

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

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Abstract

In this paper, we examine the relation between innovation and a firm's financial dependence using a sample of privately-held and publicly-traded U.S. firms. We find that public firms in external finance dependent industries spend more on R&D and generate a better patent portfolio than their private counterparts, while public firms in internal finance dependent industries do not have a better innovation profile than private firms. The results are robust to various empirical strategies that address selection bias. The findings indicate that the influence of public listing on innovation depends on the need for external capital.

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1. Introduction

While innovation is crucial for businesses to attain a strategic advantage over competitors, financing innovation tends to be difficult because of the uncertainty and information asymmetry associated with innovative activities. Firms with innovation opportunities often lack capital. Stock markets can provide various benefits as a source of external capital by reducing asymmetric information, lowering the cost of capital, as well as enabling innovation in firms (Rajan, 2012).¹ While firms can gain access to a large pool of low cost capital by going public, they may also be pressured by myopic investors to generate short-term profits (Stein, 1989). Such short-termism could potentially be detrimental to long-term innovation.² In this study, we investigate how innovation depends on access to stock markets and the need for external capital.

Innovation is particularly worth studying due to its uniqueness, as well as the evidence that economic forces influence innovation and other investments differently. First, Derrien

¹An analysis of the number of initial public offerings (IPOs) cross industries shows that the majority of IPOs come from external finance dependent sectors and innovation intensive sectors (Figure 1). Financing research and development is often stated as one of the uses of proceeds in the Securities and Exchange Commission Form S-1. For example, Evergreen Solar Inc. is a manufacturer of solar power products in the semiconductors and related devices industry, which is external finance dependent. In the registration statement for its initial public offering on November 2, 2000, Evergreen Solar disclosed that the company would “anticipate using at least \$3 million to finance research and development activities.” InforMax Inc., a bioinformatics company, is also in an industry that relies on external capital for investments. It went public on October 3, 2000. In the use of proceeds section of the registration statement, InforMax declared that it would “anticipate that the remaining portion of the offering proceeds would be allocated approximately one-third to expanding research and development.”

²In September 2009, the Aspen Institute, along with 28 business 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).

and Kecskes (2013) show that financial analysts enhance capital expenditures because they reduce information asymmetry. However, Benner and Ranganathan (2012) and He and Tian (2013) find that analysts hamper innovation by pressuring managers to meet or beat earnings targets, exacerbating the managerial myopia problem. Second, stock liquidity increases capital expenditures by improving price informativeness (Fang et al., 2009) and reducing the cost of capital (Becker-Blease and Paul, 2006). In contrast, the effect on innovation is negative as stock liquidity exposes firms to hostile takeovers and attracts short-term institutional investors (Fang et al., 2014). Third, while short sellers drive stock prices down (Grullon et al., 2015), thereby impeding capital expenditures, they enhance innovation by via information production and detection of managerial shirking (He and Tian, 2014). Additionally, we use patent data to measure the quality of the investment output, which is difficult to quantify for other investments.

We analyze a large sample of private and public firms in order to understand the relation between a firm’s financial dependence and innovation. Perhaps the biggest challenge of our empirical design is that a firm’s decision to gain access to stock markets is 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 private and public firms. While controlling for observable time series and cross-sectional variables that are related to innovation and the choice of going public, we estimate the treatment effect model to isolate unobservable private information that influences a firm’s IPO decision. Furthermore, we employ a fuzzy regression discontinuity (RD) design to mitigate the concern

about the non-randomness of public and private firms.

In the fuzzy RD design, we explore the discontinuity in the probability of delisting from the NASDAQ when observable variables cross the delisting criteria. The fuzzy RD design is an experiment with imperfect compliance when the treatment does not solely depend on one cutoff rule. Identification in a RD design relies on the assumptions of discontinuity in the probability of treatment and the plausibility of agents' imprecise control over the forcing variable near the known threshold. Internal validity tests are performed to ensure the satisfaction of these assumptions.

To examine the effect of delisting on innovation, we conduct the graphic analyses and formal fuzzy RD estimations for firms in external finance dependent (EFD) and internal finance dependent (IFD) industries. Industries with internal cash flows lower (higher) than their investments are considered as EFD (IFD) industries. For firms in EFD industries, delisted firms invest relatively less in innovation and have fewer subsequent innovation outputs compared to listed firms. In contrast, there is no such effect for firms in IFD industries. The placebo analyses that use artificial NASDAQ delisting requirements and artificial delisting year exhibit no jump in innovation of firms around the threshold.

To understand the differential effects of public listing on the innovation of firms in EFD and IFD industries, we explore several factors that may affect the cost-benefit trade-offs associated with being public. First, the financing benefits from public listing may be stronger for firms in EFD industries than for firms in IFD industries. Second, managers of public firms, under pressure from myopic investors, may have incentives to pursue short-term stock

performance (Stein, 1989; Bolton et al., 2006). Such agency issues could have differential impacts on firms with distinctive needs for external capital. Third, to the extent that product market competition may impose short-term pressure on managers, public firms in competitive industries may innovate less than private firms with sufficient internal cash flows. Fourth, short-term pressure from financial analysts may impede the innovation activities of public firms. Fifth, firms differ in the efficiency of converting R&D into patents. Sixth, public firms may purchase more patents and new technology through mergers and acquisitions (Bena and Li, 2014; Seru, 2014). Our analyses indicate that innovative firms with external financing needs benefit from listing in stock markets, while innovative firms without such needs may potentially be hurt due to exposure to myopic investors.

We also conduct four tests to alleviate concern that the technological innovation in firms in EFD and IFD industries might differ in importance. First, an investigation of the relation between an industry's external finance dependence and its innovation intensity shows an insignificant correlation of 0.080 (or 0.075) using patents (or R&D) as a measure for industry innovation intensity. Second, we match each matched pair of private and public firms in IFD industries with a matched pair of firms in EFD industries that are the same in age, year, and closest in size. Third, we match the industry-size matched pairs of private and public firms in EFD and IFD industries by age, year, and R&D in order to minimize the influence of differences in R&D investments among these firms. Using these two sub-samples of matched pairs, we still observe that public listing has larger positive benefits on firms in EFD industries than firms in IFD industries. Fourth, we restrict our analysis to firms with

a minimum of one patent and our results remain intact.

Our study contributes to the nascent literature on identifying various economic factors driving firm innovation. The literature shows that innovation is affected by investors' tolerance for failure (Tian and Wang, 2014), the development of financial markets (Amore et al., 2013; Chava et al., 2013; Hsu et al., 2014; Cornaggia et al., 2015), legal system (Brown et al., 2013), bankruptcy laws (Acharya and Subramanian, 2009), labor laws (Acharya et al., 2014), institutional ownership (Aghion et al., 2013), and private equity (Lerner et al., 2011). In related work, Bernstein (2015) investigates the innovation activities of IPO firms using an instrumental variable approach. Gao et al. (2014) investigates corporate innovation strategies using a sample of public and private firms. Complementing their works, we focus on the relation between a firm's financial dependence and innovation and highlight the importance of considering a firm's external financing need when evaluating the role of stock markets in innovation activities.

This paper adds new evidence to the recent surge of debate on the trade-off between public listing and staying private and its influence on a firm's real activities. On the one hand, the benefits of an easier access to cheaper capital allow a public firm to conduct more mergers and acquisitions (Maksimovic et al., 2013), to raise more equity capital (Brav, 2009), and to pay more dividends (Michaely and Roberts, 2012). Public firms are more responsive to changes in investment opportunities than their private counterparts (Gilje and Taillard, 2012; Mortal and Reisel, 2013; Phillips and Sertsios, 2014). 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) and investments (Asker et al., 2015). Our findings indicate that the financing benefits associated with public listing are important for the innovation activities of firms with external capital needs, while market short-termism has a stronger influence on the innovation activities of firms in IFD industries.

The rest of the paper is organized as follows. We develop hypotheses in Section 2. In Section 3, we describe the data, innovation, external finance dependence, and innovation intensity measures. In Section 4, we present the differences in innovation of private and public firms in EFD and IFD industries. In Section 5, we exploit a regression discontinuity designs to isolate the treatment effects. In Section 6, we discuss the potential explanations for the observed differential effects. We conclude in Section 7.

2. Theoretical Motivation and Empirical Hypotheses

The theoretical literature presents two opposing views on the impact of stock market listing on innovation. One view focuses on the myopic nature of stock markets and/or managers. These models show that stock markets tend to target short-term earnings and such myopia could induce public firms to invest suboptimally (Stein, 1989). With their compensation linked to stock performance, the managers of public firms have incentives to sacrifice long-term investments in order to boost short-term stock returns. Innovation activities typically require a substantial amount of investment over a long period of time and the probability of success is highly uncertain. Holmstrom (1989) and Acharya and Lambrecht (2015) suggest that managers, under 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. (2014) develop a model to demonstrate that managers of public companies are rationally biased against innovative projects, which typically have a higher failure rate. An implication of these models is that stock markets hinder firms from investing in innovation.

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

Second, the literature documents 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 (Stiglitz, 1985). Moreover, Rajan (2012) points out that the possibility of losing critical assets to creditors in the event of project failure discourages entrepreneurs from being innovative. 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, stock market listing lowers the cost of capital as investors' portfolios become more liquid and diversified (Pagano et al., 1998). It also helps to lower borrowing costs because of the reduced asymmetry of information and increased lender competition.

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

For firms with insufficient internal cash flows to finance investments, the infusion of public equity could relax their financial constraints, thereby facilitating innovation. Additionally, bearing a higher cost of funding, they would likely attempt to utilize their capital more efficiently. However, with a need to raise equity in the future, they may also face pressure to choose short-term projects designed to satisfy quarterly earnings growth.

For firms with cash flows in excess of their investment needs, the additional capital raised from stock markets may enable them to acquire innovation externally. However, ample free cash flows may give rise to agency problems, which will reduce innovation efficiency. In addition, the exposure to stock market short-termism might potentially stifle the innovative

activities of these firms. With the implications of theoretical models in mind, we conjecture that the impact of listing in stock markets on innovation varies with the degrees of external finance dependence.

3. Data and Measures

3.1. Data

To measure innovation activities, we collect firm-year patent counts and patent citations data from the 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.

The financial data on U.S. private and public firms were obtained from S&P Capital IQ for 1994-2004.³ The sample stops in 2004 because the average time lag between the patent application date and the grant date is two to three years (Hall et al., 2001).⁴ S&P Capital IQ categorizes a firm as public or private based on its most recent listing 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 the 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

³S&P Capital IQ provides coverage for U.S. private firms with minimum revenues of \$5 million or with public debt issuances. Sageworks is another database that covers the financial information of private firms. However, Sageworks is not suitable for our study for two reasons. First, Sageworks does not contain R&D spending data. Second, the firms in Sageworks are difficult to be matched with the patent database, since the firms in the Sageworks are anonymous. See Asker et al. (2015) for details of Sageworks database.

