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

Viral V. Acharya* and Zhaoxia Xu†

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.

*Department of Finance, New York University, 44 West Fourth Street, New York, 10012. Email: vacharya@stern.nyu.edu. Phone: (212) 998-0354. Fax: (212) 995-4256.

†Department of Finance and Risk Engineering, New York University, 6 MetroTech Center, New York, 11201. Email: zhaoxiaxu@nyu.edu. Phone: (718) 260-3808.

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

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.

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 (Hall and Lerner (2010)). 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)). 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 degrees of dependence on external finance.

By analyzing the innovation activities of a large sample of private and public firms between 1994 and 2004, we observe that public firms on average have patents of higher quantity, quality, and novelty than private firms. 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 why public firms in industries with a greater need of external capital perform better in innovation, we explore four potential explanations. One potential explanation could be that public listing relaxes the financial constraints faced by those firms. If this is the case, one would expect that firms with a higher propensity to innovate will benefit more from obtaining access to stock market financing. Consistent with this conjecture, we find that firms in more innovation intensive industries with a greater need for external capital are more likely to go public compared to firms in less innovation intensive industries and they are more innovative when having access to public equity capital compared to firms without such access.

The observed difference in innovation may also be driven by the variation in firms' ability to use R&D to generate patents. To explore this second possibility, we test whether public and private firms 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 industries dependent on external finance, but no significant difference for private and public 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)).[1] In light of the short-termism model, we investigate public firms' real earnings management activities in relation to their degree of external finance dependence and innovation. We find that more innovative public firms in EFD industries engage less in earnings management through their alteration of their real activities. 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

[1] 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)).

earnings at the expense of long-term values.

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 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. 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.

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.

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.[2] Furthermore, we adopt several quasi-experimental

[2]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

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 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.[3] Applying the triple differences approach in a multivariate framework, we find an increase in the quantity and originality of patents for firms that

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.

[3]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.

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 1 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.

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.[4] 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 2 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 3). Our formal fuzzy regression discontinuity estimations indicate that IPO

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

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 is related 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))[5]. Differing from previous work focusing on public firms, we analyze a large sample of private and public firms and find that the innovation capacity of firms in external finance dependent industries is influenced by access to stock market financing.

This paper also 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

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

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)), and innovation (Bernstein (2012)).[6] Our findings suggest that the lower cost of capital associated with public listing are important for innovation of firms with large capital needs, while the financing benefits of stock markets are weaker for innovation of firms in internal finance dependent industries.

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 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 man-

[6]Differing from Bernstein (2012) who focuses only on the innovation activities of IPO firms, we investigate the innovation of public and private firms in general and link it to their financial dependence. Among the battery of identification strategies that intend to address the endogeneity concern, one of our analyses involves a subsample of firms that experience the IPO transition. 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. Our results suggest that the effect of public listing on innovation depends on firms' need on external capital.

agers. 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 captial 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. 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*. 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. For firms with excess cash flows over their investment needs, the infusion of public equity should not affect the marginal cost of capital and therefore may not increase their innovation. With the exposure to stock market short-termism, going public might even potentially stifle the innovative activities of those firms. However, for firms with insufficient internal cash flows for their investments, the additional capital raised from stock markets could relax their financial constraints and facilitate innovation. Consequently, stock markets should matter more for firms in industries with a greater need for external funds. Considering the differential needs for external capital, we hypothesize that public listing should promote the innovation of firms in industries dependent more on external finance.

3 Data and Innovation Measure

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. 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)).[7] S&P Capital

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

IQ categorizes a firm as public or private based on its most recent status. For 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. The final sample has 2,392 private firms and 8,863 public firms.

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 an industry-and-size-matched sample of private and public firms. 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.[8] The time-series observations for each match are kept in order to preserve the panel structure of the data. This procedure results 1,717 matched pairs of private and public firms.

3.2 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 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 break-through 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.

[8] 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.

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).[9] This measure shows the relative citation counts 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.

[9] 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.

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.

3.3 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. 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.[10] An industry with a higher index value of external finance dependence relies more on external capital to finance its investment.

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

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.[11] 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 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

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

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:

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

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.

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: $ATE = E(Y_i|Public = 1) - E(Y_i|Public = 0)$. 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 self-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.

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 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 4 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.[12] The result suggests that being publicly listed has a stronger impact on

[12]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.3. 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 more important. 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 C 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.

