Trademark Office (USPTO) from 1976 to 2006, including patent assignee names, the number of citations received by each patent, a patent's application year, a patent's grant year, and the technology class of the patent, among other items.

The financial data on U.S. private and public firms are obtained from S&P Capital IQ for the 1994-2004.[8] The sample stops in 2004 because the average time lag between patent application date and grant date is two to three years (Hall et al. (2001)).[9] S&P Capital IQ categorizes a firm as public or private based on its most recent status. For

[8]Sageworks is another database that covers financial information of private firms. However, Sageworks is not suitable for our study for two reasons. First, Sageworks does not contains R&D spending data. Second, firms in Sageworks are difficult to be matched with the patent database, since firms in Sageworks are anonymous. See Asker et al. (2011) for details of Sageworks database.

[9]Using a sample period of 1994 to 2003 yields similar results.

example, Google Inc. is classified as public in 2002 although it went public in 2004. We reclassify a firm's private (or public) status with IPO date from Compustat, Thomson One, Jay Ritter's IPO database, the first trading date information from CRSP, and delisting date information from Compustat. Financial institutions and utilities (SIC code 6000-6999 and 4900-4999) and firms with no SIC codes are excluded. We require non-missing data on total assets and non-negative value on total revenue. Firm-years with total assets less than $5 million USD are excluded. Cash, leverage, capital expenditure ratios, and R&D ratios are winsorized at 1% and 99% to avoid the effect of outliers.

We merge financial data with the patent database by GVKEY and by company names when GVKEY is unavailable. We manually check the names to ensure the accuracy of the match. In cases where the names are not exactly identical, we conduct internet searches and include the observation only if we are confident of the match. Following the innovation literature (e.g. Atanassov (2013)), the patent and citation counts are set to zero when no patent and/or citation information is available. Including firm-year observations with no patents alleviates the sample selection concern. After this process, there are 2,392 private firms and 8,863 public firms left in the sample.

3.2 Matched Sample

A potential concern regarding the above sample is that private firms in S&P Capital IQ may be larger and less innovative than public firms. S&P Capital IQ provides coverage for U.S. private firms with minimum revenues of $5 million or with public debt issuances. Following the literature, we require both private and public firms to have a minimum $5 million of total assets. Previous studies have shown that innovation varies substantially across industries and by firm size (Acs and Audrestsch (1988)).

To minimize the differences in industry and size distributions, we identify a sample of industry-and-size-matched private and public firms.[10] Specifically, for each private firm from the beginning of the sample period, we find a public firm closest in size and in the same four-digit SIC industry.[11] We plot the distribution of the logarithm of total assets for the matched private and public firms in the first graph of Figure 1. The two distributions are almost perfectly overlapped. The time-series observations for each matched pairs are kept in order to preserve the panel structure of the data. This procedure results 1,717 matched pairs of private and public firms. Our reported results are mainly based on this matched sample, which will mitigate the concern about comparing small public firms with large private firms.[12] In addition, we also control for the differences in firm size, age and other characteristics in our estimations.

3.3 Innovation Measure

We use R&D spending to measure innovation input and patent-based metrics to measure innovation output (Hall et al. (2001, 2005)). The first measure of innovation output is

[10]We also match by firm age, which leads to a smaller sample. Our results are robust to the industry-size-and-age matched sample.

[11]Closest in size means that two firms have the smallest ratio of their total assets (TA). The ratio of total assets is defined as $max(TA_{private}, TA_{public})/min(TA_{private}, TA_{public})$. Asker et al. (2011) use a similar method to identify firm's closest in size.

[12]The unmatched sample includes both firms that remain private or public during the entire sample period and firms that go from private to public. The matched sample consists of firms that experience no transition during the period. We find similar results using both matched and unmatched sample. Nevertheless, our findings might not be generalized to small public and private firms with total assets below $5 million.

the number of patents applied by a firm in a given year. The patent application year is used to construct the measure since the application year is closer to the time of the actual innovation (Griliches (1990)). Patent innovation varies in their technological and economic significance. A simple count of patents may not be able to distinguish breakthrough innovations from incremental technological discoveries (Trajtenberg (1990)). Thus, we use the citation count each patent receives in subsequent years to measure the importance of a patent. Citations are patent-specific and are attributed to the applying firm at the time of application, even if the firm later disappears due to acquisition or bankruptcy. Hence, the patent citation count does not suffer survivorship bias. Hall et al. (2005) show that the number of citations is a good measure of the quality of an innovation.

However, the patent citation is subject to a truncation bias. This is because citations are received over a long period of time, but we only observe the citations up to 2006. Compared to patents created in earlier years, patents created in later years have less time to accumulate citations. Additionally, the citation intensities of patents might vary across different industries. Lerner et al. (2011) suggest that the frequency of patent citations, as well as patents in technologically dynamic industries have increased in recent years. To correct for this time trend in citations, we scale the raw patent citation counts by the average citation counts of all patents applied in the same year and technology class following Hall et al. (2001, 2005).[13] This measure shows the relative citation counts

[13] An alternative way to adjust patent citations for truncation bias is to weight the number of citations with the estimated distribution of citation-lag. That is, each patent citation is adjusted using the citation truncation correction factor estimated from a diffusion model. The weakness of this adjusted citation is that it does not measure the relative importance of the patent compared to similar patents. Using this truncation-bias-adjusted citation yields similar results.

compared to matched patents after controlling for time and technology fixed effects.

Innovative projects differ in their novelty. Fundamental research tends to be risky and produce more influential innovations. Following Trajtenberg et al. (1997), we use the originality and generality of patents to measure the novelty of innovation. These two proxies also reflect the degree of risk that firms are bearing in their pursuit of R&D. Originality is computed as the Herfindahl index of cited patents:

$$Originality_i = 1 - \sum_{j}^{n_i} F_{ij}^2,$$

where F_{ij} is the ratio of the number of cited patents belonging to class j to the number of patents cited by patent i. The originality of a patent indicates the diversity of the patents cited by that patent. A patent that cites a broader array of technology classes has a higher originality value.

Similarly, generality is measured as the Herfindahl index of citing patents:

$$Generality_i = 1 - \sum_{j}^{n_i} G_{ij}^2,$$

where G_{ij} is the number of patents citing patent i belonging to class j scaled by the number of patents citing patent i. The generality of a patent indicates the diversity of the patents citing that patent. A patent that is cited by a broader array of technology classes has a higher value of generality.

3.4 External Finance Dependence Measure

Rajan and Zingales (1998) argue that the degree of dependence on external financing varies across different industries. Industries such as biotechnology rely more on external capital, while industries such as tobacco are less external capital dependent. To construct an industry's dependence on external finance, we follow Rajan and Zingales (1998) and first measure a firm's need for external finance in a year as the fraction of capital expenditure not financed through internal cash flow.[14] The time series industry-level external finance dependence is constructed as the median value of the external finance needs of all firms in the two-digit SIC code industry in each year. We then measure each industry's external finance index as a percentile ranking of its time series median during 1994-2004.[15] An industry with a higher index value of external finance dependence relies more on external capital to finance its investment.

4 Empirical Analysis

4.1 Univariate Analysis

In Table 1, we compare firm characteristics and innovation activities of private and public firms in the full sample (Panel A) and the matched sample (Panel B). In the full sample, public firms on average are bigger in size and older compared to private firms. Age is defined as the difference between current year and founding year of a firm.[16] Private firms have more tangible assets and higher sales growth. In terms of cash holdings, private firms hold a lower percentage of their assets as cash (14.66% of

[14]We also include R&D as part of investments in order to construct the external finance dependence measure. Our results are robust to this alternative measure.

[15]Hsu et al. (2013) use a similar approach to measure an industry's dependence on external finance.

[16]To compute firm age, we cross-check the founding year data in Capital IQ and Jay Ritter IPO databases to ensure accuracy.

total assets), while public firms reserve a higher percentage of cash (18.89% of total assets). The average return on assets (ROA) of private firms is lower than that of public firms. Private firms have a capital expenditure ratio of 7.20% relative to total assets, while public firms have a ratio of 6.31%.

As for innovation activities, Panel A of Table 1 shows that public firms have a slightly lower R&D ratio, defined as R&D expenses as a ratio of total assets, than private firms. The ratio of R&D expenditure to total assets is 5.48% for private firms, while the ratio is 4.93% for public firms. In terms of the outcome of investments in innovation, private companies on average have significantly fewer patents compared to public firms (1 vs. 7). The patents applied by public firms are on average of better quality than those of private companies as measured by the truncation bias adjusted citations. The patents of public companies receive more citations compared to those of private companies (0.32 vs. 0.18). The difference in the average number of citations to the patents of private and public firms is statistically significant. Public firms also tend to produce more original patents with wider applications.

Similar differences between private and public firms are observed in the matched sample, with a few exceptions. Panel B of Table 1 shows that the matched private and public firms are similar in size after we match firms on size and industry. Public firms have fewer tangible assets, lower sales growth, fewer tangible assets, more cash, lower ROA, and lower capital expenditure ratios than otherwise similar private firms. For the size-and-industry matched sample, public firms on average have a higher R&D ratio. The patent profile of matched public firms is better than their private counterparts. For example, the average number of patents generated by public firms is 2, while it is fewer than 1 for matched private firms.

4.2 Multivariate Analysis

The univariate analysis indicates that public firms on average outperform private firms when it comes to their innovation activities. However, the difference in innovation outcome between private and public firms may be confounded by the difference in firm characteristics. To control for the distinctness in observable firm attributes and the influences of industry characteristics and time on innovation, we estimate the following panel data model:

$$Y_{ikt} = \alpha + \beta Public_{it} + \gamma X_{ikt} + \eta_k + \zeta_t + \varepsilon_{ikt}, \tag{1}$$

where Y_{ikt} measure innovation activities. The measures include R&D ratio, number of patents, truncation bias adjusted citations, originality, and generality. $Public_i$ is a dummy variable equal to one for public firms and zero for private firms; X_{ikt} is a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$ (log of total revenue), $Tangible$ (tangible assets scaled by total assets), $Cash$ (total cash scaled by total assets), Age (the difference between current year and founding year); $Capex$ (capital expenditures scaled by total assets), $S.Growth$ (the first difference of the natural logarithm of total revenue), ROA (EBITDA divided by total assets); η_k control for industry effects based on two-digit SIC codes; and ζ_t control for year fixed effects. The coefficient β estimates the effect of public listing on innovation while the confounding variables are controlled.

Since the full sample and the industry-and-size matched sample yield similar results, we report the main results based on the matched sample. In Panel A of Table 2, the first specification has R&D ratio as the dependent variable. The coefficient on the dummy variable *Public* is positive, indicating that public firms spend more on R&D than private firms once the confounding effects have been controlled. R&D ratio of public firms is 0.48% higher than matched private firms. With regard to the outcome of investments in innovation, there is a significant difference between the two types of firms. The estimated coefficients on *Public* are positive and significant in all specifications. Public firms on average have one more patents than private firms. The patents of public firms are also more influential in terms of citations compared to those of private firms. The originality and generality of the patents developed by public firms are also higher than those by private firms.

As for control variables, we observe that larger firms tend to have a higher R&D ratio, produce more patents, receive more citations to their patents, and have more novel innovation. Firms with more tangible assets produce more patents that have a broader impact. The coefficients on *Cash* are positive and significant, which suggests that firms with more cash are more innovative. The incentives to invest in innovation may vary among firms during different stages of their lifecycles. We use the age variable to control for a firm's lifecycle effects. Mature firms tend to have lower R&D spending as a percentage of total assets. Regarding innovation outcome, there is no significant difference between older and younger firms in terms of patent quantity and citations.

However, patents produced by older firms are more novel. The coefficients on *Capex* are positive but insignificant in general. The coefficients on *ROA* are negative, while those on sales growth are mixed.