⁴Using a sample period of 1994 to 2003 yields similar results.

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 are excluded. Cash, tangible, ROA, and capital expenditure 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 identical, we conduct Internet searches and include the observation only if we are confident of the match. Following the innovation literature (e.g., Atanassov, 2013), the patent and citation counts are set to zero when no patent and/or citation information is available. Including firm-year observations with no patents alleviates the sample selection concern. After this process, there are 2,392 private firms and 8,863 public firms in the full sample.

3.2. Matched Sample

A potential concern regarding the full sample is that private firms in S&P Capital IQ may be larger than public firms. Innovation varies substantially across industries and by firm size. To minimize the differences in industry and size distributions, we identify a sample of industry-and-size-matched private and public firms. Specifically, for each private firm from the beginning of the sample period, we match it with a public firm closest in size and in the same three-digit SIC industry.⁵ We plot the distribution of the logarithm of total assets for

⁵Closest 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. (2015) use a similar

the matched private and public firms in Figure 2. The two distributions almost perfectly overlap. The time series observations for each matched pair are kept to preserve the panel structure of the data. This procedure results in 2,214 matched pairs of private and public firms.

3.3. Innovation Measure

We use R&D spending to measure innovation input and patent-based metrics to measure innovation output (Hall et al., 2001, 2005). The first measure of innovation output is the number of patent applications filed 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 innovations vary in their technological and economic significance. A simple count of patents may not be able to distinguish breakthrough innovations from incremental technological discoveries (Trajtenberg, 1990). Thus, we use the citation count each patent receives in subsequent years to measure the importance of a patent. Citations are patent-specific and are attributed to the applying firm at the time of application, even if the firm later ceases to exist 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 innovation quality. However, patent citations are subject to truncation bias because they accrue over a long period of time; but we only

method to identify firms closest in size. We perform one-to-one matching with no replacement. We also match by firm age, which leads to a smaller sample. Our results are robust to the industry-size-and-age matched sample.

observe citations up to 2006. Following Hall et al. (2001, 2005), truncation bias is corrected by the estimated distribution of citation-lag. That is, each patent citation is adjusted using the citation truncation correction factor estimated from a diffusion model.⁶

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

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

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

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

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

where G_{ij} is the number of patents citing patent i belonging to class j scaled by the number

⁶Lerner 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 patent applications in the same year and technology class. This measure shows the relative citation counts compared to matched patents after controlling for time and technology fixed effects. Using this truncation bias-adjusted citation measure yields similar results.

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 patents in a broader array of technology classes has a higher value of generality.

3.4. External Finance Dependence and Innovation Intensity Measures

Rajan and Zingales (1998) argue that the degree of dependence on external financing varies across industries. Industries such as biotechnology rely more on external capital, while industries such as tobacco are less external capital dependent. To determine 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 expenditures not financed through internal cash flows.⁷ 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 1994-2004.⁸ An industry with a higher index value of external finance dependence relies more on external capital to finance its investment.

We construct an innovation intensity index to measure the importance of innovation to an industry. Following Acharya and Subramanian (2009), we first compute the time series industry-level innovation intensity as the median number of patents for all patent-producing

⁷We also include R&D as part of investments in order to construct the external finance dependence measure. Our results are robust to this alternative measure.

⁸Hsu et al. (2014) use a similar approach to measure an industry's dependence on external finance.

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. As an alternative measure, we use R&D spending to construct each industry's innovation intensity. The R&D-based innovation intensity index is constructed following the same procedure as the patent-based innovation intensity index. The only difference is that the median value of R&D for all firms with non-zero R&D spending in the two-digit SIC code industries in each year is used to compute the time series industry-level innovation intensity.

4. Empirical Analysis

4.1. Univariate Analysis

In Table 1, we report the 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. The age of the firm is the difference between the current year and the founding year of a firm.⁹ 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%), while public firms reserve a higher percentage of cash (18.89%). The average return on assets (ROA) of private firms is lower than that of public firms (2.67% vs. 3.79%). Private firms have a capital expenditure ratio of 7.20% relative to total assets, while public firms have a ratio of 6.31%.

⁹To compute firm age, we cross-check the founding year data in S&P Capital IQ and Jay Ritter IPO databases to ensure accuracy.

As for innovation activities, Panel A of Table 1 shows that public firms spend more on R&D, measured as the natural logarithm of one plus R&D expenses ($\ln(R\&D)$), than private firms. We use $\ln(R\&D)$ instead of R&D as a ratio of total assets to minimize the influence of a drop in R&D ratio resulting from equity issuances during IPOs. We also conduct our analyses using the sum of capital expenditures and R&D spending and find similar results. In terms of the outcome of investments in innovation, private companies on average have significantly fewer patents compared to public firms (1.02 vs. 7.48). The patents of 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 (4.09 vs. 2.84). The difference in the average number of citations to the patents of private and public firms is statistically significant. Public firms also tend to generate more original patents. Similar differences between private and public firms are observed in the matched sample, except for ROA (Panel B of Table 1).

4.2. External Finance Dependence and Innovation

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

We estimate the following panel data model separately for firms in EFD and IFD indus-

tries:

$$Y_{i,k,t} = \alpha + \beta Public_{i,k,t} + \gamma X_{i,k,t-1} + \eta_k + \zeta_t + \varepsilon_{i,k,t}, \quad (1)$$

where $Y_{i,k,t}$ measures innovation activities, including $\ln(R\&D)$, natural logarithm of one plus the number of patents, natural logarithm of one plus the truncation bias-adjusted citations, originality, and generality. $Public_{i,k,t}$ is a dummy variable equal to one for public firms and zero for private firms; $X_{i,k,t-1}$ is a set of characteristic variables that affect a firm's innovation activities, including $\ln(Sales)$, *Tangible*, *Cash*, *Age*, *Capex*, *S.Growth*, and *ROA*; η_k controls for industry effects based on two-digit SIC codes; and ζ_t controls for year fixed effects. The coefficient β is used to estimate the effect of public listing on innovation while the confounding variables are controlled. The unreported fixed effects estimation show that the coefficients on *Public* are positive and significant in all specifications for firms in EFD industries. For firms in IFD industries, the coefficients on *Public* are insignificant.

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. Therefore, we need to control for unobservables that could drive both innovation and the decisions to go public. We apply the treatment effect model to correct for selection bias using the inverse Mills ratio.¹⁰ The treatment effect model includes two equations. The first

¹⁰Li and Probhala (2007) provide a survey of selection models in corporate finance and show that self-selection is an omitted variable problem. Self-selection can be corrected by adding the inverse Mills ratio in the second step. Differing from the standard Heckman model that is used to estimate a self-selected subsample, the treatment effect model involves both the self-selected and unselected samples and has an endogenous indicator variable (*Public* dummy in our context) as an independent regressor. The variable of interest is the coefficient on the indicator variable. Identification of the treatment effect model relies on the

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:

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

where Z is a set of firm characteristic variables that affect a firm's decision to go public. The treatment effect model is estimated using a two-step approach. In the first step, the probability of being public listed is estimated from the probit model in equation (2). The second step adds the inverse Mills ratio (*Mills*) to equation (1) to adjust for the selection bias.

We estimate the treatment effect model for all firms and separately for firms in EFD and IFD industries. Panel A of Table 2 reports the first-step estimation of the treatment effect model. The coefficient on EFD is positive and significant, indicating that firms in EFD industries are more likely to go public. The positive and significant coefficient on *Intensity* indicates a higher probability of going public for firms in more innovation-intensive industries. Capital expenditure, sales growth, ROA, and innovation intensity affect the probability of going public for firms in EFD industries, but not for firms in IFD industries.

The second-step estimation results are reported in Panels B and C of Table 2. The

nonlinearity of the inverse Mills ratio. We perform diagnostic analysis and verify that the inverse Mills ratio is nonlinear.

coefficients on the dummy variable *Public* are positive and significant for firms in EFD industries, but are insignificant for firms in IFD industries.¹¹ For example, the number of patents is approximately 66% higher for public firms than for private firms in EFD industries, while the difference between public and private firms is negative and insignificant in industries that depend less on external capital. The patents of public firms in the EFD industries are also of higher quality. Additionally, the differences in the originality and generality of patents produced by public and private firms are only significant in EFD industries.

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

$$Y_{i,k,t} = \alpha + \beta Public_i + \delta EFD_{i,k} + \theta Public_i \times EFD_{i,k} + \gamma X_{i,k,t-1} + \lambda X_{i,k,t-1} \times EFD_{i,k} + \phi Mills_i + \varepsilon_{i,k,t}, \quad (3)$$

where $EFD_{i,k}$ is the industry external finance index. The coefficients on θ are positive and significant in most of the specifications (Table 2, Panel D), indicating that the impact on innovation of being publicly listed is stronger in EFD industries than in IFD industries.¹²

¹¹To ease the concern about the imbalance in the number of firms in EFD and IFD industries, we divide firms in EFD industries into tertiles and estimate the treatment effect model using firms in the top tertile. In the unreported results, we still observe that public firms in EFD industries have relatively better innovation profiles than private firms and the difference is statistically significant.

¹²We do not argue that public listing promotes innovation in general. Instead, our results highlight that the benefits and costs of going public depend on firms' financial dependence. Our study focuses on the differential impacts of public listing on the innovation of firms in EFD and IFD industries. Our empirical strategy is not a difference-in-differences framework with EFD as a treatment variable and firms in IFD sectors as a control group. External finance dependence measures the need for external capital rather than the strength of benefits or costs of being public. It is possible that firms in both EFD and IFD industries enjoy the same benefits, but face different costs.

4.3. Robustness

One concern is that the differential effects of public listing on innovation between EFD and IFD industries may simply reflect the importance of innovation in each industry. Firms in EFD industries may be younger and more innovative by nature, while firms in IFD industries may be older and less innovative. To ease this concern, we investigate whether or not innovation matters more for EFD industries.

In Figure 3, each industry's innovation intensity index is plotted against its EFD index. The figure shows no obvious relationship between an industry's dependence on external financing and the importance of innovation in that industry. The correlation between the innovation intensity index and the EFD index is 0.080 and statistically insignificant. Using the R&D-based innovation intensity measure, we also find a low and insignificant correlation (0.075) between the two indexes. There is no evidence that EFD industries are systematically more innovation intensive than IFD industries.¹³

As a further investigation, we examine whether or not our results are driven by the age differences between firms. We plot the distribution of firm age for the matched private and public firms, as well as for matched firms in EFD and IFD industries separately. Figure 2 shows there are more younger private firms than public firms in the sample, consistent with what is observed in Table 1. This firm age difference is more pronounced in IFD industries.