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.[13] The matched firms are required to operate in the same industry. The sample used for the logit regression includes 961

[13]We use propensity score matching with no replacement and a caliper of 0.25×standard deviation.

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.

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.

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.

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

$$Y_{ikt} = \alpha + \beta Success_i + \delta Success_i \times After_{it} + \theta After_{it} + \delta EFD_{ik} \tag{4}$$

$$+ \theta Success_i \times EFD_{ik} + \kappa Success_i \times After_{it} + \rho Success_i \times After_{it} \times EFD_{ik}$$

$$+ \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt},$$

where Y_{ikt} is the measures of innovation activities: R&D, 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 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.[14] Figure 1 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 four dummy variables to capture any effects during four 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*); the IPO year and one year after the IPO

[14] 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.

($After^{0,1}$); and two years after the IPO and beyond ($After^{2+}$). The following model is estimated:

$$Y_{ikt} = \alpha + \beta Pre\text{-}Withdrawn_{it} + \delta Pre\text{-}IPO_{it} + \theta After_{it}^{0,1} + \delta After_{i}^{2+} + \gamma X_{ikt-1} + \varepsilon_{ikt}. \quad (5)$$

We find that the coefficients on the dummy variables $Pre\text{-}Withdrawn$ and $Pre\text{-}IPO$ are all statistically insignificant (Table 7). There is no evidence of a pre-trend. The coefficients on $After^{2+}$ are positive and significant in the specifications of patent and generality, which suggests that innovation begins to increase two years 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.[15] 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

[15]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.

(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[16]:

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

where Y_i is the outcome variable including the average number of patents, citations, and novelty, respectively;[17] β_1 estimates the treatment effect, i.e., the difference in the

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

[17]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.

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 21, 1997 to June 21, 2001.[18] 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:

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

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.

[18] 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 21, 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 2 shows a jump in the average number of patents and the average truncation bias adjusted citations at the cutoff, supporting our identification strategy.

One may be concerned that the jump in innovation observed in Figure 2 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 3 presents the analysis using a firm's first 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.

Table 8 presents the results of the fuzzy RD estimations. 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 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 Innovation Intensity and Innovation

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 with a higher propensity to innovate will be more likely to go public and benefit more from being publicly listed. To test this conjecture, we investigate innovation and public listing in relation to innovation intensity.

Following Acharya and Subramanian (2009), we first construct 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. We include the innovation intensity index in the first step of the treatment effect model. We estimate the model for all firms and separately for firms in external finance dependent and internal finance dependent industries. Panel A of Table 9 reports the estimation results. The coefficients on the innovation intensity index are positive and significant in the specifications of using all 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.

We next examine whether or not firms in industries with differential innovation intensity benefit differently from being publicly listed. We include an interactive term between innovation intensity and the public dummy, as well as the interaction between EFD index and public dummy, innovation intensity, and their interaction in the second stage of the treatment effect model. Panel B of Table 9 shows that the coefficients on $Public \times Intensity$ are positive, suggesting that public firms in more innovative industries have a better innovation profile than their private counterparts. The positive coefficients on $EFD \times Public \times Intensity$ in specifications related to patent portfolios indicate that the benefits associated with public listing for innovative firms are stronger in external finance dependent industries. In sum, 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.

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. To investigate the possibility that the difference in patent portfolios between public and private firms may be related to the variation in their 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 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.

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.

In our context, the model of short-termism predicts that public firms would have incentives to engage in real earnings management. Nevertheless, we expect the extent of REM depends both on whether the firm is in an external finance dependent industry and the firm's innovation capacity. To investigate these relationships, 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 more 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.

We then further 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. Nevertheless, this acquisition-based explanation is 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 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.

References

Acharya, Viral, Ramin Baghai, and Krishnamurthy Subramanian, 2013, Wrongful discharge laws and innovation, *Review of Financial Studies* forthcoming.

Acharya, Viral, and Krishnamurthy Subramanian, 2009, Bankruptcy codes and innovation, *Review of Financial Studies* 22, 4949–4988.

Acs, Zoltan J., and David B. Audrestsch, 1988, Innovation in large and small firms: An empirical analysis, *American Economic Review* 78, 678–690.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005, Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics* 120, 701–728.

Aghion, Philippe, John Van Reenen, and Luigi Zingales, 2013, Innovation and institutional ownership, *American Economic Review* 103, 227–304.

Allen, Franklin, and Douglas Gale, 1999, Diversity of opinion and financing of new technologies, *Journal of Financial Intermediation* 8, 68–89.