4.3 Treatment Effect Model Estimation

The panel data estimations provide suggestive evidence that the public listing status of a firm is associated with its innovative ability. Clearly the decision of being public or staying private is not random. The effect of treatment (being public) may differ across firms and may affect the probability of firms going public. To establish causality, we need to control for unobservables that could drive both innovation and the decisions to go public. To address the potential endogeneity of the treatment dummy, we estimate the treatment effect model that explicitly corrects for selection bias using the inverse Mills ratio.[17]

The treatment effect model includes two equations. The first one is the outcome equation (equation (1)) with the dummy variable *Public* indicating the treatment condition (i.e., being public). The coefficient β denotes the average treatment effect:

[17]Li and Probhala (2007) provide a survey of selection models in corporate finance and show that self-selection is an omitted variable problem. Self-selection can be corrected by adding the inverse Mills ratio in the second-step. The identification of the treatment effect model relies on nonlinearity of inverse Mills ratio. Differing from the standard Heckman model that estimates a self-selected subsample, the treatment effect model involves both the self-selected and unselected samples and has an endogenous indicator variable (*Public* dummy in our context) as an independent regressor. The variable of interest is the coefficient on the indicator variable.

$ATE = E(Y_i|Public = 1) - E(Y_i|Public = 0)$. The second one is the selection equation:

$$Public_i = \begin{cases} 1 & \text{if} \quad Public_i^* > 0 \\ \\ 0 & \text{if} \quad Public_i^* \leq 0 \end{cases} \qquad Public_i^* = \pi + \delta Z_i + \upsilon_i \tag{2}$$

where Z is a set of firm characteristic variables that affect a firm's decision to go public. The treatment model is estimated with a two-step approach. The first step estimates the probability of being public from the probit model in equation (2). The second-step includes the inverse Mills ratio ($Mills$) to equation (1) in order to adjust for the selection bias. We report the first step of the estimation in the first column of Table A.2. The results for the second step of the estimation are reported on Panel B of Table 2. The negative coefficient on the inverse Mills ratio indicates that the covariance between the error terms in the selection and outcome equations is negative. Firms are more likely to choose go public when the impact on innovation is smaller. The coefficients on the *Public* dummy are all positive and significant. After correcting for selection bias, public firms still appear to spend more on R&D, get more patents, and have higher quality and more novel innovation. Public firms' R&D to total assets ratio is 1.24% higher than the size-and-industry matched private firms. Public firms on average produce three more patents per year compared to their private counterparts.[18]

[18]Since public firms also have debt, the results that public firms have a better innovation profile than similar private firms do not necessarily imply that debt is bad for innovation. What is the impact of debt financing on innovation is an interesting research question beyond the scope of this study.

4.4 External Finance Dependence and Innovation

To investigate the relationship between innovation and a firm's access to stock market financing conditional on its need for external finance, we classify firms into external finance dependent and internal finance dependent industries. We regard industries with a positive value of the external finance dependence measure as external finance dependent, while those with a negative value as internal finance dependent.

We first compare the characteristics and innovation of private and public firms in external and internal finance dependent industries. Table A.3 shows that the differences in characteristics between private and public firms are similar among industries with differential levels of dependence on external finance. Regarding innovation activities, public firms produce significantly more patents than private firms and their patents are more important and of better quality too. The differences between private and public firms are larger in EFD industries than in IFD industries. The average difference in patent is 1.54 for public and private firms in EFD industries, while the difference is 0.23 for those in IFD industries.

We then estimate the treatment effect model separately for firms in EFD and IFD industries. Table 3 shows that the coefficients on the dummy variable *Public* are positive and significant for firms in EFD industries, but are insignificant for firms in IFD industries.[19] The result suggests that being publicly listed has a stronger impact on

[19] To ease the concern about the imbalance in the number of firms in EFD and IFD industries, we divide firms in external finance dependent industries into tertiles and estimate the treatment effect model using firms in the top tertile. The results are reported in Table A.4. We still observe that public firms in external finance dependent industries have relatively better innovation profiles than private firms and the difference is statistically significant.

innovation in industries with a greater need for external capital. For example, public firms on average have about 4 more patents than private firms in EFD industries, while the difference between public and private firms is negative and insignificant in industries dependent less on external capital. The patents of public firms in the EFD industries are also of higher quality. Additionally, the differences in the originality and generality of patents produced by public and private firms are only significant in EFD industries.

To test whether the impact of public listing on innovation is significantly different between EFD and IFD industries, we include several interaction terms to the second step of the treatment effect model. The estimated model is as following:

$$Y_{ikt} = \alpha + \beta Public_i + \delta EFD_{ik} + \theta Public_i \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}, \tag{3}$$

where EFD_{ik} is the industry external finance index. Panel A of Table 4 reports the coefficients on θ. The coefficients are positive and significant, indicating that the impact on innovation of being publicly listed is stronger in EFD industries than in IFD industries. Overall, the results are consistent with the view that having a public listing status positively affects the innovation of firms with a greater need for external capital.

4.5 Robustness

One may concern that the differential effects of public listing on innovation between EFD and IFD industries may simply reflect different orders of importance of innovation in each industry. Firms in EFD industries may be younger and more innovative by nature; while firms in IFD industries may be older and less innovative. To ease this concern, we investigate whether or not innovation matters more for EFD industries. We construct an innovation intensity index to measure the importance of innovation to an industry. Following Acharya and Subramanian (2009), we first compute the time-series industry-level innovation intensity as the median number of patents for all patent-producing firms in the two-digit SIC code industries in each year. We then measure each industry's innovation intensity as its time series median during 1994-2004 and use percentile ranking of innovation intensity as the innovation intensity index.

Figure 2 plots each industry's innovation intensity index against its EFD index. The figure exhibits no obvious relationship between an industry's dependence on external financing and the importance of innovation in that industry. The correlation between innovation intensity index and EFD index is 0.08 and statistically insignificant. As an alternative measure, we use R&D spending to construct each industry's innovation intensity.[20] We also find a low and insignificant correlation (0.075) between this R&D-based innovation intensity index and EFD index. There is no evidence that EFD industries are innovation intensive than IFD industries.

As a further investigation, we examine whether or not our results are driven by the age differences. We plot the distribution of firm age for the matched private and public firms, as well as for matched firms in EFD and IFD industries. Figure 1 shows there are more younger private firms than public firms in the sample, consistent with what is

[20]The R&D based innovation intensity index is constructed following the same procedure as the patent-based innovation intensity index. The only difference is that the median value of R&D for all firms with non-zero R&D spending in the two-digit SIC code industries in each year is used to compute the time-series industry-level innovation intensity.

observed in Table 1. This age difference is more pronounced in IFD industries.

To mitigate the concern regarding the difference between EFD and IFD industries, we match firms in EFD and IFD by age, year, and size. Specifically, for each matched pair of public and private firms in IFD industries, we find a matched pair of public and private in EFD industries. We identify 193 age-year-and-size matched pairs and repeat our estimations. Table 4 Panel B shows similar finding that public listing matters more for innovation of firms in EFD industries. Moreover, our analyses also directly control for size and age, along with other variables that may affect innovation.

Another concern is that many firms have zero patents, which may create a bias in an OLS framework (Griliches (1990)). We adopt two approaches to to alleviate this potential bias. First, we employ poisson models to our sample. Second, we conduct our main analyses using a sub-sample of firms with non-zero patents. Our results are robust to these tests.

5 Quasi-Experiments

The estimations so far are based on the treatment effect model, which directly controls for selection bias through an inverse Mills ratio. To further ease the concern about the non-randomness of public and private firms, we explore three quasi-experimental designs: (1) the propensity score matching (PSM) combined with the difference-in-differences (DD) approach that compares firms transitioning from private to public with those remain private, (2) the triple differences (DDD) approach investigating firms that experienced withdrawal of an IPO, and (3) a fuzzy regression discontinuity approach investigating discontinuity in the probability of going public as a function of NASDAQ listing requirement for net tangible assets. These quasi-experiments are used to isolate the causal effect of public listing on innovation .

5.1 Difference-in-Differences

The first quasi-experiment uses the DD approach involving two groups: a treatment group consisting of firms transitioning from private to public during the sample period and a control group including firms that remain private. To estimate the treatment effect, we compare the changes in the outcome variables of the treatment group (before and after the implementation of the treatment) with those of the control group.

Following the suggestion of Blundell and Dias (2000), we combine the PSM with the DD approach. To investigate the dynamics, we require firms to have at least four consecutive years of data and require IPO firms to have data at least two years before and one year after the IPO. We use the PSM method to match the IPO firms and private firms by the propensity scores of being public from the logit regression based on their total assets, capital expenditure, ROA, and leverage.[21] The matched firms are required to operate in the same industry. The sample used for the logit regression includes 961 IPO firms and 695 private firms. We use the year that an IPO firm goes public as the fictitious IPO year for its matched private firm. The matched sample consists of 370 pairs of private and IPO firms; 318 pairs are in external finance dependent industries.

[21]We use propensity score matching with no replacement and a caliper of $0.25\times$standard deviation.

After obtaining the closely matched treatment and control groups, we apply the DD approach to difference out the cross-sectional heterogeneity or common time trend that affects both groups of firms. Panel A of Table 5 presents the results from the DD analysis for firms in EFD industries. We compute the DD estimator as the difference of changes in the average patent portfolios of the treatment and control groups around the IPO. For external finance dependent industries, firms that transition from private to public experience an increase in the number of patents, and patent citations, as well as the originality of the patents, while firms that remain private experience a marginal decrease in patents. R&D as a percentage of total assets declines slightly after firms go public, although the dollar amount of spending on innovation development increases. The DD for the treatment and the control groups in EFD industries are statistically significant, except for generality (Panel A). However, the DD for patent portfolios of the treatment and control groups in IFD industries are generally insignificant (Panel B). To the extent that the innovation activities of the private firms represent the counterfactual scenario if the IPO firms did not go public, the results provide no evidence that going public impairs a firm's ability to innovate, especially for firms in EFD industries.

5.2 Triple Differences

A potential concern with the first quasi-experiment is that the treatment effect may be confounded by a firm's choice of the timing of its IPO. Therefore, we explore the second quasi-experiment which involve firms that withdrew their IPO registrations for reasons unrelated to innovation and adopt a DDD approach. The treatment group includes firms that eventually completed the IPO after the initial withdrawal (success sample). The control group comprises of firms that ultimately failed to go public (withdrawn sample). The withdrawn sample can act as a counterfactual for how the success sample would have performed if they failed to go public.[22]

We focus on firms that experienced withdrawal of an initial registration statement for two reasons. First, it eases the concern that a comparison of innovation dynamics of IPO firms around the transition with the matched private firms may simply reflect the difference in the lifecycles of those firms. Second, it minimizes the concern that a comparison of the innovation activities of IPO firms without the experience of IPO filing withdrawal with those of withdrawn firms may be confounded by endogeneity of the decision to withdraw.[23]

We identify firms that withdrew their initial registrations from S&P Capital IQ and

[22]Seru (2013) and Savor and Lu (2009) adopt a similar empirical design in the context of mergers. Bernstein (2012) also use withdrawn firms as the control group for IPO firms in order to examines the difference in innovation between the control and treated group. Distinct from Bernstein (2012)'s comparison of patents of *successful* IPO firms with IPO withdrawn firms, we investigate a group of firms with shared experience, that is, firms that eventually completed the IPO process following the withdrawal of their initial filings and firms that ultimately did not go public after the withdrawal. We find similar results using a sample a IPO firms and withdrawn firms.

[23]Dunbar and Foerster (2008) find that "weak market conditions" is the most commonly stated reason for IPO withdrawals. To test whether or not firms in our sample withdraw or complete their IPOs for the "exogenous" market conditions reason, we investigate the timing of withdrawals and subsequent successful attempts. In our withdrawn sample, 24.86% of withdrawals happened in 2001, followed by 21.04% in 2000. In the success sample, the withdrawals happened more in 1998 (27.61%) 2001 (15%) and the follow-on successful attempts mainly completed in 2004 (23.11%), 2000 (22.7%), and 1999 (17.38%). Hot market appear to feature more successful attempts, while cold markets have more withdrawals. It is consistent with the view that market conditions matter for the decision of withdrawal and returning to the market. We also randomly select firms in the sample and search for their requests to withdraw registration statement from the SEC website. The market condition appears to be a main reason for withdrawal. For example, Viewlocity Inc. withdrew its IPO on January 9, 2001 and stated in the registration withdrawal request that "At this time, due to the volatility of the public capital markets, the Company has determined not to proceed with the public offering contemplated by the Registration Statement". On August 2, 2000, Theravance Inc. terminated its IPO "in light of unfavorable market conditions" and completed its IPO on October 5, 2004 in order to "facilitate access to public capital markets".