To mitigate the concern regarding the differences between EFD and IFD industries, we

¹³Note that our sample consists of all industries. EFD industries in our analysis include not only some high-tech sectors, but also low-tech or non-manufacturing sectors.

match firms in EFD and IFD by age, year, and size. Specifically, for each matched pair of public and private firms in IFD industries, we find a matched pair of public and private firms in EFD industries. We identify 303 age-year and size-matched pairs and repeat our estimations. The differential effects of public listing on innovation among firms in EFD and IFD industries persist (Table 2, Panel E). Moreover, our analyses also directly control for size and age, along with other variables that may affect innovation.

We recognize that firms in EFD industries on average spend more on R&D than those in IFD industries. To alleviate the influence of difference in R&D among firms in EFD and IFD industries, we match the industry-size matched pairs in EFD and IFD by age, year, and $\ln(\text{R\&D})$. In other words, we search EFD industries for an industry-size matched pair where the private firm has the same age and similar R&D in the same year as the private firm in the matched pair in IFD industries. Specifically, we require the absolute difference in $\ln(\text{R\&D})$ of private firms in EFD and IFD industries to be smaller than 0.5 and obtain 230 double-matched pairs. While controlling for other covariants, we report in Panel F of Table 2 the coefficients on the interaction between the EFD index and the *Public* dummy. We show that public listing matters more for the innovation of firms in EFD industries. Compared to the industry and sized matched sample (Panel D), the differential effects using this subsample is marginally smaller in the specifications of patent and originality.¹⁴

¹⁴Following Paternoster et al. (1998), we use the Z-test to examine whether or not the differences in the regression coefficients are statistically significant. The Z-statistic for the coefficients for $\ln(\text{Patent})$ in Panel D versus Panel E of Table 2 is: $Z = (0.5538 - 0.3929) / \sqrt{0.0633^2 + 0.0740^2} = 1.65$. The Z-statistic for $\ln(\text{Patent})$ in Panel D versus Panel F is 1.00. It is not statistically significant at the 5% level.

Another issue is that many firms have no patents, which may create a bias in an OLS framework (Griliches, 1990). We adopt two approaches to alleviate this potential bias. First, we apply poisson models to our sample. Second, we conduct our main analyses using a sub-sample of firms with non-zero patents. Our results are robust to these tests.

Figure 1 shows that IPO activities vary over time. To check whether our results are sensitive to time periods, we conduct robustness analyses by dividing the sample into two sub-sample periods (not reported). The result on external finance dependence driving the link between being public and innovation remains in both time periods.

5. Quasi Experiments

5.1. Identification Strategy

To further ease the concern about the non-randomness of public and private firms, we explore a fuzzy regression discontinuity (RD) design, as discussed in Angrist and Lavy (1999) and Hahn et al. (2001). The fuzzy RD design exploits the discontinuous nature in the probability of delisting from the NADASQ as firm characteristic variables cross the delisting threshold. This quasi-experiment is used to isolate the treatment effect of public listing on innovation.

Identification of RD design relies on “local” exogeneity in treatment status generated by observations just below and above the discontinuity threshold. RD design does not require a random treatment status and instead assumes that “randomized variation is a consequence of agents’ inability to precisely control the forcing variable near the known cutoff” (Lee and

Lemieux, 2010, p.282). Fuzzy RD exploits discontinuity in the probability of treatment as a function of the forcing variable and uses the discontinuity as an instrumental variable for treatment.

Sharp regression discontinuity is not suitable for our setting because whether or not a firm is delisted from a stock exchange is not simply determined by one measurable delisting criterion. Since the probability of treatment (delisting) is also affected by factors other than the forcing variable, the probability of treatment does not jump from 0 to 1 when the forcing variable crosses the threshold, as in the case of sharp RD. Fuzzy RD is a randomized experiment with imperfect compliance where the treatment is not solely determined by the strict cutoff rule (Lee and Lemieux, 2010). It does not require the forcing variable to be a binding constraint for treatment.

5.2. Regression Discontinuity: Delisting

In the RD design, we use the NASDAQ continued listing requirements as the forcing variable c_i and exploit discontinuity in the probability of delisting (treatment) at the minimum delisting requirements (c_0) following Bakke et al. (2012). The forcing variable is constructed using the core requirements (net tangible assets, market capitalization, and net income) and one of the non-core criteria (bid price).¹⁵ We first normalize each variable as $\log\left(\frac{\text{Variable}}{\text{NASDAQ continued listing requirements}}\right)$. We then take the maximum of the three normalized core

¹⁵Between July 1997 and July 2001, firms were required to maintain their net tangible assets above \$2 million or market capitalization above \$35 million or net income above \$500,000 and a minimum bid price of \$1. Since July 2001, the net tangible assets requirement was replaced by a shareholder equity requirement of \$2.5 million. See Bakke et al. (2012) for details.

variables and use the minimum of this maximum core variable and the normalized bid price as the forcing variable. At the threshold c_0 , there is a jump in the probability of delisting

$$P(\text{Delisting}_i = 1|c_i) = \begin{cases} f_1(c_i) & \text{if } c_i < c_0 \\ f_0(c_i) & \text{if } c_i \geq c_0, \end{cases} \quad (4)$$

where $f_1(c_0) \neq f_0(c_0)$. The fuzzy RD allows for the jump in the probability of treatment to be less than one at the threshold. The probability of treatment is a function of c_i :

$$E[\text{Delisting}_i|x_i] = P(\text{Delisting}_i = 1|c_i) = f_0(c_i) + [f_1(c_i) - f_0(c_i)]z_i, \quad (5)$$

where the dummy variable, $z_i = 1(c_i \leq c_0)$, indicates the point where the probability of treatment discontinues. Assuming $f_1(c_i)$ and $f_0(c_i)$ follow the p th-order of polynomials, the probability of treatment can be written as follows:

$$E[\text{Delisting}_i|x_i] = \gamma_0 + \gamma_1 c_i + \gamma_2 c_i^2 \dots + \gamma_p c_i^p + \lambda z_i + \delta_1 c_i z_i + \delta_2 c_i^2 z_i + \dots \delta_p c_i^p z_i. \quad (6)$$

Fuzzy RD can be estimated using a two-stage least squares approach with z_i and the interaction terms $[c_i z_i, c_i^2 z_i, \dots, c_i^p z_i]$ as instruments for Delisting_i . We specify three functional forms for the forcing variable including the first-order polynomial and the interaction term, as well as the second-order polynomials. Under the simple linear specification, the fuzzy RD reduced form model controlling for the covariates is:¹⁶

$$Y_{i,t+N} = \alpha + \beta_1 z_{i,t} + \beta_2 c_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t}, \quad (7)$$

where $Y_{i,t+N}$ is the firm innovation outcome variable that includes the natural logarithm of

¹⁶The reduced form models for the other two cases are $Y_{i,t+N} = \alpha + \beta_1 z_{i,t} + \beta_2 c_{i,t} + \beta_3 c_{i,t} \times z_{i,t} + \beta_4 X_{i,t} + \varepsilon_{i,t}$ and $Y_{i,t+N} = \alpha + \beta_1 z_{i,t} + \beta_2 c_{i,t} + \beta_3 c_{i,t}^2 + \beta_4 X_{i,t} + \varepsilon_{i,t}$.

one plus the number of patents, the natural logarithm of one plus citations, originality, and generality. Considering the long-term nature of innovation output, we examine how delisting in year t affects a firm's innovation input and output over the period of $t + 1$ through $t + 3$. β_1 estimates the treatment effect. The forcing variable, $c_{i,t}$, is centered at the threshold. $X_{i,t}$ is a set of covariates that may affect firm innovation, including $\ln(Assets)$, $Tangible$, $Cash$, Age , $Capex$, and ROA .

In fuzzy RD, the average treatment effect cannot simply be measured by the jump in the relationship between the outcome and the forcing variable. To account for the probability of treatment lower than one at the threshold, the treatment effect is estimated by dividing the jump by the fraction induced to participate in the treatment:

$$\beta = \frac{\lim_{c \rightarrow c_0^+} E[Y_i | c_i] - \lim_{c \rightarrow c_0^-} E[Y_i | c_i]}{\lim_{c \rightarrow c_0^+} E[Delisting_i | c_i] - \lim_{c \rightarrow c_0^-} E[Delisting_i | c_i]}. \quad (8)$$

The numerator of equation (8) is the difference in expected outcomes for firms with the forcing variable just above and below the minimum delisting requirement of the NASDAQ. The denominator is the difference in the fraction of delisted firms just above and below the threshold.

As the first step in any RD analysis, we plot the relation between the outcome and the forcing variable for firms that fall below the NASDAQ delisting requirements over the post-delisting period and for firms above the NASDAQ delisting requirements. We conduct the graphic analysis separately for firms in EFD and IFD industries. Figure 4 shows a jump in the average R&D spending, the average number of patents, and the average truncation

bias-adjusted citations at the cutoff for firms in EFD industries (left panel). There is no obvious jump in the outcome at the threshold for firms in IFD industries (right panel).

The jump in innovation for firms in EFD industries observed in Figure 4 could be driven by differences in other characteristics rather than by the delisting. To address this concern, we conduct two placebo graphic analyses. In the first placebo analysis, we use artificial delisting criteria as the threshold. In the second placebo analysis, we use an artificial delisting year. If the effect is caused by delisting, we should not observe a discontinuity in innovation at the cutoff in the placebo tests. Figure 5 presents the the results of using an artificial delisting threshold (left panel) and an artificial delisting year (right panel).¹⁷ We observe no downward jump in the average R&D spending, the average number of patents, or the average truncation bias-adjusted citations as the forcing variable below the cutoff for firms in EFD industries.

The fuzzy RD analysis relies on the assumption of discontinuity in the probability of treatment at the threshold. To check this assumption, the probability of delisting as a function of the forcing variable is plotted in Figure 6 (top). The graph shows a jump in the probability of treatment at the minimum level of the NASDAQ continued listing requirement ($c = 0$). As expected, the jump is less than one in the case of the fuzzy RD design. The evidence of discontinuity in the probability of treatment supports our identification strategy.