Amore, Mario Daniele, Cedric Schneider, and Alminas Zaldokas, 2013, Credit supply and corporate innovations, *Journal of Financial Economics* forthcoming.

Angrist, Joshua D., and Victor Lavy, 1999, Using maimonides rule to estimate the effect of class size on scholastic achievement, *Quarterly Journal of Economics* 114, 533–575.

Asker, John, Joan Farre-Mensa, and Alexander Ljungqvist, 2011, Does the stock market distort investment incentives, Working paper.

Aspen Institute, 2009, Overcoming short-termism: A call for a more responsible approach to investment and business management.

Atanassov, Julian, 2013, Do hostile takeovers stifle innovation? evidence from antitakeover legislation and corporate patenting, *Journal of Finance* 68, 1097–1131.

Bebchuk, Lucian Arye, and Lars A. Stole, 1993, Do short-term objectives lead to under- or over-investment in long-term projects, *Journal of Finance* 48, 719–729.

Bena, Jan, and Kai Li, 2013, Corporate innovations and mergers and acquisitions, *Journal of Finance* forthcoming.

Benninga, Luigi, Fabio Schiantarelli, and Alessandro Sembenelli, 2005, The timing of initial public offerings, *Journal of Financial Economics* 75, 115–132.

Bernstein, Shai, 2012, Does going public affect innovation?, *Working Paper, Available at SSRN: http://ssrn.com/abstract=2061441* .

Bertrand, Marianne, and Sendhil Mullainathan, 2003, Pyramids, *Journal of the European Economic Association* 1, 478–483.

Blundell, Richard, and Monica Costa Dias, 2000, Evaluation methods for non-experimental data, *Fiscal Studies* 21, 427–468.

Bolton, Patrick, Jose Scheinkman, and Wei Xiong, 2006, Executive compensation and short-termist behaviour in speculative markets, *Review of Economic Studies* 73, 577–610.

Brav, Omer, 2009, Access to capital, capital structure, and the funding of the firm, *Journal of Finance* 64, 263–308.

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen, 2009, Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom, *Journal of Finance* 64, 151–185.

Brown, James R., Gustav Martinsson, and Bruce C. Petersen, 2013, Law, stock markets, and innovation, *Journal of Finance* forthcoming.

Chava, Sudheer, Alexander Oettl, Ajay Subramanian, and Krishnamurthy Subramanian, 2013, Banking deregulation and innovation, *Journal of Financial Economics* forthcoming.

Chemmanur, Thomas J., and Karthik Krishnan, 2012, Heterogeneous beliefs, IPO valuation, and the economic role of the underwriter in IPOs, *Financial Management* forthcoming.

Dunbar, Craig, and Stephen R. Foerster, 2008, Second time lucky? Withdrawn IPOs that return to the market, *Journal Of Financial Economics* 87, 610–635.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferreira, Daniel, Gustavo Manso, and Andre Silva, 2012, Incentives to innovate and the decision to go public or private, *Review of Financial Studies* forthcoming.

Gao, Huasheng, Jarrad Harford, and Kai Li, 2013, Determinants of corporate cash policy: Insights from private firms, *Journal of Financial Economics* 109, 623–639.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40, 3–73.

Griliches, Zvi, 1990, Patent statistics as economic indicators: A survey, *Journal of Economic Literature* 28, 1661–1707.

Hahn, Jinyong, Petra Todd, and Wilbert van der Klaauw, 2001, Estimation of treatment effects with a quasi-experimental regression-discontinuity design, *Econometrica* 69, 201–209.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent and citation data file: Lessons, insights and methodological tools, NBER Working paper.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 36, 16–38.

Hall, Bronwyn H., and Josh Lerner, 2010, *Handbook of the Economics of Innovation*, chapter The Financing of R&D and Innovation (Elsevier-North-Holland).

Healy, Paul, and James Wahlen, 1999, A review of the earnings management literature and its implications for standard setting, *Accounting Horizons* 17, 365–383.

Holmstrom, Bengt, 1989, Agency costs and innovation, *Journal of Economic Behavior and Organization* 12, 305–327.

Hsu, Po-Hsuan, Xuan Tian, and Yan Xu, 2013, Financial development and innovation: Cross-country evidence, *Journal of Financial Economics* forthcoming.