Thomson One equity issuance databases and apply the DD and DDD estimations. Our identification strategy compares innovation activities (1) before and after IPO, (2) across the success and withdrawn samples, and (3) across firms in the EFD industries and the IFD industries. The DDD estimating equation is thus:

$$\begin{aligned} Y_{ikt} = {} & \alpha + \beta Success_i + \delta Success_i \times After_{it} + \theta After_{it} + \delta EFD_{ik} \\ & + \theta Success_i \times EFD_{ik} + \kappa Success_i \times After_{it} + \rho Success_i \times After_{it} \times EFD_{ik} \\ & + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}, \end{aligned} \tag{4}$$

where Y_{ikt} is the measures of innovation activities: R&D, number of patents, truncation-bias adjusted citations; $Success_i$ is a dummy variable equal to one for firms that completed an IPO after withdrawal of the initial filing and zero for firms that did not complete an IPO after withdrawal of the initial filing; $After_{it}$ is a dummy variable that takes a value of one for post-withdrawn years of withdrawn firms and post-IPO years of successful IPO firms; EFD_{ik} is an industry external finance index; and X_{ikt-1} is a set of characteristic variables that affect a firm's innovation activities.

Table 6 reports the results of DD (Panel A) and DDD (Panel B) estimations. Panel A shows that the coefficients on $Success \times After$ are insignificant, suggesting that, on average, there is no significant difference in the innovation of successful and withdrawn firms in all industries. In Panel B, we condition our analysis on firms' dependence on external capital. The coefficient (δ) represents the differential post-IPO impact between the treatment and control groups in IFD industries. The negative coefficients in all specifications suggest no improvement in the innovation profile of firms in IFD after they complete an IPO. The coefficients on the three-way interactive term (ρ) are significant and positive in the specifications of patent, citations, and originality. The positive coefficients indicate that external finance dependent firms that eventually went public produce more patents after IPO. The patents of these successful IPO firms are of higher originality than the patents produced before IPO. The coefficients are positive but not significant in the specifications of citations and generality. Overall, the DDD results are consistent with the view that the access to stock markets helps the innovation of firms in a greater need of external capital.

5.3 Parallel Test

The key identifying assumption of DDD approach is the parallel trend assumption under which, in absence of treatment, the average outcomes for the treatment and control groups would have the same variation. We perform two diagnostic tests to ensure the parallel trend assumption is satisfied. The first test is a graphic diagnosis. We plot the patent dynamics of the treatment group over the pre-withdrawn, pre-IPO, and post-IPO periods and that of the control group over the pre-withdrawn and post-withdrawn periods.[24] Figure 3 shows that the treatment and control groups follow similar trends in patents during the pre-withdrawn and pre-IPO eras.

As a second test to investigate whether or not there is pre-trend in innovation prior to the transition from private to public, we adopt an approach similar to Bertrand and Mullainathan (2003) and Acharya and Subramanian (2009). We use three dummy

[24] In order to examine changes in patents around the transitions, we require that firms in the treatment group have at least one observation in each of the three periods.

variables to capture any effects during three separate time periods: before withdrawal of the initial registration statement (*Pre-Withdrawn*); during the period between the withdrawn year and the IPO year (*Pre-IPO*); and after the IPO years (*After*). The following model is estimated:

$$Y_{ikt} = \alpha + \beta Pre\text{-}Withdrawn_{it} + \delta Pre\text{-}IPO_{it} + \theta After_{it} + \gamma X_{ikt-1} + \varepsilon_{ikt}. \quad (5)$$

We find that the coefficients on the dummy variables *Pre-Withdrawn* and *Pre-IPO* are all statistically insignificant (Table 7). There is no evidence of a pre-trend. The coefficients on *After* are positive and significant in the specifications of patent and generality, suggesting that innovation begins to increase after the completion of an IPO.

5.4 Regression Discontinuity

As the third strategy to examine the causal effect of an IPO on innovation, we apply a quasi-experimental fuzzy regression discontinuity (RD) design discussed in Angrist and Lavy (1999) and Hahn et al. (2001). Identification in a fuzzy RD relies on the assumption that observations sufficiently close to the discontinuity threshold (x_0) are similar. Fuzzy RD exploits discontinuity in the probability of treatment as a function of the forcing variable (x_i) and uses the discontinuity as an instrumental variable for treatment.[25] In our context, we use the log normalized NASDAQ listing requirement for net tangible assets as the forcing variable x_i and exploit discontinuity in the probability of an IPO

[25]Sharp regression discontinuity is not suitable for studying public listings because an IPO is not solely determined by the observable listing criteria. The probability of treatment (IPO) is affected by factors other than the forcing variable. Thus, the probability of treatment does not jump from 0 to 1 when the forcing variable crosses the threshold. Fuzzy RD is a randomized experiment with imperfect compliance where the treatment is not solely determined by the strict cutoff rule (Lee and Lemieux (2010)).

(treatment) at the minimum listing requirement x_0 so that:

$$P(IPO_i = 1|x_i) = \begin{cases} f_1(x_i) & \text{if} \quad x_i \geq x_0 \\ \\ f_0(x_i) & \text{if} \quad x_i \leq x_0, \end{cases} \tag{6}$$

where $f_1(x_0) \neq f_0(x_0)$. The fuzzy RD allows for a jump in the probability of treatment to be less than one at the threshold. The probability of treatment is a function of x_i:

$$E[IPO_i|x_i] = P(IPO_i = 1|x_i) = f_0(x_i) + [f_1(x_i) - f_0(x_i)]z_i, \tag{7}$$

where the dummy variable, $z_i = 1(x_i \geq x_0)$, indicates the point where the probability of treatment discontinues. Assuming $f_1(x_i)$ and $f_0(x_i)$ are described by pth-order of polynomials, we have:

$$E[IPO_i|x_i] = \gamma_0 + \gamma_1 x_i + \gamma_2 x_i^2 ... + \gamma_p x_i^p + \lambda z_i + \delta_1 x_i z_i + \delta_2 x_i^2 z_i + ...\delta_p x_i^p z_i. \tag{8}$$

Fuzzy RD can be estimated using a two-stage least square approach with z_i and the interaction terms $[x_i z_i, x_i^2 z_i, ...x_i^p z_i]$ as instruments for IPO_i. We specify four functional forms for the forcing variable including the first order and the second order polynomials and the interaction terms. Under the simple linear specification using only z_i as an instrument, the fuzzy RD reduced form model is[26]:

$$Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \varepsilon_i, \tag{9}$$

where Y_i is the outcome variable including the average number of patents, citations, and novelty, respectively;[27] β_1 estimates the treatment effect, i.e., the difference in the

[26] The reduced form models for the other three cases are $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i \times z_i + \varepsilon_i$; $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i$; $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i^2 + \beta_4 x_i^2 \times z_i + \varepsilon_i$.

[27] The mean number of patents, citations, novelty of IPO firms are averaged over the post-IPO years, while the means of private firms are averaged over the sample period. The sample is restricted between 1994 to 2001 when the value of net tangible assets was used as a NADSAQ listing criterion.

outcome of listing and not listing on the NADSAQ; and x_i is the forcing variable centered at the threshold.

The forcing variable x_i is defined as the log normalized level of net tangible assets and the probability is discontinuous at the normalized minimum listing requirement, x_0. NASDAQ required a minimum listing requirement of \$4 million in net tangible assets from February 7, 1989 to August 21, 1997 and a minimum of \$6 million in net tangible assets from August 22, 1997 to June 28, 2001.[28] Following Chemmanur and Krishnan (2012), we normalize the net tangible assets of NASDAQ IPO firms in the last fiscal year before going public and the net tangible assets of private firms in the first sample year as,

$$x_i = log(\frac{\text{Net tangible assets}}{\text{NASDAQ asset listing requirements}}).$$

Firms with assets larger than the listing standard ($x_i \geq 0$) are more likely to list on the NASDAQ.

The average treatment effect is estimated by:

$$\beta = \frac{\lim\limits_{x \to x_0^+} E[Y_i|x_i] - \lim\limits_{x \to x_0^-} E[Y_i|x_i]}{\lim\limits_{x \to x_0^+} E[IPO_i|x_i] - \lim\limits_{x \to x_0^-} E[IPO_i|x_i]}. \tag{10}$$

The numerator of equation (10) is the difference in expected outcomes for firms with net tangible assets just above and below the minimum assets requirement of the NASDAQ and the denominator is the difference in the faction of listed firms just above and below the threshold.

[28]See Semenenko (2012) for changes initial listing requirements on NASDAQ. The net tangible assets requirement was replaced by the total shareholder equity requirement after June 28, 2001. Net tangible assets are defined as total assets exclude total liabilities and intangible assets. We use the lowest quantitative standards as the cut-off points for listing at NASDAQ.

As the first step in any RD analysis, we plot the relationship between the outcome and the forcing variable for firms with net tangible asset larger than the NASDAQ listing requirement over the post-IPO period and for firms with net tangible assets less than the NASDAQ listing requirement over the sample period. Figure 4 shows a jump in the average number of patents and the average truncation bias adjusted citations at the cutoff.

One may be concerned that the jump in innovation observed in Figure 4 could be driven by the size difference of firms rather than by the IPO. To ease this concern, we conduct a placebo graphic analysis using normalized net tangible assets in a random year as the forcing variable. If the effect is caused by an IPO, we should not observe a discontinuity in innovation at the cutoff in the placebo test. Figure 5 presents the analysis using a firm's first (top panel) and second (bottom panel) available normalized net tangible asset as the forcing variable. We observe no jump in the average number of patents and the average truncation bias adjusted citations at the cutoff.

An underlying assumption of the RD is that firms cannot precisely manipulate the forcing variable near the known cutoff. Even in the presence of manipulation, an exogenous discontinuity still allows for random assignment to the treatment providing that firms do not have precise control over the forcing variable (Lee (2008)). To test whether or not firms have precise control over normalized net tangible assets, we adopt the McCrary (2008) test of a discontinuity in the density of the forcing variable. The unreported figure plots the normalized net tangible assets distribution and shows little indication of a strong discontinuity around the threshold. The formal test provides a discontinuity estimate (i.e. log difference in heights) of 0.13 with a standard error of 0.10. Therefore, there is no evidence of precise manipulation of the forcing variable at the threshold.

Table 8 presents the results of the fuzzy RD estimations using two-stage least square approach. We report the estimates of the average treatment effect for four functional form specifications: linear model, linear model with a treatment interaction, quadratic model, and quadratic model with treatment interactions. The F-statistics of the first stage are all above 10 and the p-values associated with the F-statistics are 0. There is no evidence that the instruments are weak. The coefficients on the indicator variable z_i are positive and statistically significant in most specifications. Firms listed on the NASDAQ on average tend to have more patents after the listing than private firms. The quality and novelty of patents for listed firms also appear to be higher than those for private firms.

6 Potential Explanations

The results suggest that public firms in EFD industries are more innovative than private firms, but not public firms in IFD industries. The differences in the patent portfolios of private and public firms are not likely due to our sampling or estimation method choices. In this section, we investigate the potential explanations for the observed differences.

6.1 Financing Benefits

One potential reason for the observed larger patent portfolios of public firms in EFD industries could be that public listing relaxes the financial constraints of firms needing external capital. Funding is especially important for innovation since design, development, manufacturing, and patenting are costly. If stock markets facilitate technological innovation through enabling cheaper capital, we would expect that firms in innovation intensive industries will be more likely to go public in order to take advantage of the financing benefits of being publicly listed. To test this conjecture, we investigate public listing in relation to innovation intensity.

We include the innovation intensity index in the probit model that estimates the probability of being public. We estimate the model for the industry-and-size matched sample and separately for firms in external finance dependent and internal finance dependent industries. Table 9 reports the estimation results. The coefficients on the innovation intensity index are positive and significant in the specifications of all matched firms, suggesting that firms in innovation-intensive industries on average are more likely to go public. However, the separate estimations show that only the more innovative firms in EFD industries have a higher propensity to go public, while more innovative firms in IFD industries do not. The results are consistent with our conjecture and suggest that the access to stock markets is beneficial for innovative firms in a greater need of capital.