An underlying assumption of the RD design is that firms cannot precisely manipulate

¹⁷We perform the placebo test using several alternative artificial delisting thresholds and artificial delisting years and obtain similar results.

the forcing variable near the known cutoff. Lee (2008) shows that, even in the presence of manipulation, localized random assignment can occur when firms do not have precise control over the forcing variable. Treatment is randomized as long as delisting is not completely under a firm’s own control. This assumption is likely to be satisfied since the continued listing requirements such as the bid price and market capitalization are difficult to manipulate. To formally test whether firms have precise control over the forcing variable, we adopt the McCrary (2008) test of a discontinuity in the density of the forcing variable. The distribution of the forcing variable is plotted in Figure 6 (bottom) and shows little indication of a strong discontinuity around the threshold. The formal test provides a discontinuity estimate (i.e., log difference in heights) of 0.11 with a standard error of 0.11. Therefore, there is no evidence of precise manipulation of the forcing variable at the threshold.

We also perform a balancing test to check whether there is a discontinuity in the observable firm characteristics at the cutoff point. In Table 3, we present the covariates of firms with the forcing variable within an interval of $[-0.1, +0.1]$.¹⁸ The balancing test shows no significant difference in the underlying distributions of $\ln(Assets)$, $\ln(Sales)$, $S.Growth$, $Cash$, $Leverage$, or $Capex$ for firms close to the threshold. The difference is significant in the distributions of $Tangible$, ROA , and Age . As pointed out by Van der Klaauw (2008), differences in covariates do not necessarily invalidate a RD design. Lee (2008, p.676) emphasizes that “natural randomized experiments can be isolated even when treatment status

¹⁸We follow the window selection procedure of Cattaneo et al. (2014) to select the interval. There are 129 firms (63 treated and 66 controlled) within this interval.

is driven by non-random self-selection”.¹⁹ A direct way to account for possible differences in covariates is to control for such differences in estimation. Therefore, we include covariates in our RD estimations following Chava and Roberts (2008) and Van der Klaauw (2008).

Table 4 presents the two-stage least squares estimation results of the fuzzy RD with the forcing variable of the first-order polynomial functional form for firms in the EFD and IFD industries.²⁰ We report the estimates of the average treatment effect for different functional form specifications. In Panel A, the coefficients on the indicator variable z_i are negative and statistically significant in the majority of the specifications. The impacts are also economically significant. For example, delisted firms in EFD industries on average spend 57% less on R&D and generate about 47% fewer patents than their public counterparts in the third year subsequent to delisting.²¹ The coefficients on *Originality* are negative, but significant only in $t + 1$. It seems that the adverse impact of delisting on originality is relatively weaker. A potential reason could be that delisted firms in EFD industries reallocate their reduced investments to innovative projects of higher originality in order to minimize the negative impact of delisting. The F-statistics of the first stage are all above 10 and the p -values associated with the F-statistics are 0. There is no evidence for weak instruments. In contrast,

¹⁹Lee (2008, p.676) establishes a relative weak condition for a valid regression discontinuity design where individuals are allowed to “influence their own score in a very unrestrictive way.” Using U.S. house elections as a setting for the regression discontinuity analysis, he illustrates that “although winners of elections on average are systematically more experienced and more ambitious, treatment status is statistically randomized given that there is a random chance error component to the voting share.”

²⁰Using the other functional forms for the forcing variable yields similar results.

²¹The Z-statistic for $\ln(Patent)$ in $t + 1$ versus $t + 2$ and $t + 1$ versus $t + 3$ in Panel A of Table 4 is -0.04 and 0.06, respectively. The differences are not statistically significant at the 1% level.

the coefficient β_1 is not statistically significant in specifications for firms in IFD industries, except for R&D in $t + 3$ (Panel B). The results indicate that NASDAQ delisted firms in EFD industries on average tend to perform worse in innovation than their public counterparts, while delisted firms in IFD industries do not innovate less.

6. Potential Explanations

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

6.1. *Financing Benefits*

One potential reason for the observed larger patent portfolios of public firms in EFD industries could be that public listing relaxes the financial constraints of firms needing external capital. Funding is especially important for innovation since design, development, manufacturing, and patenting are costly.²² If stock markets facilitate technological innovation through enabling cheaper external financing, we would expect that firms in innovation-intensive industries will be more likely to go public to take advantage of the financing benefits of being publicly listed. To test this conjecture, we investigate how public listing relates to innovation intensity.

²²Rajan (2012) points out that “because of the difficulties in financing, start-ups are likely to stay away from capital intensive fundamental innovation where the commercialization possibilities are uncertain.”

As shown in Panel A of Table 2, the coefficient on the innovation intensity index is positive and significant in the specification of all matched firms, indicating that private firms in innovation-intensive industries on average are more likely to go public. However, the separate estimations show a higher propensity of going public only for innovative firms in EFD industries, but not for those in IFD industries. These results are consistent with our conjecture that the access to stock markets is important for innovative firms with more needs for external capital.

The difference in the probability of going public between firms in EFD and IFD industries also helps to further mitigate the concern that the observed difference in innovation of public and private firms is because more innovative firms may self-select into stock markets. If self-selection drives our results, we would expect that more innovative firms in all industries will choose to go public. However, we find that firms in innovation-intensive industries with a need for external capital, but not firms in industries without such need, are more likely to go public.

Moreover, we conduct our analyses by excluding industries in the top tercile of the innovation intensity index. Using this sub-sample of firms in relatively lower innovation-intensive industries, we still observe that public firms in EFD industries on average have a better innovation profile than private firms in EFD industries.

As a further check, we examine whether firms spend their proceeds from an IPO on R&D. Unfortunately, the “use of proceed” section in the public offering prospectus rarely discloses the specific amount that a firm planned to use for R&D. We therefore use changes in R&D as

a proxy for the amount from the proceeds that is actually spent on innovation. A difference in the percentage of net proceeds devoted to expand R&D investments between firms in EFD and IFD industries is found. Firms in EFD industries on average spend 4.35% of proceeds on R&D in the IPO year and 5.99% the year following IPO. In contrast, firms in IFD industries on average only spend 0.25% in the IPO year and 1.15% in the year subsequent to IPO. The analysis shows that firms in EFD industries indeed increase their R&D spending following their IPOs.

6.2. Short-Termism: Real Earnings Management

Stock markets have been criticized for providing incentives for 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 targets, managers of public firms may behave in a myopic manner. Acharya and Lambrecht (2015) suggest that managers have incentives to conduct real income smoothing by manipulating production in an attempt to manage market expectations. These models, however, do not feature financial dependence.

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

industries. Particularly, we focus on firms' manipulation of real activities to achieve the desired level of earnings.

There is substantial evidence that the managers of public firms engage in earnings management in order to meet earnings targets.²³ Accruals management and real earnings management (REM) are the two typical types of earnings management. Accruals management involves manipulation of accruals through the choice of accounting methods with no direct cash flow consequences. REM is accomplished by changing the firm's underlying operations that affect cash flows. Examples of REM activities include decreasing discretionary selling, general and administrative expenses (SGA), and cutting R&D expenses (Roychowdhury, 2006). Graham et al. (2005) suggest that managers prefer REM to accruals management since it is harder for auditors and regulators to detect real activities manipulation.

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

$$DISX_{i,t}/TA_{i,t-1} = \alpha + \beta_1(1/TA_{i,t-1}) + \beta_2(Sales_{i,t-1}/TA_{i,t-1}) + \varepsilon_{i,t}, \quad (9)$$

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 the total assets of firm i at 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

²³See Healy and Wahlen (1999) for a review.

across time.

We estimate the normal discretionary expenses by the fitted values from equation (9). 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 REM.

We first examine whether public firms in IFD industries engage in less REM than those in EFD industries. We conduct the test using public firms in both the full sample and the matched sample. Panel A of Table 5 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 indicates that public firms in industries dependent on internal capital are more likely to cut their discretionary spending, but public firms in industries dependent on external capital are less likely to do so. This result is not consistent with the view that firms with a financing need are more likely to smooth their earnings through real activities in order to raise equity capital. The result does not imply that equity financing reduces short-termism. A potential explanation could be that firms in EFD industries may refrain from REM in order to maintain their reputation and avoid losing investors.

We then investigate REM 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 REM. To answer this question, we classify firms into three groups according to the innovation intensity index. Group 1 includes firms in industries with the lowest innovation intensity and Group 3 consists of firms in industries with the highest innovation intensity.

Panel B of Table 5 shows that firms in more innovation-intensive industries (Group 3) tend to engage less in REM than firms in lower innovation-intensive industries (Group 1).

In Column (4) in Panel C of Table 5, we present the estimation results of the following regression model:

$$\begin{aligned}
REM_{i,k,t} = & \alpha + \beta_1 Intensity_{i,k} + \beta_2 EFD_{i,k} + \beta_3 Intensity_{i,k} \times EFD_{i,k} \\
& + \beta_4 MVE_{i,k,t-1} + \beta_5 MB_{i,k,t-1} + \beta_6 ROA_{i,k,t} + \beta_7 MVE_{i,k,t-1} \times EFD_{i,k} \\
& + \beta_8 MB_{i,k,t-1} \times EFD_{i,k} + \beta_9 ROA_{i,k,t} \times EFD_{i,k} + \zeta_t + \zeta_t \times EFD_{i,k} + \varepsilon_{i,k,t},
\end{aligned} \tag{10}$$

where the dependent variable is the REM measure, *Intensity* is the innovation intensity index, and *EFD* is the external finance dependence dummy. Following Roychowdhury (2006), we include the logarithm of market value of equity (*MVE*), market-to-book ratio (*MB*), and return on assets (*ROA*). ζ_t controls for year effects.

In Column (1) of Panel C in Table 5, we present the estimation results of equation (10) without *Intensity* and *Intensity* \times *EFD*. The coefficient on *EFD* is negative and significant, indicating that public firms in EFD industries are less likely to manage their earnings through real activities. Columns (2) and (3) present the estimation results for firms in EFD and IFD industries, respectively. The coefficient on *Intensity* is negative and significant for firms in EFD industries, but is positive and insignificant for firms in IFD industries. The differential effect is significant, as shown by the coefficient on *Intensity* \times *EFD* in Column (4). The results indicate that innovative firms in EFD industries tend to engage less frequently in REM, while innovative firms in IFD industries do not necessarily refrain from REM. Overall,

the results indicate that more innovative public firms that have a great need for external capital have lower incentives to behave myopically than less innovative public firms with a lower need for external capital.

6.3. *Short-Termism: Competition*

Aghion et al. (2013) suggest that product market competition may impose short-term pressure on firms. Since firms are evaluated by investors based on their relative performance to their peers, they may have more incentives to engage in investments that generate short-term returns when facing high competition. To the extent that market competition exacerbates short-termism, we expect that being publicly traded may hurt the innovation of firms in IFD industries when product market competition is fiercer.