Lerner, Josh, Morten Sorensen, and Per Stromberg, 2011, Private equity and long-run investment: The case of innovation, *Journal of Finance* 66, 445–477.

Maksimovic, Vojislav, Gordon Philips, and Liu Yang, 2012, Private and public merger waves, *Journal of Finance* forthcoming.

Michaely, Roni, and Michael R. Roberts, 2012, Corporate dividend policies: Lessons from private firms, *Review of Financial Studies* 25, 711–746.

Mortal, Sandra, and Natalia Reisel, 2012, Capital allocation by public and private firms, *Journal of Financial and Quantitative Analysis* forthcoming.

Pagano, Marco, Fabio Panetta, and Luigi Zingales, 1998, Why do companies go public? An empirical analysis, *Journal of Finance* 53, 27–64.

Rajan, Raghuram G., 2012, Presidential address: The corporation in finance, *Journal of Finance* 67, 1173–1217.

Rajan, Raghuram G., and Luigi Zingales, 1998, Financial development and growth, *American Economic Review* 88, 393–410.

Roychowdhury, Sugata, 2006, Earnings management through real activities manipulation, *Journal of Accounting and Economics* 42, 335–370.

Saunders, Anthony, and Sascha Steffen, 2011, The costs of being private: Evidence from the loan market, *Review of Financial Studies* 24, 4091–4122.

Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465–479.

Schenone, Carola, 2010, Lending relationships and information rents: Do banks exploit their information advantages, *Review of Financial Studies* 23, 1149–1199.

Semenenko, Igor, 2012, Listing standards and IPO performance: Is more regulation better?, *Journal of Applied Finance and Banking* 2, 209–248.

Seru, Amit, 2013, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* forthcoming.

Sevilir, Merih, and Xuan Tian, 2013, Acquiring innovation, Working Paper.

Stein, Jeremy C., 1989, Efficient capital markets, inefficient firms: A model of myopic corporate behavior, *Quarterly Journal of Economics* 104, 655–669.

Stigliz, Joseph, 1985, Credit markets and capital control, *Journal of Money, Credit and Banking* 17, 133–152.

Tian, Xuan, and Tracy Yue Wang, 2012, Tolerance for failure and corporate innovation, *Review of Financial Studies* forthcoming.

Trajtenberg, Manuel, 1990, A penny for your quotes: Patent citations and the value of information, *Rand Journal of Economics* 21, 325–342.

Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe, 1997, University versus corporate patents: A window on the basicness of invention, *Economics of Innovation and New Technology* 5, 19–50.

Figure 1: 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.

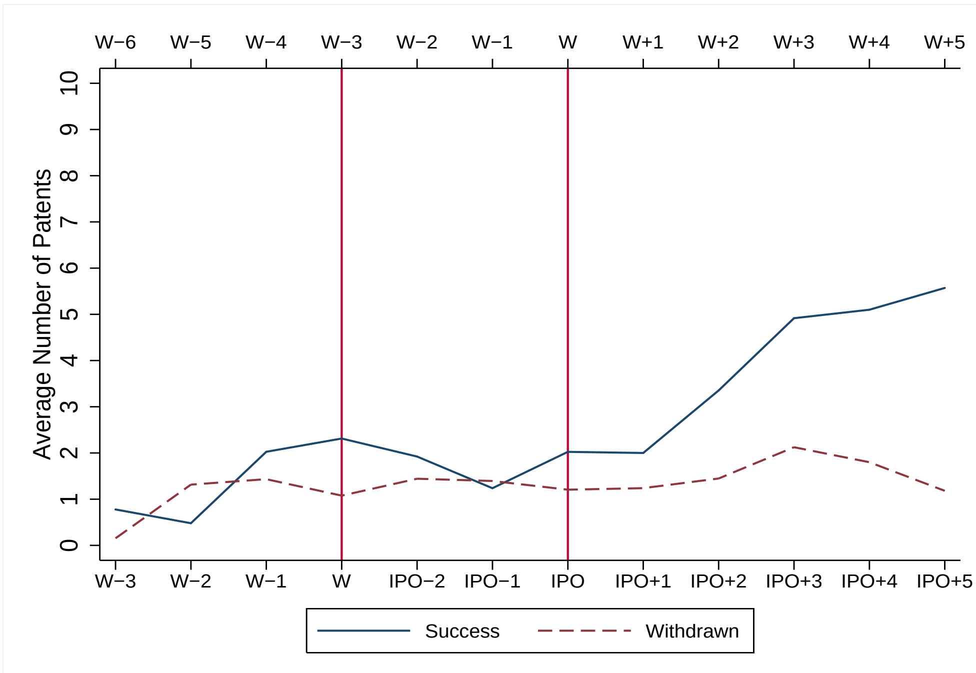


Figure 2: Discontinuous Effect of NASDAQ Listing and Innovation

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 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.