One concern regarding the observed difference in innovation of public and private firms is that more innovative firms may self-select into stock markets. To isolate the financing effect of stock markets from the selection effect, we use the treatment effect models to directly correct for selection bias and also design three quasi-experiments to control for differences in the matched sample along many dimensions. If selection drives our results, we would expect more innovative firms in all industries will choose to go public. The finding that firms in innovation intensive industries with a need for external capital, but not firms in industries without such need, are more likely to go public helps to mitigate the selection concern.

It is also possible that the better innovation profile of public firms than private firms in EFD industries may be mainly driven by firms in innovation intensive industries. To investigate this possibility, we conduct our analyses by excluding industries in the top tercile of the innovation intensity index. Using this sub-sample of firms in relatively less innovation intensive industries, we still find that public firms are more innovative than private firms in EFD industries.

6.2 Innovation Efficiency

R&D investment is an input to innovation and innovative output is usually revealed by patents (Griliches (1990)). Firms differ in their abilities to convert their spending on R&D to fruitful output. Relying on more costly external capital for their innovation, firms in EFD industries are more likely to use their resources efficiently. To investigate the possibility that the differential effects of public listing on patent portfolios of firms in EFD and IFD industries may be related to the variation in firms' innovation efficiency, we measure innovation efficiency as the natural logarithm of one plus patents per dollar R&D investment.

In Table 10, we test whether public and private firms in EFD and IFD industries differ in their production of patents from R&D. We estimate the treatment effect model separately for firms in external and internal finance dependent industries and then examine the differential effect. The coefficient on the public dummy is positive and significant in the specification of EFD industries, but insignificant in the specification of IFD industries. The coefficient on the interaction between EFD and $Public$ dummy is positive and significant. The results indicate that public firms in EFD industries outperform private firms in innovation efficiency. However, public firms in IFD industries are not necessarily able to generate more patents from their investments in R&D than their private counterparts. Overall, our results suggest that higher efficiency augmented with more capital associated with public listing improves the innovation profile of public firms in external finance dependent industries.

6.3 Short-Termism

Stock markets have been criticized for providing incentives to managers to pursue short-term performance at the expenses of long-term value (Stein (1989), Bolton et al. (2006)). Facing the pressure of meeting short-term earnings, managers of public firms may behave in a myopic manner. Acharya et al. (2013) suggest that managers have incentives to conduct real income smoothing by manipulating production in an attempt to manage market expectations. These models, however, do not feature financial dependence.

Theoretically, firms with different levels of dependence on external capital may be affected differently by stock market myopia. In order to raise the capital needed, public firms in EFD industries might have more incentives to undertake short-term projects that can provide quarterly earnings growth. Firms in IFD industries, without an immediate need for external capital, might face less pressure from stock market short-termism. We therefore investigate empirically whether there is a difference in myopic activities between firms in EFD and IFD industries. Particularly, we focus on firms' manipulation of real activities in order to achieve the desired level of earnings.

There is substantial evidence that the managers of public firms engage in earnings management in order to meet earnings targets (see Healy and Wahlen (1999) for a review). Accruals management and real earnings management (REM) are the two types of typical earnings management. Accruals management involves manipulation of accruals through the choice of accounting methods with no direct cash flow consequences. Real earnings management is accomplished by changing the firm's underlying operations that affect cash flows. Examples of real earnings management activities include decreasing discretionary selling, general & administrative expenses (SGA), and cutting R&D expenses (Roychowdhury (2006)). Graham et al. (2005) suggest that managers prefer real earnings management to accruals management since it is harder for auditors and regulators to detect real activities manipulation.

To investigate the relationship between REM and external finance dependence, we estimate the normal discretionary expenses from the cross-sectional regression for every two-digit SIC industry and year, following Roychowdhury (2006):

$$DISX_{i,t}/TA_{i,t-1} = \alpha + \beta_1(1/TA_{i,t-1}) + \beta_2(Sales_{i,t-1}/TA_{i,t-1}) + \varepsilon_{i,t} \tag{11}$$

where $DISX_{i,t}$ is the discretionary expenditures of firm i in time t, including advertising expenses and SGA expenses; $TA_{i,t-1}$ is total assets of firm i in time $t-1$; and $Sales_{i,t-1}$ is total revenue. The model is estimated using the Fama and MacBeth (1973) method. This approach partially controls for industry-wide shocks while allowing the coefficients to vary across time.

We estimate the normal discretionary expenses by the fitted values from the Equation (11). The abnormal discretionary expenses are computed as the difference between the normal level of discretionary expenses and the actual discretionary expenses. A higher value of abnormal discretionary expenses indicates that a firm engages more in real earnings management.

In Table 11, we first examine whether public firms in IFD industries engage less real earnings management than those in EFD industries. We conduct the test using both the full sample and the matched sample. Panel A shows that abnormal discretionary expenses (REM) are on average positive for public firms in IFD industries and negative for public firms in EFD industries. The result suggests that public firms in industries dependent on internal capital are more likely to cut their discretionary spending, but public firms in industries dependent on external capital are less likely to do so. This result is inconsistent with the view that firms with a financing need are more likely to behave myopically in order to raise equity capital. A potential explanation could be that innovative firms may refrain from REM in order to maintain their reputation as an innovator.

We thus investigate real earnings management activities in EFD industries based on the degree of innovation. Specifically, we examine whether more innovative public firms in EFD industries do more or less real earnings management. To answer this question, we classify firms into four groups according to their R&D ratios. Group 1 includes firms with no spending on R&D (non-innovative firms) and Group 4 consists of firms with the highest R&D ratio. Panel B of Table 11 presents a monotonic relationship between real earnings management and the degree of innovation. More innovative firms (Group 4) tend to engage less in real earnings management than less innovative firms (Group 1). Overall, our results suggest that more innovative public firms in a great need for external capital have lower incentives to behave myopically. The results also help to explain our finding that public firms in EFD industries have a better innovation profile.

6.4 Acquisitions

Innovation can be achieved both internally and externally. Seru (2013) shows that innovation acquisition can be a more efficient way to innovate for mature firms with internal capital markets. Firms may engage in mergers & acquisitions (M&A) for the purpose of purchasing innovative technologies and enhancing innovation productivity (Bena and Li (2013), Sevilir and Tian (2013)). M&A transactions require a substantial amount of capital. Public listing enables firms to raise the capital that they need for M&A. Indeed, Bernstein (2012) documents that capital infusion from an IPO allows firms to purchase better quality external patents through M&A. Hence, the better innovation profile of public firms compared to private firms in EFD industries may also be because public listing facilitates innovation-acquisition-driven M&A.

To directly control for the influence of M&A on innovation, we include a variable that measures the acquired in-process technology (*in-process R&D*/total assets) to equation (1). We estimate the treatment effect model separately for firms in EFD and IFD industries, as well as equation (3). The main findings in Table 3 remain intact after controlling for technology acquisitions.[29]

As a further investigation, we investigate whether or not public firms that do not engage in innovation acquisitions still have greater quantity, quality and novelty of innovations than similar private firms. Specifically, we identify the buyers of M&A transactions from S&P Capital IQ database and exclude those firms from the sample. Table 4 Panel C reports the estimation results using firms without M&A. We observe that innovations of public firms in EFD industries remain stronger than their private counterparts after excluding innovation acquisitions.

Overall, the analyses suggest that our findings are not mainly driven by innovation-acquisition-driven M&A. Nevertheless, the acquisition-based explanation is in fact consistent with the financing-based explanation since the access to stock markets provides the financing needed for patent acquisitions.

7 Conclusions

This paper examines how innovation depends on whether a firm is listed on a stock market and the need for external capital by studying the innovation activities of a large sample of private and public firms. We estimate the treatment effect model that directly controls for selection bias caused by the endogenous choice of going public. Our results

[29]The results are unreported and available upon request.

show that public firms in external finance dependent industries on average have more patents, their patents receive more citations, and are more novel than private firms. To establish causality, we exploit three quasi-experiments to estimate the treatment effect. We find that public listing appears to be beneficial to the innovation of firms in industries dependent more on external finance. The benefits on innovation likely come from the access to public equity which may help to alleviate the financial constraints faced by those firms.

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Figure 1: Size and Age Distribution of Public and Private Firms

This figure presents the size and age distributions of the matched public and private firms in the sample, as well as in EFD and IFD industries. The graphs plot Epanechnikov kernel densities of the natural logarithm of total assets and firm age when a firm first appears in the sample.

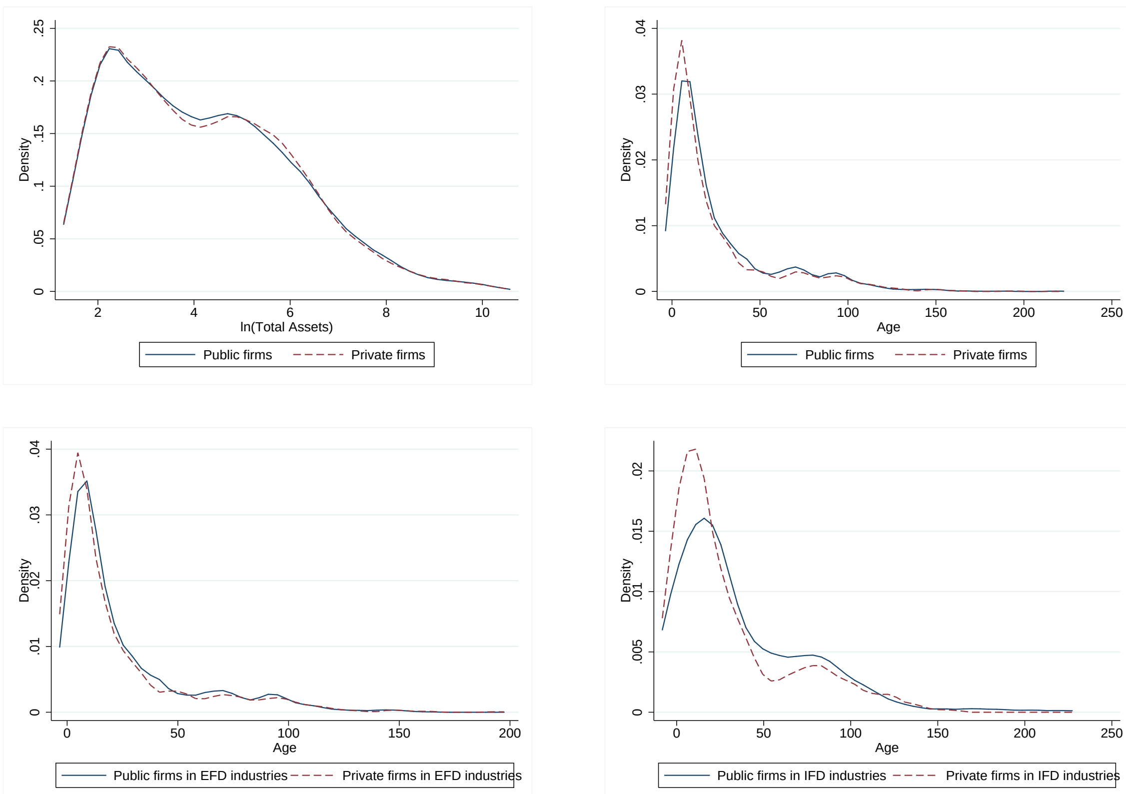


Figure 2: Innovation Intensity and EFD

This figure shows the relationship between innovation intensity and external finance dependence of an industry. We plot each industry's innovation intensity index again its EFD index. A higher value of innovation intensity index indicates that the industry is more innovation intensive. An industry that relies more on external finance has a higher EFD index.