We measure the industry competition according to Hoberg and Phillip (2010) industry concentration measure (HPICM). An industry in the bottom (top) tercile of HPICM is defined as competitive (non-competitive). The advantage of HPICM is that it is constructed using both public and private companies in each industry based on three-digit SIC codes. We add a *Competitive* dummy, as well as its interaction with the *Public* dummy and the control variables to equation (1).

Table 6 reports the estimation results for the differential effects of competition on innovation between competitive and non-competitive industries. A treatment effect model is estimated separately for firms in EFD and IFD industries. The coefficients on the interactive term, $Competitive \times Public$, are mostly negative and significant for firms in IFD industries,

but insignificant for firms in EFD industries. The results indicate that public firms in IFD industries innovate less than private firms when there is more competition.

6.4. Short-Termism: Analyst Coverage

In a survey of 401 financial executives of U.S. public companies, Graham et al. (2005) find that the analyst consensus estimate is an important earnings benchmark and a majority of executives are willing to sacrifice long-term value creation in order to meet or beat analyst expectations. Facing the pressure of meeting earnings targets, managers would reduce or delay investments in long-term projects such as innovation. He and Tian (2013) provide evidence that analyst coverage imposes short-term pressure on public firms and impedes firm innovation.

Following He and Tian (2013), we use the number of analysts covering the firm to capture short-term pressure from analysts and investigate the effect of analyst coverage on innovation of firms in EFD and IFD industries. Specifically, the following model is estimated:

$$Y_{i,k,t+3} = \alpha + \beta \ln(Coverage)_{i,k,t} + \theta EFD_{i,k} \times \ln(Coverage)_{i,k,t} + \gamma X_{i,k,t-1} \quad (11)$$

$$+ \lambda X_{i,k,t-1} \times EFD_{i,k} + \xi_i + \zeta_t + \varepsilon_{i,k,t},$$

where the dependent variable, $Y_{i,k,t+3}$, is the innovation outcome measure including the three-year-ahead natural logarithm of one plus the number of patents, the natural logarithm of one plus truncation bias-adjusted citations, originality, and generality. The independent variable $\ln(Coverage)_{i,k,t}$ is the natural logarithm of one plus the average of the monthly numbers of analyst earnings forecasts for firm i over fiscal year t from the Institutional Brokers'

Estimate System (*I/B/E/S*). $EFD_{i,k}$ is the external finance dependence dummy. $X_{i,k,t-1}$ includes $\ln(Assets)$, $Tangible$, $Cash$, Age , $Capex$, $G.Sales$, ROA , $\ln(R\&D)$, and $leverage$. ξ_i controls for firm fixed effects and ζ_t captures year fixed effects. Note that $EFD_{i,k}$ itself is not included in the model as it is absorbed by the firm fixed effects.

Table 7 shows that the coefficients on $\ln(Coverage)$ are negative, while the coefficients on $EFD \times \ln(Coverage)$ are positive. The coefficients are statistically significant, except for originality. The results indicate that firms in IFD industries have a lower level of three-year-ahead innovation output when there is more coverage from analysts. However, the negative impact of analyst coverage on innovation is significantly smaller for firms in EFD industries. Taken together, the findings indicate that public listing may not be optimal for the innovation of firms in IFD industries.

6.5. 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 into fruitful output. Relying on more costly external capital for their innovation activities, firms in EFD industries are likely to use their resources more efficiently. To investigate the possibility that the differential effects of public listing on the patent portfolios of firms in EFD and IFD industries may be related to the variation in firms' innovation efficiency, we measure innovation efficiency as the natural logarithm of one plus patents per dollar of R&D investment ($\ln(1 + (patents/R\&D))$).

We next test whether public and private firms in EFD and IFD industries differ in their production of patents from R&D. We estimate the treatment effect model separately for firms in external and internal finance dependent industries and then examine the differential effect. Table 8 shows that the coefficient on the public dummy is positive and significant for EFD industries, but insignificant for 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.

6.6. Acquisitions

Innovation can be achieved both internally and externally. Seru (2014) shows that innovation acquisition can be a more efficient way for mature firms with internal capital markets to secure the new technology they require. Firms may engage in mergers and acquisitions (M&A) for the purpose of purchasing innovative technologies and enhancing innovation productivity (Sevilir and Tian, 2013; Bena and Li, 2014). M&A transactions require a substantial amount of capital. Public listing enables firms to raise capital for M&As. Indeed, Bernstein (2015) documents that capital infusion from an IPO allows firms to purchase better quality external patents through M&As. Hence, the better innovation profile of public firms compared to private firms in EFD industries may also be because public listing facilitates innovation acquisitions.

To directly control for the influence of M&As on innovation, we include a variable that measures the acquired in-process technology (*in-process R&D/total assets*) to equation (1).

We estimate the treatment effect model separately for firms in EFD and IFD industries, as well as equation (3). The main findings in Table 2 remain intact after controlling for technology acquisitions.²⁴

As a further investigation, we examine whether or not public firms without innovation acquisitions still have greater quantity, quality, and novelty of innovations than similar private firms. Specifically, we identify the buyers in M&A transactions from the S&P Capital IQ database and exclude those firms from the sample. Panel G of Table 2 reports the estimation results using firms without M&As. The innovations of public firms in EFD industries remain stronger than their private counterparts after excluding innovation acquisitions.²⁵

Overall, the analyses indicate that our findings are not mainly driven by acquisitions aimed at capturing innovations. Nevertheless, the acquisition-based explanation is in fact consistent with the financing-based explanation, since the access to stock markets enables firms to secure the external financing needed for patent acquisitions.

7. Conclusions

In this paper, we examine how innovation depends on the need for external capital and on whether a firm is listed on a stock exchange by studying the innovation activities of a large sample of private and public firms. We estimate the treatment effect model to address selection bias related to the choice of going public, as well as exploit a fuzzy regression

²⁴The results are unreported and available upon request.

²⁵The Z-statistic for $\ln(Patent)$ in Panel D vs Panel G of Table 2 is 2.34. The difference between the matched sample (Panel D) and the matched sample excluding M&As (Panel G) is statistically significant at the significance level of 5%.

discontinuity design to gauge the treatment effect. The results show that public firms in EFD industries on average invest more in R&D and have a better patent portfolio than private firms. However, we observe no such difference between public and private firms in IFD industries.

Being publicly traded has differential effects on innovation of firms with different needs for external capital. We investigate the benefits and costs associated with public listing. The results indicate that public listing facilitates the innovation of firms in industries that are more dependent on external finance because the access to public equity helps to alleviate the financial constraints those firms face. However, public listing may potentially impede the innovation of firms with less need for external capital due to the exposure to short-termism. It is important to consider a firm's dependence on external capital when evaluating the impact of public listing on innovation.

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Figure 1: Number of IPOs

This figure presents the number of IPOs in external (EFD) and internal finance dependent (IFD) industries (top), as well as in high and low innovation intensity industries (bottom) over 1994-2004 for the sample firms. Industries with a positive (negative) value of EFD measure are regarded as external (internal) finance dependent. Industries with an innovation intensity index higher (lower) than the index median value are regarded as high (low) innovation intensity industries.

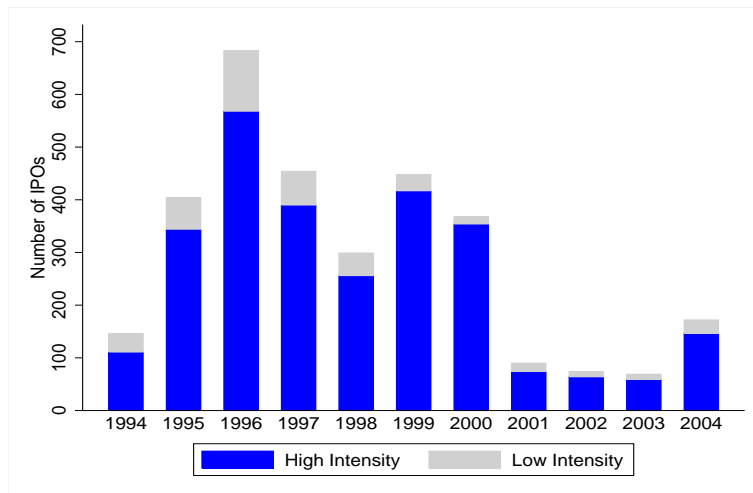
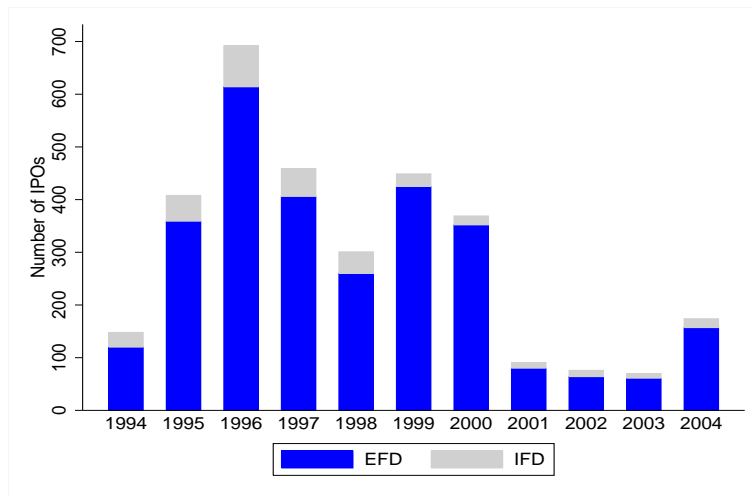