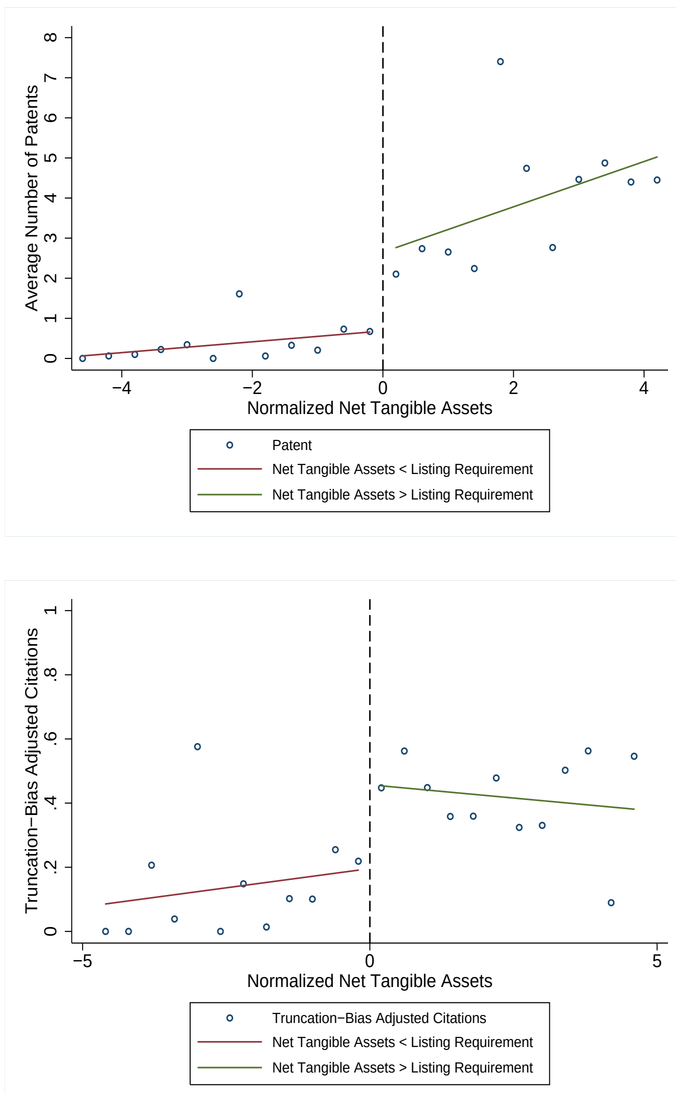
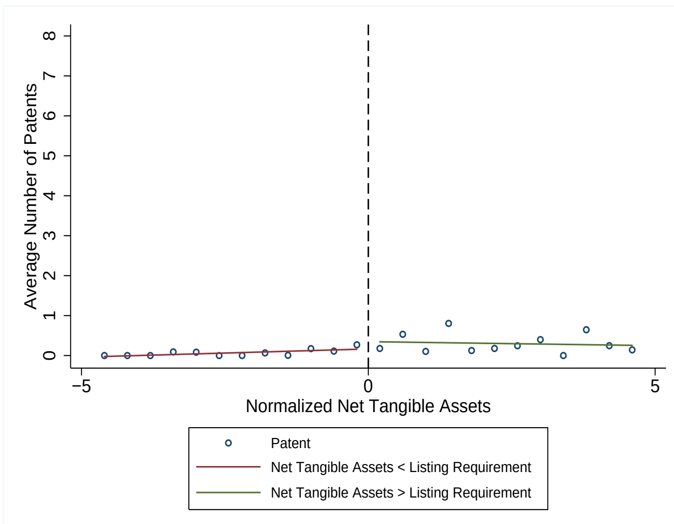


Figure 3: Placebo Test

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 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.