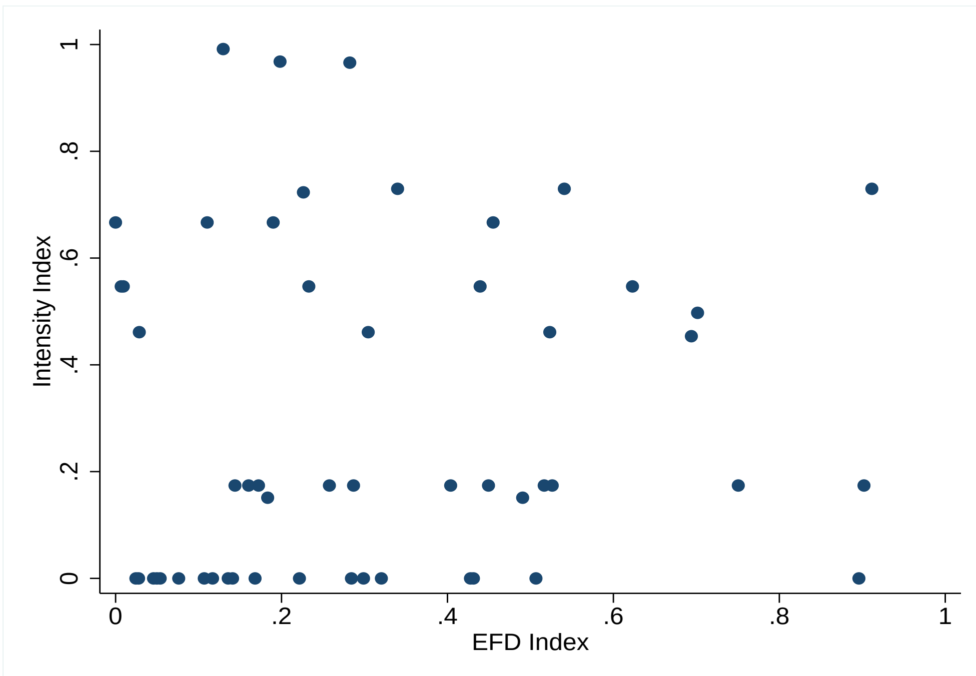


Figure 3: Patent Dynamics of Successful and Withdrawn Firms

This figure shows the patent dynamics of successful and withdrawn firms. We plot the average number of patents over the pre-withdrawn, the pre-IPO, and the post-IPO periods for firms that went public after the initial withdrawal of filings and the average number of patents over the pre-withdrawn and the post-withdrawn periods for firms that did not go public after the initial withdrawal of filings.

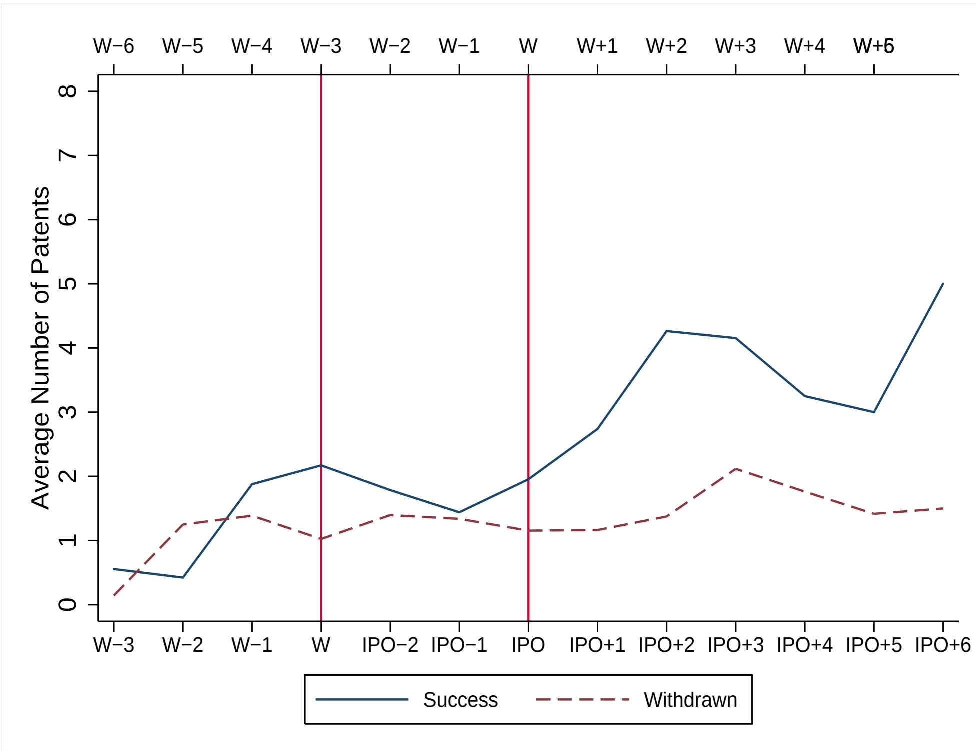
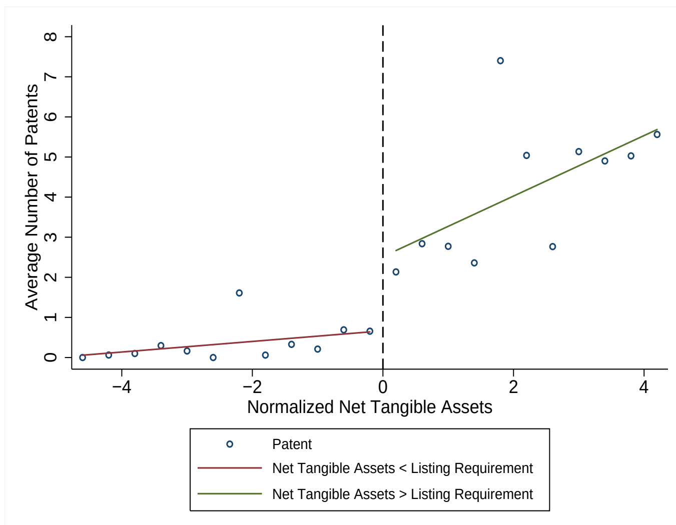


Figure 4: Discontinuous Effect of NASDAQ Listing and Innovation

This figure shows the discontinuous effect of NASDAQ listing on innovation. We plot the average number of patents (top figure) and the average truncation-bias adjusted relative citation (bottom figure) over the post-IPO period for NASDAQ IPO firms and the average number of patents (top figure) and the average truncation-bias adjusted citations (bottom figure) over the sample period for private firms on bin width of 0.4. We use net tangible assets of NASDAQ IPO firms in the pre-IPO year and the net tangible assets of private firm in the first sample year as the forcing variable and the minimum net tangible assets requirement of the NASDAQ listing as the threshold. Net tangible assets are normalized to have a value of zero at the threshold. The sample period is from 1994 to 2001.



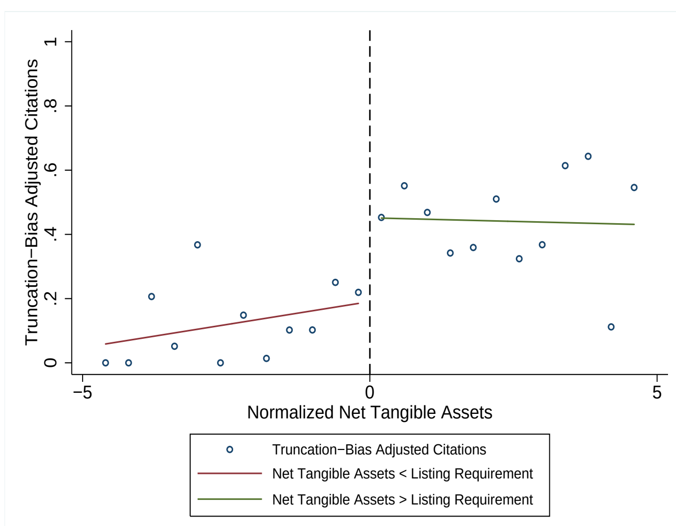


Figure 5: Placebo Test

This figure shows the placebo discontinuous effect of a NASDAQ listing on innovation. We plot the average number of patents over the sample period for private firms on bin width of 0.4. We use net tangible assets in the first year (top panel) and the second year (bottom panel) of each firm as the forcing variable and the minimum net tangible assets requirement of the NASDAQ listing as the threshold. Net tangible assets are normalized to have a value of zero at the threshold. The sample period is from 1994 to 2001.

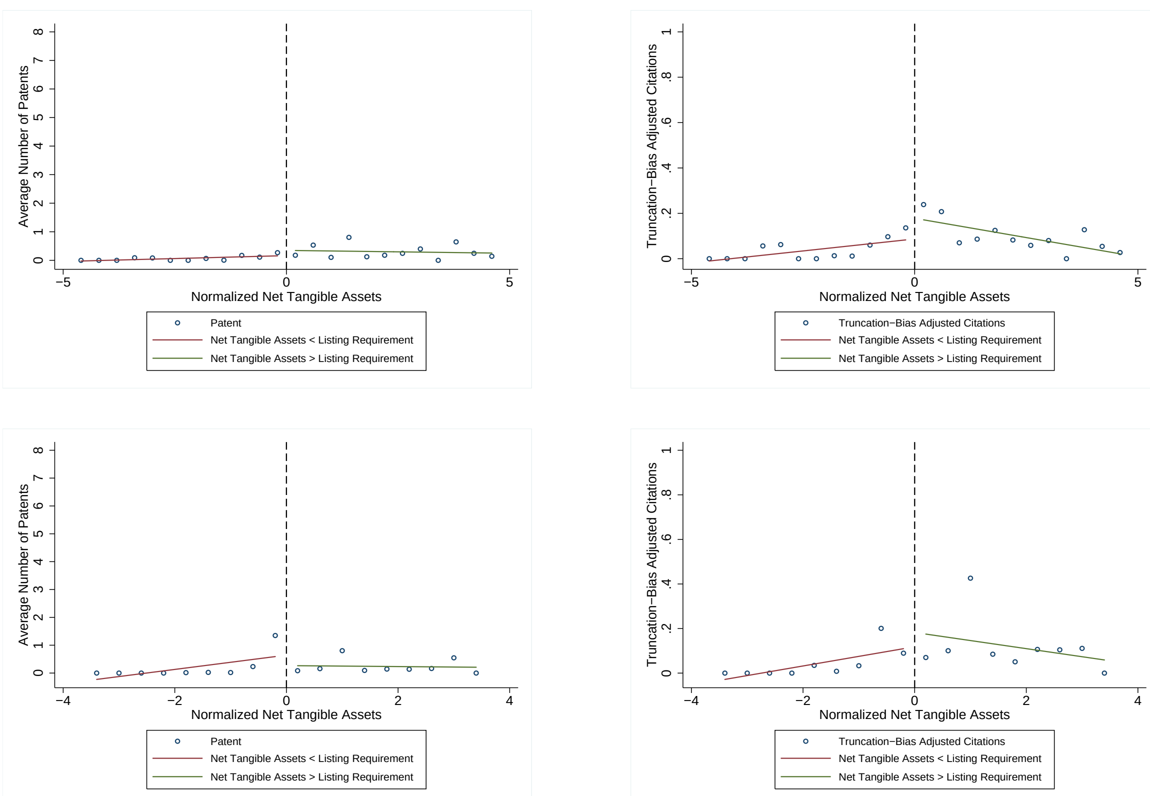


Table 1:
Firm Characteristics and Innovation Activities of Private and Public Firms

This table compares the means of characteristic variables for the full sample of private and public firms and for an industry-and-size matched sample. The full sample (Panel A) consists of 11,255 U.S. firms (2,392 private firms and 8,863 public firms) from Capital IQ from 1994 to 2004. The matched sample (Panel B) includes 1,717 matched pairs of private and public firms. $ln(Sales)$ is the log of total revenue. *S.Growth* is the first difference of natural logarithm of total revenue. $Tangible$ is tangible (fixed) assets scaled by total assets. $Cash$ is total cash scaled by total assets. ROA is EBITDA divided by total assets. *Age* is the difference between current year and founding year. *Capex* is capital expenditures scaled by total assets. *R&D* is a ratio of research and development expenditures to total assets. *Patent* is the number of patents applied by a firm in a given year. *Citations* is citations per patent adjusted for truncation bias by dividing the number of citations by the average amount of citations in in the same year and technology class. *Originality* of patent is Herfindahl index of cited patents and *Generality* is Herfindahl index of citing patent. $Tangible$, *Leverage*, *Cash*, *ROA*, *Capex*, *R&D* are reported in percentage in this table. $Diff$ is the difference in means of private and public firms from the t-test. t-stat is test statistics of the t-test.