Figure 2: Size and Age Distribution of Public and Private Firms

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

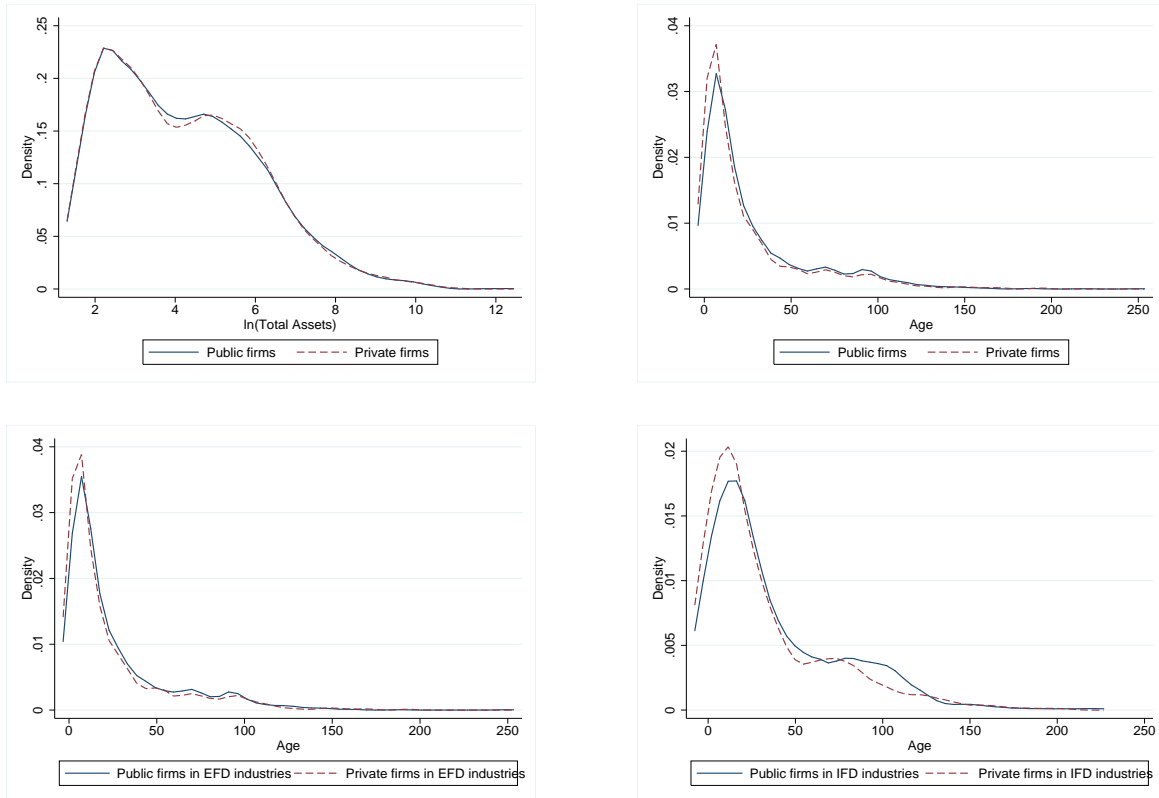


Figure 3: Innovation Intensity and EFD

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

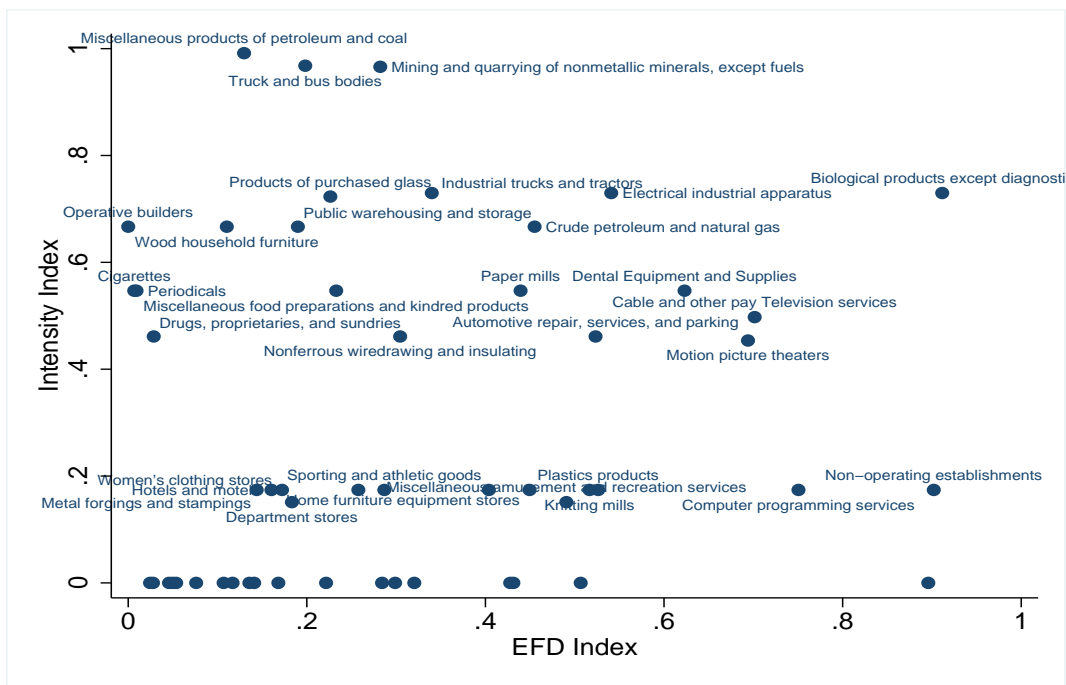


Figure 4: Regression Discontinuity: NASDAQ Delisting and Innovation

This figure shows the effect of NASDAQ delisting on innovation for firms in EFD industries (left panel) and IFD industries (right panel). We plot the average R&D expenditure (top), the average number of patents (middle), and the average truncation-bias adjusted citation (bottom) over the post-delisting period for NASDAQ delisted firms and over the pseudo post-delisted period for public firms on bin width of 0.2. We construct the forcing variable by taking the minimum between the log normalized bid price and the maximum value of the three log normalized core NASDAQ continued listing requirements. NASDAQ continued listing requirement variables are normalized to have a value of zero at the threshold. Delisting occurs when the forcing variable falls below the threshold. The sample period is from 1997 to 2004.

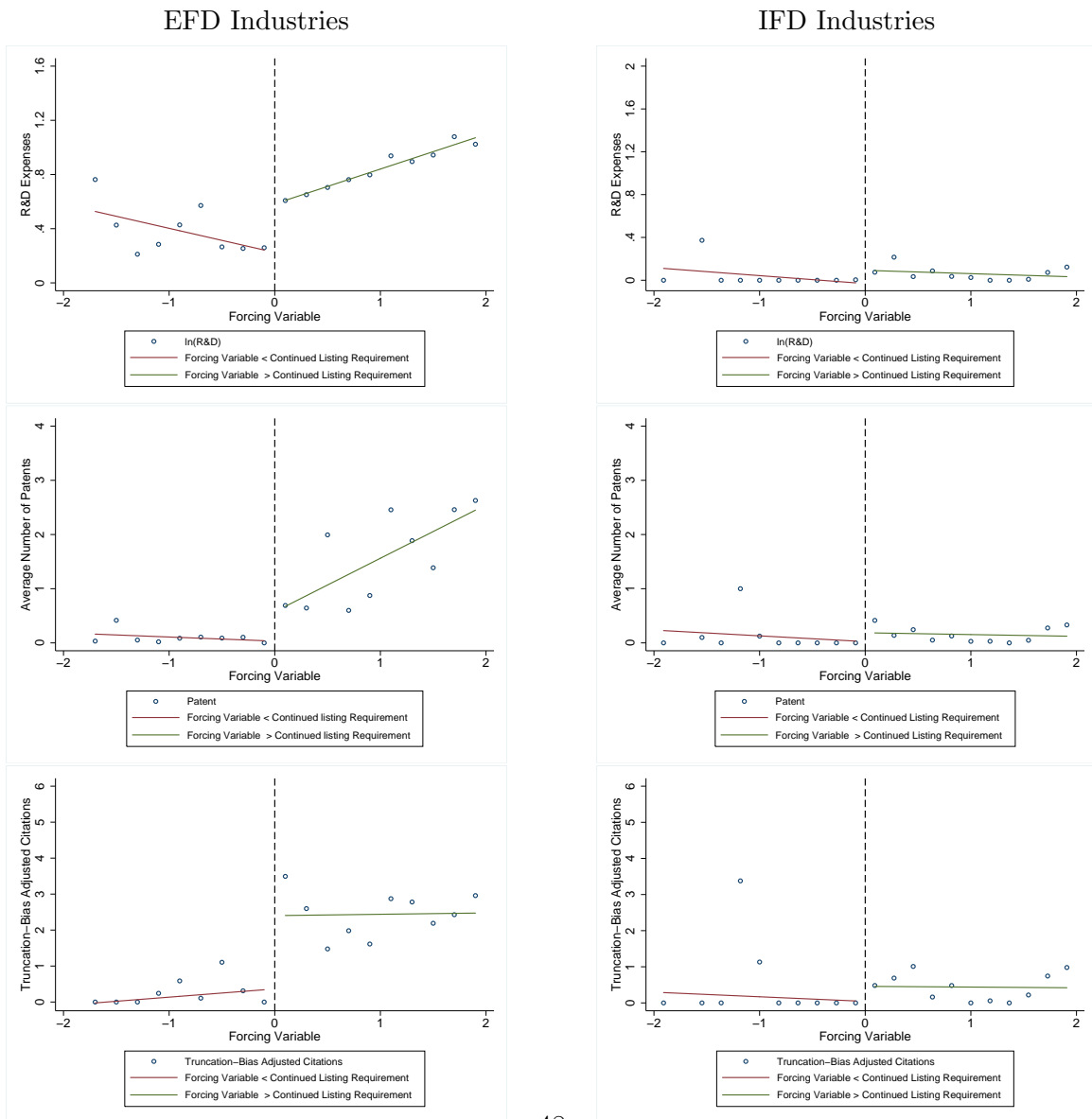


Figure 5: Placebo Test: Artificial Delisting Threshold and Artificial Delisting Year

This figure shows the placebo effect of a NASDAQ delisting on innovation using artificial minimum NASDAQ continued listing requirement (left panel) and artificial NASDAQ delisting year (right panel). We plot the average R&D spending, the average number of patents, and the average truncation-bias adjusted citations for firms in EFD industries. The sample period is from 1997 to 2004.