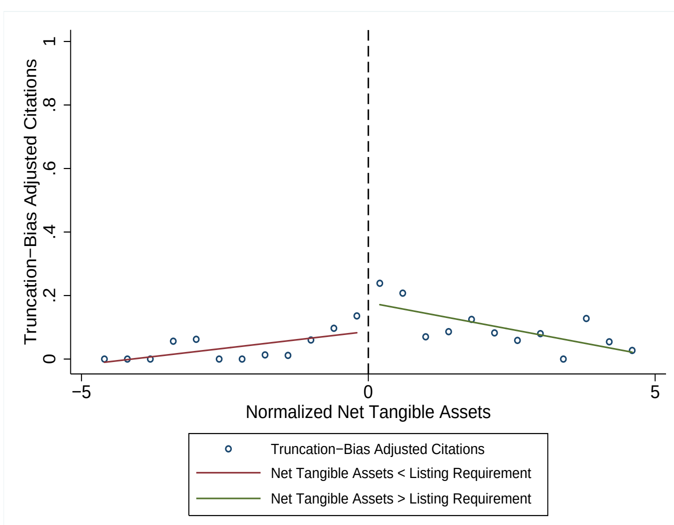


Table 1:
Firm Characteristics and Innovation Activities of Private and Public Firms

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:
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 4:
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) and the estimation results for the differential effects (Panel C). 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. In Panel C, 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	0.0179***	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

	Panel C: 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]

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. t-stat is the t-statistics 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
t-stat	-1.960	2.680	1.880	3.700	0.600

	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
t-stat	-2.050	0.790	0.800	1.960	1.060

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. 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: Transition Effect					
	R&D	Patent	Citations	Originality	Generality
Success	0.0247	2.3260	0.4691	0.0846	0.0157
	[0.0344]	[1.4483]	[0.3202]	[0.0739]	[0.0401]
After	-0.0032	0.1474	-0.2557**	-0.0095	-0.0409***
	[0.0127]	[0.5289]	[0.1152]	[0.0270]	[0.0147]
Success×After	-0.0174	-0.0190	0.2103	0.0286	0.0245
	[0.0188]	[0.7849]	[0.1711]	[0.0401]	[0.0219]
Mills	-0.0141	-1.0954	-0.3588**	-0.0518	-0.0204
	[0.0192]	[0.8072]	[0.1787]	[0.0412]	[0.0223]

Panel B: Transition Effect and EFD					
	R&D	Patent	Citations	Originality	Generality
Success	0.1129**	2.5575	0.7984*	0.1900*	0.0208
	[0.0504]	[2.1021]	[0.4714]	[0.1074]	[0.0587]
After	-0.0041	1.1549	0.0477	0.1169	0.0062
	[0.0334]	[1.4122]	[0.3156]	[0.0722]	[0.0396]
Success×After	-0.0261	-3.1825*	-0.3802	-0.2059**	-0.0494
	[0.0447]	[1.8897]	[0.4221]	[0.0966]	[0.0531]
EFD	0.3221***	16.9033***	1.5633*	0.7519***	0.3702***
	[0.0958]	[4.0365]	[0.9024]	[0.2062]	[0.1132]
EFD×After	0.0056	-2.3057	-0.5673	-0.2169*	-0.0893
	[0.0549]	[2.3221]	[0.5187]	[0.1187]	[0.0652]
Success×EFD	-0.0550	-0.2631	-0.5493	-0.1424	-0.0788
	[0.0645]	[2.7268]	[0.6090]	[0.1393]	[0.0766]
Success×After×EFD	0.0174	5.8943*	0.9592	0.3969**	0.1239
	[0.0725]	[3.0631]	[0.6844]	[0.1565]	[0.0860]
Mills	-0.0487**	-1.0666	-0.3203*	-0.0528	0.0078
	[0.0208]	[0.8527]	[0.1922]	[0.0435]	[0.0237]
N	649	649	649	649	649