Panel A: Full Sample						
	ln(Sales)	S. Growth	Tangible	Cash	ROA	Age
Private	4.55	0.21	29.74	14.66	2.67	26.21
Public	4.78	0.14	26.20	18.89	3.79	33.50
Diff	0.23	-0.07	-3.54	4.23	1.11	7.30
t-stat	9.86	-10.78	-15.27	18.18	4.41	20.57
	Capex	R&D	Patent	Citations	Originality	Generality
Private	7.20	5.48	0.99	0.18	0.04	0.06
Public	6.31	4.93	7.03	0.32	0.07	0.12
Diff	-0.89	-0.54	6.04	0.14	0.03	0.06
t-stat	-12.21	-5.01	9.66	13.89	20.29	28.20

Panel B: Matched Sample						
	ln(Sales)	S. Growth	Tangible	Cash	ROA	Age
Private	4.78	0.17	30.91	11.94	5.20	28.79
Public	4.81	0.13	27.83	17.62	4.15	34.86
Diff	0.03	-0.04	-3.08	5.68	-1.05	6.07
t-stat	0.89	-3.48	-8.07	16.89	-2.84	10.93
	Capex	R&D	Patent	Citations	Originality	Generality
Private	6.74	3.63	0.58	0.11	0.02	0.04
Public	6.40	4.15	1.94	0.28	0.06	0.10
Diff	-0.34	0.52	1.36	0.17	0.04	0.06
t-stat	-2.92	3.30	7.53	10.73	17.24	20.00

Table 2:
Regression Estimations for Innovation Activities of Private and Public Firms

The table reports the effect of being public on innovation using the fixed effect model (Panel A) and the treatment effect model (Panel B). The results are based on the matched sample In Panel A, the following fixed effect model is estimated: $Y_{ikt} = \alpha + \beta Public_i + \gamma X_{ikt-1} + \eta_k + \zeta_t + \varepsilon_{ikt}$, where Y_{ikt} is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations, originality, and generality; $Public_i$ is a dummy variable equal to one for public firms and zero for private firms; X_{ikt} is a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$ (log of total revenue), $Tangible$ (tangible assets scaled by total assets), $Cash$ (total cash scaled by total assets), Age (the difference between current year and founding year), $Capex$ (capital expenditures scaled by total assets), $S.Growth$ (the first difference of natural logarithm of total revenue), ROA (EBITDA divided by total assets); η_k control for industry effects based on two-digit SIC codes; and ζ_t control for year fixed effects. The robust standard errors adjusted for heteroskedasticity are reported in the brackets. In Panel B, we estimate the treatment effect model to address the concern that a firm's decision to go public may not be random (selection bias). The treatment effect model is estimated with a two-step approach. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, leverage, and industry external finance index from a probit model. The inverse Mills ratio ($Mills$) is included in the second-step to adjust for self-selection. Industry effects based on two-digit SIC codes and year fixed effects are controlled in the treatment model. ** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

Panel A: Fixed Effects Model					
	R&D	Patent	Citations	Originality	Generality
Public	0.0048***	1.4331***	0.1241***	0.0230***	0.0512***
	[0.0012]	[0.1809]	[0.0163]	[0.0023]	[0.0037]
ln(Sales)	0.0001	1.3572***	0.0528***	0.0077***	0.0200***
	[0.0005]	[0.1613]	[0.0059]	[0.0008]	[0.0012]
Tangible	0.0112***	2.1185***	0.0738*	0.0073	0.0065
	[0.0033]	[0.6194]	[0.0442]	[0.0068]	[0.0100]
Cash	0.1247***	3.5910***	0.7453***	0.0918***	0.1608***
	[0.0068]	[0.7282]	[0.1304]	[0.0101]	[0.0138]
Age	-0.0001***	-0.0023	0.0000	0.0001***	0.0002***
	[0.0000]	[0.0041]	[0.0002]	[0.0000]	[0.0001]
Capex	0.0005	2.9620	0.0213	0.0353	0.0665**
	[0.0118]	[2.1412]	[0.1285]	[0.0227]	[0.0318]
S.Growth	-0.0056**	-0.1837	0.0060	0.0044*	0.0052
	[0.0025]	[0.1464]	[0.0256]	[0.0025]	[0.0040]
ROA	-0.1367***	-1.2809***	-0.1212	0.0016	-0.0254*
	[0.0089]	[0.4331]	[0.0964]	[0.0088]	[0.0132]
Constant	0.0018	-7.0876***	-0.3006***	0.0014	-0.1183***
	[0.0045]	[1.5386]	[0.0732]	[0.0146]	[0.0241]
N	9,620	9,620	9,620	9,620	9,620
R^2	0.4177	0.0711	0.0560	0.1581	0.2041

Panel B: Treatment Effect Model					
	R&D	Patent	Citations	Originality	Generality
Public	0.0124***	2.7973***	0.2107***	0.0778***	0.0360***
	[0.0046]	[0.8565]	[0.0791]	[0.0128]	[0.0088]
ln(Sales)	0.0002	1.3740***	0.0538***	0.0203***	0.0079***
	[0.0005]	[0.0837]	[0.0077]	[0.0013]	[0.0009]
Tangible	0.0116***	2.1959***	0.0787	0.0080	0.0080
	[0.0045]	[0.8283]	[0.0765]	[0.0124]	[0.0085]
Cash	0.1231***	3.3087***	0.7274***	0.1553***	0.0891***
	[0.0043]	[0.8062]	[0.0745]	[0.0120]	[0.0083]
Age	-0.0001***	-0.0031	0.0000	0.0002***	0.0001**
	[0.0000]	[0.0043]	[0.0004]	[0.0001]	[0.0000]
Capex	-0.0023	2.4526	-0.0110	0.0566	0.0305
	[0.0125]	[2.3298]	[0.2152]	[0.0348]	[0.0239]
S.Growth	-0.0056***	-0.1760	0.0065	0.0053	0.0045*
	[0.0013]	[0.2405]	[0.0222]	[0.0036]	[0.0025]
ROA	-0.1360***	-1.1525	-0.1131	-0.0229**	0.0028
	[0.0042]	[0.7706]	[0.0712]	[0.0115]	[0.0079]
Mills	-0.0049*	-0.8864*	-0.0563	-0.0173**	-0.0085
	[0.0028]	[0.5203]	[0.0481]	[0.0078]	[0.0053]
Constant	-0.0046	-8.2398**	-0.3738	-0.1407**	-0.0097
	[0.0198]	[3.6744]	[0.3396]	[0.0549]	[0.0376]
N	9,620	9,620	9,620	9,620	9,620

Table 3:
External Finance Dependence and Innovation

This table reports the estimation results for private and public firms in external finance dependent (Panel A) and internal finance dependent industries (Panel B). We estimate the treatment effect model to address the concern that a firm's decision to go public may not be random (selection bias). The treatment effect model is estimated with a two-step approach. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, and leverage from a probit model. The inverse Mills ratio ($Mills$) is included in the second-step to adjust for selection bias. The dependent variable is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations, originality, and generality. $Public_i$ is a dummy variable equal to one for public firms and zero for private firms. The control variables are a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. Year and industry fixed effects are controlled. Two-step consistent standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	Panel A: External Finance Dependent Industries				
	R&D	Patent	Citations	Originality	Generality
Public	0.0179***	3.6867***	0.2817***	0.1018***	0.0495***
	[0.0055]	[1.0251]	[0.0943]	[0.0148]	[0.0102]
ln(Sales)	0.0003	1.5496***	0.0607***	0.0229***	0.0091***
	[0.0005]	[0.0973]	[0.0089]	[0.0014]	[0.0010]
Tangible	0.0118**	2.8021***	0.1021	0.0168	0.012
	[0.0052]	[0.9771]	[0.0899]	[0.0141]	[0.0097]
Cash	0.1280***	3.5547***	0.7580***	0.1606***	0.0939***
	[0.0049]	[0.9163]	[0.0843]	[0.0132]	[0.0091]
Age	-0.0001***	-0.0034	-0.0002	0.0002**	0.0001*
	[0.0000]	[0.0053]	[0.0005]	[0.0001]	[0.0001]
Capex	-0.0054	1.7553	-0.0744	0.0325	0.014
	[0.0140]	[2.6300]	[0.2419]	[0.0380]	[0.0261]
S.Growth	-0.0061***	-0.1724	0.0085	0.0063	0.0053**
	[0.0014]	[0.2694]	[0.0248]	[0.0039]	[0.0027]
ROA	-0.1394***	-1.2591	-0.1011	-0.0191	0.006
	[0.0047]	[0.8802]	[0.0809]	[0.0127]	[0.0087]
Mills	-0.0086***	-1.2782**	-0.0855	-0.0265***	-0.0133**
	[0.0033]	[0.6190]	[0.0569]	[0.0089]	[0.0061]
Constant	-0.0078	-9.8142**	-0.4547	-0.1693***	-0.017
	[0.0213]	[4.0092]	[0.3691]	[0.0578]	[0.0398]
N	8,109	8,109	8,109	8,109	8,109

	Panel B: Internal Finance Dependent Industries				
	R&D	Patent	Citations	Originality	Generality
Public	-0.0013	-0.3748	-0.0207	-0.0062	-0.0131
	[0.0044]	[0.3784]	[0.0586]	[0.0196]	[0.0128]
ln(Sales)	-0.0016***	0.2142***	0.0071	0.0036	-0.0002
	[0.0005]	[0.0454]	[0.0070]	[0.0024]	[0.0015]
Tangible	0.0034	-0.1570	-0.0526	-0.0389*	-0.0132
	[0.0048]	[0.4140]	[0.0645]	[0.0216]	[0.0141]
Cash	0.0277***	1.6146***	0.2504***	0.0818***	0.0324*
	[0.0066]	[0.5705]	[0.0888]	[0.0298]	[0.0194]
Age	0.0000	0.0034*	0.0006**	0.0003***	0.0002***
	[0.0000]	[0.0017]	[0.0003]	[0.0001]	[0.0001]
Capex	0.0304	1.6156	0.4859*	0.2300***	0.1115*
	[0.0199]	[1.7122]	[0.2653]	[0.0889]	[0.0580]
S.Growth	-0.0028	-0.2170	-0.0319	-0.0062	-0.0084
	[0.0022]	[0.1887]	[0.0292]	[0.0098]	[0.0064]
ROA	-0.0611***	-1.4910***	-0.1424*	-0.0635**	-0.0337*
	[0.0060]	[0.5152]	[0.0797]	[0.0267]	[0.0174]
Mills	0.0035	0.4055*	0.0181	0.0098	0.0072
	[0.0028]	[0.2376]	[0.0368]	[0.0123]	[0.0080]
Constant	0.0133*	-0.6258	-0.0431	-0.0312	0.0116
	[0.0073]	[0.6231]	[0.0969]	[0.0325]	[0.0211]
N	1,511	1,511	1,511	1,511	1,511

Table 4:
External Finance Dependence and Innovation: Differential Effects

This table reports the estimation results for the differential effects of public listing on innovation between EFD and IFD industries. A treatment effect model with the second-step estimation as following is estimated: $Y_{ikt} = \alpha + \beta Public_i + \delta EFD_{ik} + \theta Public_i \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$, where EFD_{ik} is an industry external finance index. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. The model is estimated for three samples: industry-and-size matched private and public firms (Panel A), age-year-and-size matched pairs of private and public firms in EFD and IFD industries (Panel B), and the sample excluding buyers of M&A (Panel C). To identify the industry-and-size matched sample, we find a public firm closest in size and in the same four-digit SIC industry for each private firm. For each size-and-industry matched private and public firms in IFD industries, we find a pair of matched private and public firms in EFD industries that are the same age, in the same year, and similar in size. The coefficients on the control variables are not reported. Two-step consistent standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	Panel A: Industry-and-Size Matched Sample				
	R&D	Patent	Citations	Originality	Generality
EFD×Public	0.0144**	2.1082*	0.1113	0.0906***	0.0406***
	[0.0062]	[1.1348]	[0.1043]	[0.0178]	[0.0121]