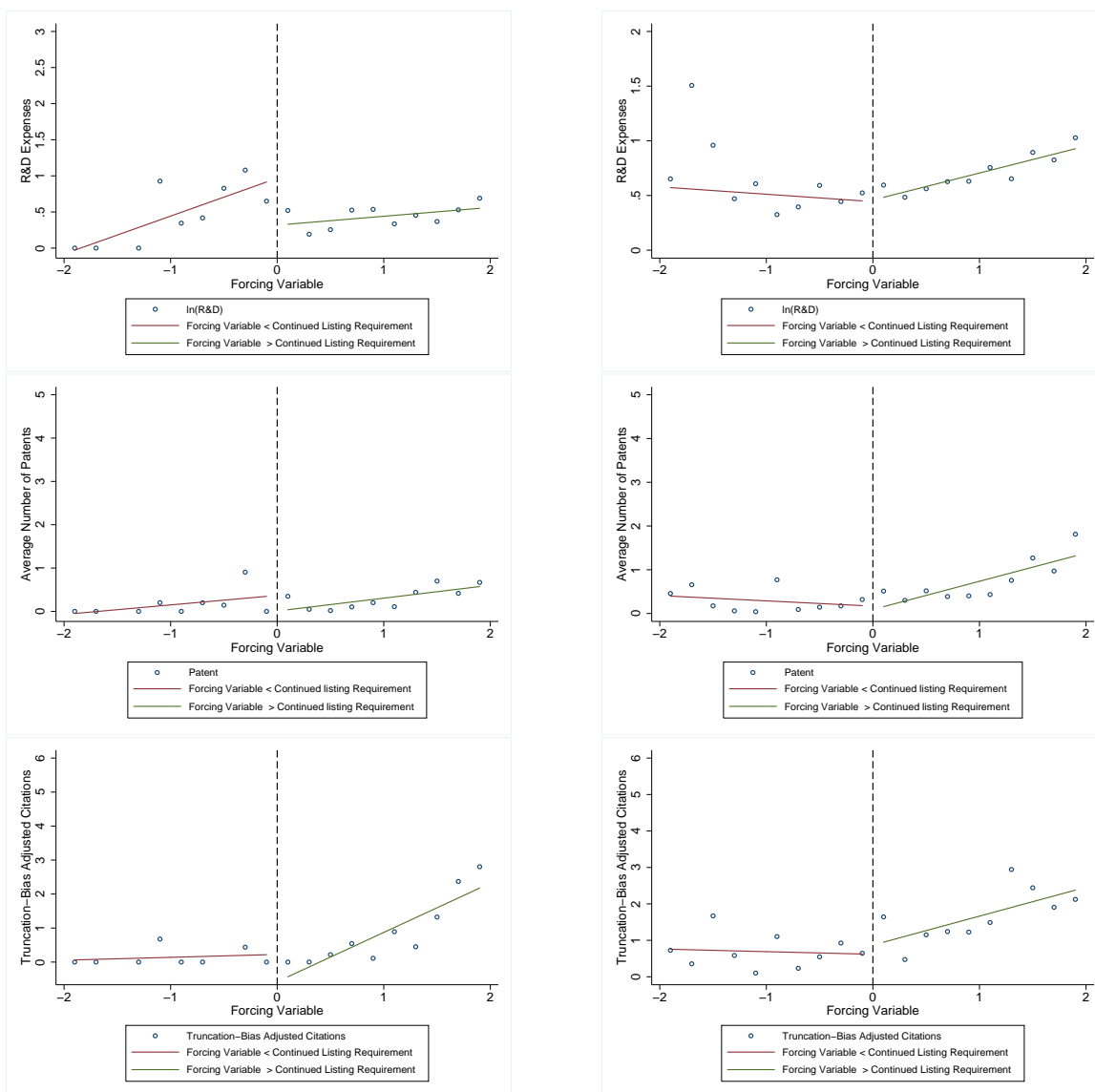


Figure 6: Tests of Regression Discontinuity Assumptions: Delisting

This figure presents the discontinuity of the probability of treatment (delisting) at the threshold (top) and the density of the forcing variable following McCrary (2008) (bottom). In the top figure, we plot the probability of delisting as a function of the forcing variable. The forcing variable is measured as the minimum between the log normalized bid price and the maximum value of the three log normalized core NASDAQ continued listing requirements. The threshold is the minimum requirements for NASDAQ continued listing. Delisting occurs when the forcing variable falls below the threshold. In the bottom figure, the circles represent the density estimate and the solid line is the fitted function of the forcing variable with a 95% confidence interval.

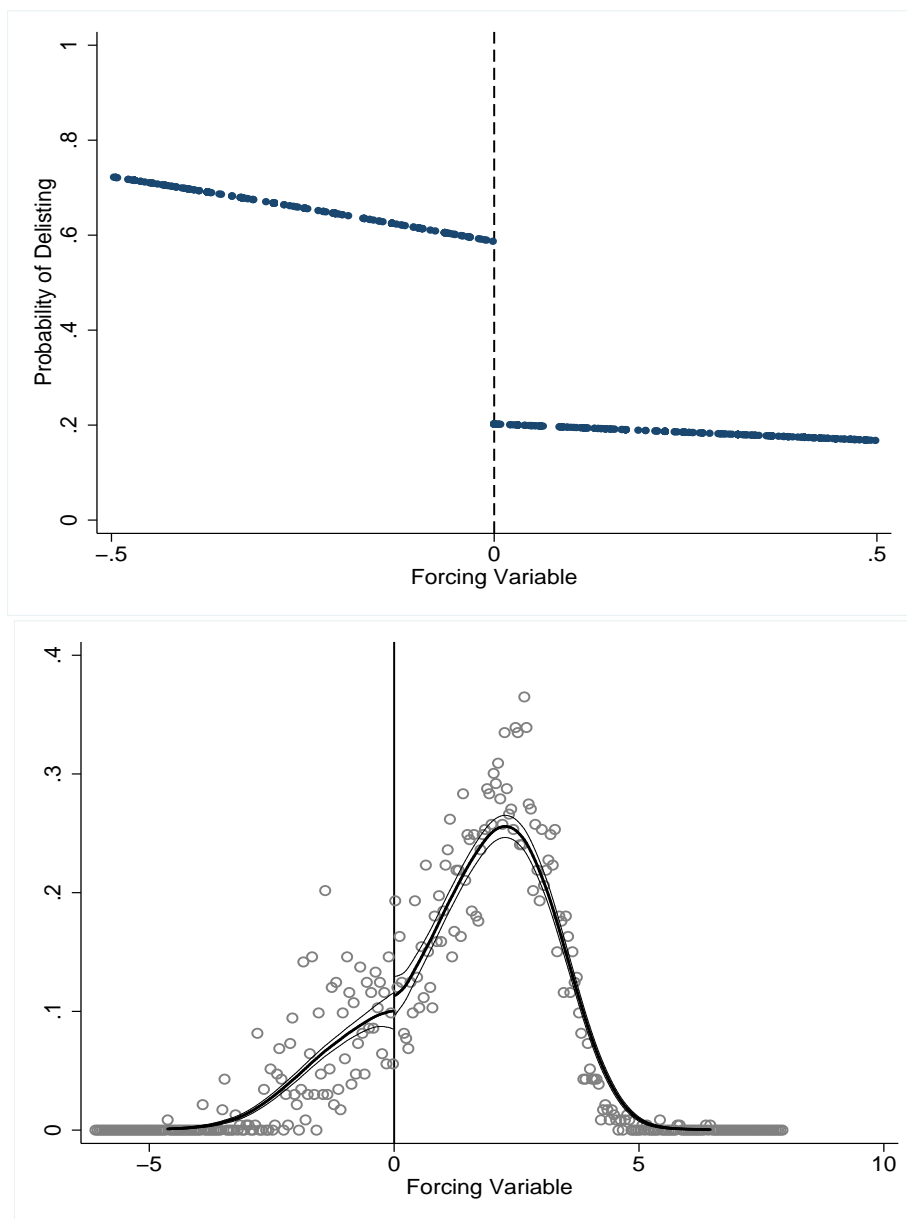


Table 1:
Characteristics and Innovation Activities of Private and Public Firms

In this table, we report 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 from Capital IQ from 1994 to 2004. The matched sample (Panel B) includes 2,214 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. $\ln(R\&D)$ is natural logarithm of one plus research and development expenditures. $Patent$ is the number of patent applications submitted by a firm in a given year. $Citations$ is citations per patent adjusted for truncation bias by weighting the number of citations with an estimated distribution of citation-lag. $Originality$ of patent is Herfindahl index of cited patents and $Generality$ is Herfindahl index of citing patent. $Tangible$, $Cash$, ROA , and $Capex$ are reported as percentages. $Diff$ is the difference in means of private and public firms from the t -test.

Panel A: Full Sample						
	$\ln(Sales)$	$S.Growth$	$Tangible$	$Cash$	ROA	Age
Private	4.55	0.27	29.74	14.66	2.67	26.21
Public	4.78	0.15	26.20	18.89	3.79	33.50
Diff	0.23	-0.12	-3.54	4.23	1.11	7.30
t -stat	9.86	-16.38	-15.27	18.18	4.41	20.57
	$Capex$	$\ln(R\&D)$	$Patent$	$Citations$	$Originality$	$Generality$
Private	7.20	0.50	1.02	2.84	0.38	0.55
Public	6.31	0.86	7.48	4.09	0.40	0.55
Diff	-0.89	0.36	6.46	1.25	0.02	0.00
t -stat	-12.21	26.24	10.18	8.98	1.80	0.11

Panel B: Matched Sample						
	$\ln(Sales)$	$S.Growth$	$Tangible$	$Cash$	ROA	Age
Private	4.81	0.21	31.28	11.64	5.78	28.96
Public	4.92	0.15	28.10	16.59	4.95	36.30
Diff	0.12	-0.06	-3.19	4.95	-0.84	7.35
t -stat	3.80	-6.13	-9.53	16.81	-2.59	14.29
	$Capex$	$\ln(R\&D)$	$Patent$	$Citations$	$Originality$	$Generality$
Private	6.76	0.37	0.59	1.59	0.55	0.34
Public	6.42	0.64	3.70	3.40	0.57	0.41
Diff	-0.34	0.26	3.11	1.82	0.03	0.07
t -stat	-3.30	17.24	7.83	11.07	2.82	4.93