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 $Y_{ikt} = \alpha + \beta Pre\text{-}Withdrawn_{it} + \delta Pre\text{-}IPO_{it} + \theta After_{it}^{0,1} + \delta After_{i}^{2+} + \gamma X_{ikt-1} + \varepsilon_{ikt}$, where Y_{ikt} is the measures of innovation activities: R&D ratio, number of patents, truncation bias adjusted citations (*Citations* and *R.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; $After_{it}^{0,1}$ is equal to one if it is IPO year or one year after IPO for successful firms; $After_{it}^{2+}$ is equal to one if it is two or more years after IPO for successful firms. X_{ikt-1} includes $ln(Sales)$, $Tangible$, $Cash$, Age; capital expenditure, sales growth, and ROA. 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	-0.0061	0.8649	0.2246	0.0043	0.0256
	[0.0171]	[0.7703]	[0.2687]	[0.0310]	[0.0510]
Pre-IPO	0.007	0.2708	-0.0214	0.0108	-0.0022
	[0.0175]	[0.5853]	[0.1274]	[0.0214]	[0.0338]
$\text{After}^{0,1}$	-0.0218*	0.4412	-0.008	-0.0018	0.0157
	[0.0126]	[0.3966]	[0.1033]	[0.0135]	[0.0253]
After^{2+}	-0.0109	0.8106*	0.0718	-0.0074	0.0401*
	[0.0110]	[0.4762]	[0.1174]	[0.0120]	[0.0239]
N	649	649	649	649	649
R^2	0.42	0.11	0.08	0.05	0.17

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. *** 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
Model 1: Linear	0.0956***	2.6623	0.6985***	0.2037***	0.0794***
	[0.0348]	[1.8166]	[0.2300]	[0.0512]	[0.0302]
Model 2: Linear Interaction	0.0442	3.5616*	0.6453**	0.1708**	0.0646
	[0.0492]	[2.0226]	[0.2973]	[0.0701]	[0.0406]
Model 3: Quadratic	0.0724	4.2284**	0.8345**	0.2022***	0.0857*
	[0.0554]	[1.7278]	[0.3659]	[0.0777]	[0.0459]
Model 4: Quadratic Interaction	0.0779	4.3687*	0.8385*	0.1572	0.0810
	[0.0697]	[2.2409]	[0.4638]	[0.0999]	[0.0573]

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

This table tests innovation of industry-and-size matched private and public firms in relation to the propensity to innovate and external finance dependence. Panel A reports the first step estimation results about the tendency to go public from the treatment effect model and Panel B reports the results of relative comparison between innovation of private and public firms with different degrees of innovation intensity in external 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 first step of the treatment effect model estimates the probability of being public based on a firm's logarithm of total assets, capital expenditure, growth in sales, ROA, leverage, external finance dependence index (all firms only), and innovation intensity index from a probit model. EFD is an industry-level external finance dependence index. $Intensity$ 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 second step of the treatment effect model is estimated as $Y_{ikt} = \alpha + \beta Public_i + \theta Intensity_{ik} + \delta Public_i \times Intensity_{ik} + \delta EFD_{ik} + \theta Public_i \times EFD_{ik} + \kappa EFD_{ik} \times Intensity_{ik} + \rho Public_i \times Intensity_{ik} \times EFD_{ik} + \gamma X_{ikt-1} + \lambda X_{ikt-1} \times EFD_{ik} + \phi Mills_i + \varepsilon_{ikt}$. 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. The inverse Mills ratio ($Mills$) adjusts for selection bias. 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: Treatment Effect Model First Step		
	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

Panel B: Treatment Effect Model Second Step					
	R&D	Patent	Citations	Originality	Generality
Public	0.0160***	2.3909**	0.1938*	0.0463***	0.0299**
	[0.0062]	[1.1296]	[0.1039]	[0.0172]	[0.0119]
Intensity	0.0078	-0.4299	0.1911	0.0509**	0.0322**
	[0.0080]	[1.4753]	[0.1359]	[0.0224]	[0.0156]
Public×Intensity	0.0235**	3.1894*	0.1392	0.0571**	0.0448**
	[0.0095]	[1.7520]	[0.1614]	[0.0267]	[0.0185]
EFD	0.0431***	-6.9643***	-0.0866	-0.0857**	-0.0423*
	[0.0127]	[2.3303]	[0.2146]	[0.0354]	[0.0246]
EFD×Public	0.0108	-1.3284	-0.227	-0.0231	-0.0035
	[0.0106]	[1.9575]	[0.1803]	[0.0298]	[0.0207]
EFD×Intensity	0.0090	3.5994	-0.1086	0.0512	0.0009
	[0.0190]	[3.4887]	[0.3215]	[0.0531]	[0.0368]
EFD×Public×Intensity	-0.0050	5.5454	0.6106*	0.1974***	0.0649
	[0.0217]	[3.9873]	[0.3673]	[0.0607]	[0.0421]
Mills	-0.0133***	-1.4467***	-0.0719	-0.0221***	-0.0166***
	[0.0029]	[0.5218]	[0.0480]	[0.0079]	[0.0055]
N	9,523	9,523	9,523	9,523	9,523

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:
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