	Panel B: Age-Year-Size Matched EFD and IFD Pairs				
	R&D	Patent	Citations	Originality	Generality
EFD×Public	0.0085	0.0739	0.3161**	0.1496***	0.0962***
	[0.0098]	[0.7608]	[0.1603]	[0.0341]	[0.0240]

	Panel C: Exclude M&A				
	R&D	Patent	Citations	Originality	Generality
EFD×Public	0.0180**	1.6346***	0.0675	0.0690***	0.0449***
	[0.0076]	[0.5622]	[0.1311]	[0.0203]	[0.0140]

Table 5:
The Influence of IPO: Difference-in-Differences

This table reports the effect of IPO on innovation for firms in external finance dependent industries (Panel A) and internal finance dependent industries (Panel B) using difference-in-differences method. We identify a group of firms transition from private to public during the sample period. For each IPO firms, we find a similar private firms based on firm characteristics and industries. IPO firms are matched to the private firms based on the the first year characteristics. In order to examine the transition, firms are required to have minimum four years of consecutive data and to have at least two year pre-IPO and one year post-IPO data. Firms in the two groups are matched by the propensity scores of being public from the logit regression based on their total assets, capital expenditure, ROA, and leverage. The sample used for the logit regression includes 695 private firms and 961 IPO firms. The matched sample consists of 370 pairs of private and IPO firms and among them 318 pairs in external finance dependent industries and 52 pairs in internal finance dependent industries. We use the year that an IPO firm go public as the fictitious IPO year for its matched private firm. Δ represents the difference between innovation activities of IPO firms after and before IPO and those of matched private firms after and before the fictitious IPO. *R&D* is a ratio of research and development expenditures to total assets. *Patent* is the number of patents applied by a firm in a given year. *Citations* is citations per patent scaled by the average citation counts of all patents applied in the same year and technology class. Originality is the Herfindahl index of cited patents. Generality is the Herfindahl index of citing patents. $Diff-in-Diff$ is the difference of differences in the average innovation activities of the treatment and control groups from the t-test. *SE* is the standard error of t-test estimated by linear regression. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	Panel A: External Finance Dependent Industries				
	ΔR&D	ΔPatent	ΔCitations	ΔOriginality	ΔGenerality
Matched Private Firms	-0.001	-0.692	-0.010	-0.005	-0.016
Matched Public Firms	-0.011	1.047	0.085	0.039	-0.011
Diff-in-Diff	-0.010*	1.739***	0.095*	0.044***	0.005
SE	0.005	0.648	0.050	0.012	0.008

	Panel B: Internal Finance Dependent Industries				
	ΔR&D	ΔPatent	ΔCitations	ΔOriginality	ΔGenerality
Matched Private Firms	0.001	-0.186	-0.042	-0.022	-0.020
Matched Public Firms	-0.003	0.374	0.006	0.006	-0.009
Diff-in-Diff	-0.004**	0.560	0.047	0.028*	0.012
SE	0.002	0.707	0.060	0.014	0.011

Table 6:
Success versus Withdrawal

This table reports the regression results on innovation of firms that withdrew their initial IPO filings. We identify a sample of firms that withdrew their IPO filings and eventually did not go public (withdrawn sample) and a sample of firms that successfully went public after initial withdrawal (success sample). We estimate the treatment effect model with a two-step approach. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, leverage, and external finance dependent index from a probit model. The inverse Mills ratio ($Mills$) is included in the second-step to adjust for selection bias. The second-step model in Panel A is estimated as $Y_{ikt} = \alpha + \beta Success_i + \theta After_{it} + \delta Success_i \times After_{it} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$. The second step model in Panel B is estimated as $Y_{ikt} = \alpha + \beta Success_i + \delta Success_i \times After_{it} + \theta After_{it} + \delta EFD_{ik} + \theta Success_i \times EFD_{ik} + \kappa Success_i \times After_{it} + \rho Success_i \times After_{it} \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$, where Y_{ikt} is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations, originality, generality; $Success_i$ is a dummy variable equal to one for firms that went public after the withdrawal of IPO filing and zero for firms that did not go public after the withdrawal of IPO filings; $After$ is a dummy variable that take a value of one for post-withdrawn years of withdrawn firms and post-IPO years of successful IPO firms. EFD is an industry external finance index. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age; capital expenditure, sales growth, and ROA. The control variables are not reported. Jackknife standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	Panel A: Transition Effect				
	R&D	Patent	Citations	Originality	Generality
Success	0.0188	2.0378*	0.5113	0.0876	0.0277
	[0.0371]	[1.2356]	[0.4628]	[0.0677]	[0.0398]
After	-0.0068	0.0144	-0.2045	-0.0017	-0.0306*
	[0.0090]	[0.4048]	[0.1657]	[0.0222]	[0.0161]
Success×After	-0.0101	0.1065	0.1531	0.0206	0.0161
	[0.0172]	[0.6954]	[0.1837]	[0.0385]	[0.0250]
Mills	-0.0122	-0.9258	-0.3597	-0.0480	-0.0232
	[0.0218]	[0.6254]	[0.3536]	[0.0367]	[0.0243]

	Panel B: Transition Effect and EFD				
	R&D	Patent	Citations	Originality	Generality
Success	0.1055**	2.3439	0.8810	0.1973**	0.0398
	[0.0454]	[1.5492]	[0.7908]	[0.0869]	[0.0679]
After	-0.0099	1.1501	0.0914	0.1326**	0.0114
	[0.0174]	[1.3593]	[0.2050]	[0.0592]	[0.0447]
Success×After	-0.0154	-2.8852*	-0.4528*	-0.2233***	-0.0581
	[0.0260]	[1.5558]	[0.2727]	[0.0711]	[0.0497]
EFD	0.3216***	16.4164***	1.6968**	0.8124***	0.3708***
	[0.0768]	[5.5675]	[0.6685]	[0.2134]	[0.1422]
EFD×After	0.0093	-2.3447	-0.5878	-0.2396**	-0.0870
	[0.0404]	[2.0421]	[0.5221]	[0.1074]	[0.0792]
Success×EFD	-0.0474	0.1209	-0.6121	-0.1584	-0.0896
	[0.0547]	[2.1146]	[0.6032]	[0.1142]	[0.0863]
Success×After×EFD	0.0112	5.5425**	1.0137*	0.4188***	0.1304
	[0.0672]	[2.4768]	[0.5973]	[0.1334]	[0.0894]
Mills	-0.0482**	-1.0930	-0.3313	-0.0484	0.0032
	[0.0234]	[0.6975]	[0.3901]	[0.0402]	[0.0289]
N	681	681	681	681	681

Table 7:
Parallel Test

This table examines the parallel trend of innovation activities in the pre-withdrawn and pre-IPO periods for firms that experience IPO filings withdrawal. We identify a sample of firms that withdrew their IPO filings and eventually did not go public (withdrawn sample) and a sample of firms that successfully went public after initial withdrawal (success sample). The model is estimated as $Y_{ikt} = \alpha + \beta Pre\text{-}Withdrawn_{it} + \delta Pre\text{-}IPO_{it} + \theta After_{it} + \gamma X_{ikt-1} + \varepsilon_{ikt}$, where Y_{ikt} is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations, originality, generality; $Pre\text{-}Withdrawn_{it}$ is a dummy variable equal to one if it is the pre-withdrawn period for firms that went public after withdrawal of IPO filing; $Pre\text{-}IPO_{it}$ is a dummy variable that take a value of one for pre-IPO years of successful firms; $After_{it}$ is equal to one if it is after-IPO years for successful firms. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age; capital expenditure, sales growth, and ROA. We also control for year effects. The coefficients on X_{ikt-1} are not reported. Heteroskedastity robust standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	R&D	Patent	Citations	Originality	Generality
Pre-Withdrawn	-0.0098	0.7256	0.1931	-0.0074	0.0211
	[0.0174]	[0.7987]	[0.2722]	[0.0294]	[0.0524]
Pre-IPO	0.0078	0.536	0.0094	0.0177	0.0071
	[0.0173]	[0.5864]	[0.1248]	[0.0209]	[0.0334]
After	-0.011	0.7785**	0.0489	0.0060	0.0381**
	[0.0095]	[0.3279]	[0.0932]	[0.0099]	[0.0187]
N	681	681	681	681	681
R^2	0.43	0.12	0.08	0.11	0.19

Table 8:
Fuzzy Regression Discontinuity Estimation

This table reports the results of fuzzy regression discontinuity estimation. We specify four functional forms for the forcing variable x_i and the reduced form models are: $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \varepsilon_i$ (Model 1); $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i \times z_i + \varepsilon_i$ (Model 2); $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i$ (Model 3); $Y_i = \alpha + \beta_1 z_i + \beta_2 x_i + \beta_3 x_i \times z_i + \beta_4 x_i^2 + \beta_5 x_i^2 \times z_i + \varepsilon_i$ (Model 4). The dependent variables are: the average R&D ratio, the average number of patents, the average number of citations, the average number of relative citations, the average originality, and the average generality. The outcome variables are averaged over the post-IPO period for NASDAQ listed firms and the variables are averaged over the period of 1994 to 2001 for private firms. The independent variable, z_i, is an indicator variable that equals 1 if the forcing variable, x_i, is larger or equal to the threshold. We use normalized net tangible assets as the forcing variable and the normalized minimum quantitative listing standard as the threshold for listing on the NASDAQ. Net tangible assets are normalized to have a value of zero at the threshold. For IPO firms, net tangible assets in the last fiscal year before going public are used. For private firms, net tangible assets in the first sample year are used. The models are estimated using the two-stage least square approach. The coefficient, β_1 for treatment assignment are reported and robust standard errors are reported in the brackets. F-Stat is F-statistic of the first stage of the two-stage least square estimation. The p-value of F-stat is reported in the bracket. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	R&D	Patent	Citations	Originality	Generality	F-Stat
Model 1: Linear	0.0985***	2.8819	0.7028***	0.2149***	0.0831***	45.49
	[0.0358]	[1.8769]	[0.2359]	[0.0523]	[0.0311]	[0.00]
Model 2: Linear Interaction	0.0488	3.9093*	0.6245**	0.1852**	0.0703	35.76
	[0.0516]	[2.1444]	[0.3088]	[0.0730]	[0.0427]	[0.00]
Model 3: Quadratic	0.0773	4.5626**	0.8115**	0.2155***	0.0912*	34.84
	[0.0577]	[1.8278]	[0.3772]	[0.0804]	[0.0480]	[0.00]
Model 4: Quadratic Interaction	0.0812	4.6170**	0.7873*	0.1657	0.0842	21.49
	[0.0714]	[2.3156]	[0.4677]	[0.1012]	[0.0587]	[0.00]

Table 9:
External Finance Dependence, Innovation Intensity, and Being Public

This table reports results about the tendency to go public in relation to external finance dependence. The probit model estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, leverage, and innovation intensity index. The model is estimated for industry-and-size matched private and public firms and separately for firms in EFD and IFD industries. *Intensity* is innovation intensity index of an industry. The time-series industry-level innovation intensity is constructed as the median number of patents for all patent-producing firms in the two-digit SIC code industry in each year. We then measure each industry's innovation intensity as its time series median during the period of 1994-2004 and use the percentile ranking of innovation intensity as innovation intensity index. The standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	All	EFD Industries	IFD Industries
Capex	0.9185***	0.9822***	0.6894
	[0.2233]	[0.2332]	[0.8810]
S.Growth	-0.0484	-0.0619*	0.1476
	[0.0308]	[0.0321]	[0.1104]
ROA	-0.6134***	-0.7771***	0.327
	[0.0947]	[0.0999]	[0.2898]
ln(A)	-0.0336***	-0.0304***	-0.0396
	[0.0083]	[0.0088]	[0.0247]
Leverage	-1.5576***	-1.5493***	-1.6974***
	[0.0471]	[0.0508]	[0.1276]
Intensity	0.1173**	0.1986***	-0.1163
	[0.0528]	[0.0595]	[0.1209]
EFD	0.2295***		
	[0.0574]		
Constant	1.3152***	1.3908***	1.3663***
	[0.0565]	[0.0582]	[0.1425]
N	9,523	8,063	1,460

Table 10:
Innovation Efficiency

This table reports the estimation results for innovation efficiency of matched private and public firms in external finance dependent and internal finance dependent industries. We estimate the treatment effect model to address the concern that a firm's decision to go public may not be random (selection bias). The treatment effect model is estimated with a two-step approach. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, and leverage from a probit model. The inverse Mills ratio ($Mills$) is included in the second-step to adjust for selection bias. The dependent variable is the innovation efficiency measured as natural logarithm of one plus the ratio of number of patents to R&D expenditures. The control variables are a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. Year and industry fixed effects are controlled. In the last column, we estimate the treatment effect model with the second step model as $Y_{ikt} = \alpha + \beta Public_i + \delta EFD_{ik} + \theta Public_i \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$, where Y_{ikt} is innovation efficiency measured as the natural logarithm of one plus patents per dollar R&D investment; EFD_{ik} is an industry external finance index. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. Industry and time effects are included. The coefficients on the control variables are not reported. Two-step consistent standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	EFD Industries	IFD Industries	All
Public	0.0490***	0.0114	0.0221*
	[0.0123]	[0.0100]	[0.0115]
EFD			0.0109
			[0.2201]
EFD×Public			0.0416***
			[0.0136]
Mills	-0.0141*	-0.0037	-0.0107*
	[0.0074]	[0.0063]	[0.0063]
N	8,109	1,511	9,620

Table 11:
Real Earnings Management and Innovation

This table reports the estimation results for the relationship between innovation activities and real earnings management for public firms with different degrees of dependence on external finance and with different degrees of innovation. In Panel A, we compare real earnings management of public firms in internal and externa finance dependent industries using both matched sample and the full sample. In Panel B, we classify public firms in external finance dependent industries into four groups based on their R&D ratio. Group 1 include firms with no R&D spending and Group 4 consists of firms with the highest R&D ratio. Real earnings management (REM) is measured as the difference between the normal level of discretionary expenses and the actual discretionary expenses. We estimate the normal discretionary expenses from the following cross-sectional regression for every industry and year: $DISX_{i,t}/TA_{i,t-1} = \alpha + \beta_1(1/TA_{i,t-1}) + \beta_2(Sales_{i,t-1}/TA_{i,t-1}) + \varepsilon_{i,t}$. where $DISX_{i,t}$ is the discretionary expenditures of firm i in time t, including advertising expenses and selling, general & administrative expenses; $TA_{i,t-1}$ is total assets of firm i in time $t-1$; $Sales_{i,t-1}$ is total revenue. The normal discretionary expenses are estimated by the fitted values from the model. A higher value of REM indicates a higher degree of real earnings management. $Diff$ is the difference in the average real earnings management between public firms in internal and external finance dependent industries. t-stat is the t-statistics of t-test.

	Panel A: REM in EFD vs. IFD Industries	
	Matched Sample	Full Sample
IFD Industries	1.36	2.55
EFD Industries	-6.11	-1.45
Diff	-7.47	-4.01
t-stat	-7.30	-6.93

	Panel B: REM of Innovative vs. Non-Innovative Firms in EFD Industries	
	Matched Sample	Full Sample
1: Non-Innovative	-2.74	2.41
2	-9.40	-0.54
3	-11.81	-7.66
4: Most Innovative	-15.94	-12.75

Table A.1:
Instrumental Variable Estimation

This table reports estimation results using the instrumental variable method. We use the percentage of public firms in each industry based on two-digit SIC codes in a given year as an instrument for the endogenous variable *Public*. The model is estimated using two-stage least square approach. The dependent variables are the measures of the nature of innovation activities: R&D ratio (research and development expenditures divided by total assets), number of patents, truncation-bias adjusted citations (*Citations*, citations per patent scaled by the average citation counts of all patents applied in the same year and technology class.); $Public_i$ is a dummy variable equal to one for public firms and zero for private firms. The other control variables are a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$ (natural logarithm of total revenue), $Tangibile$ (tangible (fixed) assets scaled by total assets), *Cash* (total cash scaled by total assets), *Age* (the difference between current year and founding year). We control for year fixed effects. The robust standard errors adjusted for heteroskedasticity are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	R&D	Patent	Citations	Originality	Generality
Public	0.1096***	11.5496***	0.6339***	0.2647***	0.1093***
	[0.0105]	[1.8713]	[0.1218]	[0.0293]	[0.0175]
ln(Sales)	-0.0005	1.1225***	0.0410***	0.0163***	0.0059***
	[0.0005]	[0.1404]	[0.0056]	[0.0013]	[0.0008]
Tangible	0.0051	1.8084***	0.0139	0.0116	-0.0063
	[0.0044]	[0.5834]	[0.0402]	[0.0118]	[0.0067]
Cash	0.1065***	1.4795**	0.6433***	0.1319***	0.0804***
	[0.0082]	[0.7397]	[0.1332]	[0.0184]	[0.0121]
Age	-0.0002***	-0.0147***	-0.0002	0.0000	0.0000
	[0.0000]	[0.0056]	[0.0003]	[0.0001]	[0.0000]
Capex	-0.0672***	-3.6208	-0.3938***	-0.1380***	-0.0342
	[0.0157]	[2.4165]	[0.1459]	[0.0414]	[0.0265]
S.Growth	-0.0054**	-0.2248	-0.0012	0.0038	0.0038
	[0.0026]	[0.1701]	[0.0266]	[0.0044]	[0.0026]
ROA	-0.1313***	-0.2561	-0.0813	-0.0235	0.0055
	[0.0093]	[0.4801]	[0.1006]	[0.0143]	[0.0090]
Constant	-0.0394***	-13.3987***	-0.5912***	-0.2358***	-0.1190***
	[0.0082]	[1.8660]	[0.1137]	[0.0217]	[0.0127]
N	9620	9620	9,620	9,620	9,620

Table A.2:
First Stage Estimation of the Treatment Effect Model

This table reports estimation results of the first stage estimation of the treatment effect model for the matched sample, the sample of firms in external finance industries, and the sample of firms in internal finance industries. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, leverage, and external finance dependence index (all firms only) from a probit model. The dependent variables $Public_i$ is a dummy variable equal to one for public firms and zero for private firms. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	All	EFD Industries	IFD Industries
Capex	0.9198***	0.9342***	0.925
	[0.2226]	[0.2323]	[0.8579]
S.Growth	-0.0493	-0.0605*	0.1367
	[0.0307]	[0.0320]	[0.1075]
ROA	-0.6064***	-0.7963***	0.4184
	[0.0941]	[0.0993]	[0.2866]
ln(A)	-0.0318***	-0.0287***	-0.0485**
	[0.0082]	[0.0088]	[0.0231]
Leverage	-1.5585***	-1.5464***	-1.7421***
	[0.0468]	[0.0505]	[0.1256]
EFD	0.2712***		
	[0.0560]		
Constant	1.3287***	1.4654***	1.3655***
	[0.0548]	[0.0531]	[0.1400]
N	9,620	8,109	1,511

Table A.3:
Firm Characteristics of Private and Public Firms in EFD and IFD Industries

This table compares the means of characteristic variables for industry-and-size matched private and public firms in external finance dependent (EFD) and internal finance dependent (IFD) industries. We regard industries with a positive value of the external finance dependence measure as external finance dependent, while those with a negative value as internal finance dependent. A firm's need for external finance in a year is measured as the fraction of capital expenditures not financed through internal cash flow. Internal cash flow defined as net income plus depreciation and amortization plus interest expense. The time-series industry-level external finance dependence is constructed as the median value of external finance needs of all firms in the two-digit SIC code industry in each year. We then measure each industry's external finance as its time series median during 1994-2004 period. $ln(Sales)$ is defined as log of total revenue. $S.Growth$ is the first difference of natural logarithm of total revenue, $Tangible$ is tangible (fixed) assets scaled by total assets. $Cash$ is total cash scaled by total assets. ROA is EBITDA divided by total assets. Age is the difference between current year and founding year. $Capex$ is capital expenditures scaled by total assets. $R\&D$ is a ratio of research and development expenditures to total assets. $Patent$ is the number of patents applied by a firm in a given year. $Citations$ is citations per patent adjusted for truncation bias by dividing the number of citations by the average amount of citations in in the same year and technology class. $Originality$ of patent is the Herfindahl index of cited patents and $Generality$ is the Herfindahl index of citing patent. $Tangible$, $Leverage$, $Cash$, ROA, and $Capex$ are reported in percentage in this table. $Diff$ is the difference in means of private and public firms from the t-test. $t-stat$ is the t-statistics of t-test.

Panel A: External Finance Dependent Industries						
	ln(Sales)	S.Growth	Tangible	Cash	ROA	Age
Private	4.64	0.18	31.91	12.94	4.08	27.50
Public	4.69	0.14	28.93	19.12	3.25	32.91
Diff	0.05	-0.05	-2.99	6.17	-0.83	5.41
t-stat	1.19	-3.80	-7.07	16.16	-1.97	9.41
	Capex	R&D	Patent	Citations	Originality	Generality
Private	7.21	4.26	0.66	0.12	0.02	0.05
Public	6.76	4.76	2.21	0.32	0.07	0.11
Diff	-0.44	0.50	1.54	0.19	0.04	0.07
t-stat	-3.36	2.72	7.28	10.45	17.19	19.59

Panel B: Internal Finance Dependent Industries						
	ln(Sales)	S.Growth	Tangible	Cash	ROA	Age
Private	5.50	0.11	25.55	6.60	11.15	35.52
Public	5.53	0.12	21.40	8.86	9.42	46.41
Diff	0.03	0.01	-4.15	2.25	-1.73	10.89
t-stat	0.39	0.36	-5.06	4.45	-2.92	6.44
	Capex	R&D	Patent	Citations	Originality	Generality
Private	4.25	0.25	0.13	0.04	0.01	0.02
Public	4.25	0.55	0.37	0.07	0.02	0.03
Diff	0.01	0.31	0.23	0.03	0.01	0.02
t-stat	0.05	2.68	2.87	2.01	1.95	3.69

Table A.4:
External Finance Dependence and Innovation: Top Quartile

This table reports the estimation results for private and public firms in external finance dependent industries (Panel A) and for comparison between external and internal finance dependent industries (Panel B). An industry with a positive value of external finance dependence index and belongs to the top tertile of the index is classified as external finance dependence. We estimate the treatment effect model with a two-step approach. The first step estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, and leverage from a probit model. The inverse Mills ratio ($Mills$) is included in the second-step to adjust for selection bias. The dependent variable is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations, originality, generality. $Public_i$ is a dummy variable equal to one for public firms and zero for private firms. The control variables are a set of characteristic variables that affect a firm's innovation activities, including $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. Year and industry fixed effects are controlled. We report the coefficients on $Public$ and inverse Mills ratio only in Panel A. In Panel B, we estimate the treatment effect model with the second step model as $Y_{ikt} = \alpha + \beta Public_i + \delta EFD_{ik} + \theta Public_i \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$, where EFD_{ik} is an industry external finance index. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age, capital expenditure, growth in sales, and ROA. The coefficients on the interactive term, θ, are reported. Two-step consistent standard errors are reported in the brackets. *** indicates the 1% significant level of the t-test; ** denotes the 5% significant level; and * denotes the 10% significant level.

	Panel A: External Finance Dependent Industries				
	R&D	Patent	Citations	Originality	Generality
Public	0.0284	7.0336***	0.2515	0.2010***	0.0576**
	[0.0209]	[1.5324]	[0.2492]	[0.0408]	[0.0273]
Mills	-0.0109	-3.8815***	-0.1005	-0.0791***	-0.0234
	[0.0120]	[0.8770]	[0.1435]	[0.0234]	[0.0157]
N	2,064	2,064	2,064	2,064	2,064

	Panel B: External vs. Internal Finance Dependent Industries				
	R&D	Patent	Citations	Originality	Generality
EFD×Public	0.0144**	2.1082*	0.1113	0.0906***	0.0406***
	[0.0062]	[1.1348]	[0.1043]	[0.0178]	[0.0121]
N	9,620	9,620	9,620	9,620	9,620