Table 2:
External Finance Dependence and Innovation

This table reports the first-step estimation results of the treatment effect model for industry-and-size matched firms in all industries, as well as firms in EFD and IFD industries (Panel A), the second-step estimation results for private and public firms in EFD (Panel B) and IFD (Panel C), and the differential effects of public listing on innovation between EFD and IFD industries (Panel D-Panel G). The treatment effect model is estimated with a two-step approach. In the first step, we estimate the probability of being public based on a firm's logarithm of sales, capital expenditure, growth in sales, ROA, leverage, and innovation intensity index 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: the natural logarithm of one plus R&D, the natural logarithm of one plus the number of patents, the natural logarithm of one plus 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 include $\ln(Assets)$, *Tangible*, *Cash*, *Age*, *Capex*, growth in sales, and *ROA*. Year and industry fixed effects are controlled. In Panel D-Panel G, a treatment effect model with the second-step estimation as following is estimated: $Y_{i,k,t} = \alpha + \beta Public_i + \delta EFD_{i,k} + \theta Public_i \times EFD_{i,k} + \gamma X_{i,k,t-1} + \lambda X_{i,k,t-1} \times EFD_{i,k} + \phi Mills_i + \varepsilon_{i,k,t}$, where $EFD_{i,k}$ is an industry external finance index and $X_{i,k,t-1}$ are the control variables. The model is estimated for four samples: industry-and-size matched private and public firms (Panel D), age-year-and-size matched pairs of private and public firms in EFD and IFD industries (Panel E), age-year-and-R&D matched pairs of private and public firms in EFD and IFD industries (Panel F), and the sample excluding acquirers in the M&A transactions (Panel G). The coefficients on the control variables are not reported. N is the number of observations. Two-step consistent standard errors are reported in the brackets. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Panel A: Treatment Effect Model First Step			
	All	EFD Industries	IFD Industries
<i>Capex</i>	0.7917*** [0.1971]	0.9105*** [0.2083]	0.9592 [0.6897]
<i>S.Growth</i>	-0.0646** [0.0266]	-0.0882*** [0.0286]	0.0904 [0.0807]
<i>ROA</i>	-0.5451*** [0.0858]	-0.6769*** [0.0915]	0.1305 [0.2625]
<i>Sales</i>	-0.0023 [0.0071]	0.0059 [0.0077]	-0.0681*** [0.0188]
<i>Leverage</i>	-1.6542*** [0.0430]	-1.6941*** [0.0473]	-1.5700*** [0.1057]
<i>Intensity</i>	0.1570*** [0.0510]	0.3182*** [0.0598]	0.0625 [0.1029]
<i>EFD</i>	0.1679*** [0.0542]		
<i>N</i>	12,253	10,137	2,116

Panel B: External Finance Dependent Industries					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
Public	0.7535*** [0.0699]	0.5072*** [0.0511]	0.5109*** [0.0589]	0.1301*** [0.0371]	0.1709*** [0.0502]
Mills	-0.3759*** [0.0421]	-0.1745*** [0.0309]	-0.1812*** [0.0356]	-0.0315 [0.0207]	-0.0623** [0.0280]
<i>N</i>	10,137	10,137	10,137	2,480	2,480

Panel C: Internal Finance Dependent Industries					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
Public	0.0538 [0.0602]	-0.0844 [0.0644]	-0.0911 [0.0902]	-0.0495 [0.1212]	-0.2141 [0.1540]
Mills	-0.0180 [0.0370]	0.0787** [0.0395]	0.0832 [0.0554]	0.0487 [0.0734]	0.0891 [0.0930]
<i>N</i>	2,116	2,116	2,116	192	192

Panel D: Industry-and-Size Matched Sample					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
EFD×Public	0.4996*** [0.0845]	0.5538*** [0.0633]	0.5340*** [0.0746]	0.2422*** [0.0608]	0.1122 [0.0906]
<i>N</i>	12,253	12,253	12,253	2,672	2,672

Panel E: Age-Year-Size Matched EFD and IFD Pairs					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
EFD×Public	0.2663** [0.1437]	0.3929*** [0.0740]	0.4642*** [0.0976]	0.2485** [0.1215]	0.1202 [0.1830]
<i>N</i>	3,531	3,531	3,531	525	525

Panel F: Age-Year-R&D Matched EFD and IFD Pairs					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
EFD×Public	0.9247*** [0.1094]	0.4452*** [0.0873]	0.4207*** [0.0914]	0.2035 [0.2033]	0.3482* [0.2104]
<i>N</i>	2,533	2,533	2,533	356	356

Panel G: Exclude M&A					
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>
EFD×Public	0.1741* [0.0892]	0.3429*** [0.0640]	0.4533*** [0.0846]	0.3315*** [0.0701]	0.2113** [0.1015]
<i>N</i>	8,703	8,703	8,703	1,715	1,715

Table 3:
Covariates in the Fuzzy RD Sample

This table presents differences in characteristics of delisted and non-delisted firms near the NASDAQ continued listing requirements. The tests are conducted for the forcing variable within the interval of $[-0.1, +0.1]$. $\ln(Assets)$ is the natural logarithm of total assets. $\ln(Sales)$ is the natural logarithm of total revenue. $S.Growth$ is the first difference of the natural logarithm of total revenue. $Tangible$ is tangible 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. $Leverage$ is the ratio of total debt to total assets. $Capex$ is capital expenditures scaled by total assets. $Tangible$, $Cash$, ROA , $Leverage$, and $Capex$ are reported as percentages. $Diff$ is the difference in medians of the two groups of firms. p -value is the p -value of the Wilcoxon rank-sum test.

	$\ln(Assets)$	$\ln(Sales)$	$S.Growth$	$Tangible$	$Cash$
Non-Delisted	3.12	3.14	0.02	15.64	5.09
Delisted	3.02	3.10	0.05	10.25	7.87
Diff	0.10	0.04	-0.03	5.39	-2.78
p-Value	0.54	0.90	0.78	0.02	0.12

	ROA	$Leverage$	Age	$Capex$
Non-Delisted	-1.35	29.00	18.00	3.13
Delisted	-5.42	33.94	10.00	2.56
Diff	4.07	-4.94	8.00	0.57
p-Value	0.01	0.57	0.01	0.19

Table 4:
Fuzzy Regression Discontinuity Estimation with Covariates

This table reports the results of the fuzzy RD estimation with covariates using the NASDAQ continued listing requirement for firms in EFD (Panel A) and IFD industries (Panel B). The two-stage least squares approach is used to estimate the reduced form model $Y_{i,t+N} = \alpha + \beta_1 z_{i,t} + \beta_2 c_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t}$. The dependent variables are: the natural logarithm of one plus R&D, the natural logarithm of one plus the number of patents, the natural logarithm of one plus truncation bias-adjusted citations, originality, generality in the post-delisting years ($t+1, t+2, t+3$). The independent variable $z_{i,t}$ an indicator variable that equals 1 if the forcing variable $c_{i,t}$ is less or equal to the threshold. We use the minimum between the log normalized bid price and the maximum value of the three log normalized core NASDAQ continued listing requirements as the forcing variable and the normalized minimum continued listing standard as the threshold for delisting from the NASDAQ. $X_{i,t}$ is a set of covariates that may influence innovation. The coefficient, β_1 , for treatment assignment are reported and 2SLS standard errors are reported in brackets. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Panel A: EFD Industries						
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>	<i>N</i>
$t + 1$	-0.3828*** [0.0854]	-0.3770*** [0.0646]	-0.7300*** [0.0989]	-0.1691* [0.0965]	-0.3998*** [0.1253]	3,247
$t + 2$	-0.4666*** [0.1221]	-0.3722*** [0.0942]	-0.7521*** [0.1304]	-0.044 [0.1278]	-0.5027*** [0.1758]	2,795
$t + 3$	-0.4512*** [0.1745]	-0.3863*** [0.1304]	-0.6488*** [0.1540]	-0.0307 [0.1197]	-0.2968* [0.1697]	2,464
Panel B: IFD Industries						
	$\ln(R\&D)$	$\ln(Patent)$	$\ln(Citations)$	<i>Originality</i>	<i>Generality</i>	<i>N</i>
$t + 1$	-0.1384 [0.0978]	-0.0440 [0.0812]	-0.1340 [0.1435]	-0.1703 [0.5199]	0.2531 [0.7140]	440
$t + 2$	-0.2135 [0.1398]	0.0044 [0.1410]	-0.0874 [0.2468]	0.8540 [0.7145]	-0.2882 [0.8207]	377
$t + 3$	-0.6308*** [0.2328]	-0.1627 [0.2303]	-0.5316 [0.3497]	-0.2873 [0.3130]	-0.3300 [0.4322]	338

Table 5:
Real Earnings Management and Innovation

This table reports the results for the relation between innovation and real earnings management (*REM*) for public firms. In Panel A, we compare the *REM* of firms in EFD and IFD industries using both the matched and full samples. In Panel B, we classify public firms in EFD industries into three groups based on the innovation intensity index. *REM* is measured as the difference between the normal level of discretionary expenses and the actual discretionary expenses. We estimate the normal discretionary expenses by the fitted values 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* is the discretionary expenditures, including advertising expenses and selling, and general & administrative expenses; *TA* is total assets; and *Sales* is total revenue. A higher value of *REM* indicates a higher degree of *REM*. *Diff* is the difference in the average *REM* between public firms in EFD and IFD industries. Panel B reports the average *REM* of the three groups and the significance levels of differences from Group 1. In Panel C Column (4), we report the estimation results of the regression model: $REM_{i,k,t} = \alpha + \beta_1 Intensity_{i,k} + \beta_2 EFD_{i,k} + \beta_3 Intensity_{i,k} \times EFD_{i,k} + \beta_4 MVE_{i,k,t-1} + \beta_5 MB_{i,k,t-1} + \beta_6 ROA_{i,k,t} + \beta_7 MVE_{i,k,t-1} \times EFD_{i,k} + \beta_8 MB_{i,k,t-1} \times EFD_{i,k} + \beta_9 ROA_{i,k,t} \times EFD_{i,k} + \zeta_t + \zeta_t \times EFD_{i,k} + \varepsilon_{i,k,t}$, where *Intensity* is the innovation intensity index; *EFD* is the external finance dependence dummy; *MVE* is the logarithm of market value of equity; *MB* is market-to-book ratio; and *ROA* is return on assets. Column (1) presents the estimation results of the model without *Intensity* and *Intensity* \times *EFD*. Columns (2) and (3) present the estimation results for firms in EFD and IFD industries, respectively. The coefficients on the control variables are not reported. The robust standard errors are reported in brackets. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Panel A: 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****	

Panel B: Innovative vs. Non-Innovative Firms in EFD Industries		
	Matched Sample	Full Sample
1: Least Innovative	0.76	9.01
2: Moderately Innovative	-6.19***	-2.46***
3: Most Innovative	-15.94***	-12.25***

Panel C: Real Earnings Management				
	(1)	(2)-EFD Only	(3)-IFD Only	(4)
<i>EFD</i>	-19.5767*** [4.9566]			6.7438 [9.9192]
<i>Innovation Intensity</i>		-16.9262*** [1.2159]	2.7254 [7.3189]	2.7254 [7.2858]
<i>Intensity</i> \times <i>EFD</i>				-19.6516*** [7.3867]
<i>N</i>	7,648	6,312	1,096	7,408

Table 6:
Competition and Innovation

This table reports the estimation results for the differential effects of competition on innovation between competitive and non-competitive industries. A treatment effect model with the second-step estimation as follows is estimated: $Y_{i,k,t} = \alpha + \beta Public_i + \delta Competitive_{i,k} + \theta Public_i \times Competitive_{i,k} + \gamma X_{i,k,t-1} + \lambda X_{i,k,t-1} \times Competitive_{i,k} + \phi Mills_i + \varepsilon_{i,k,t}$, where $Competitive_{i,k}$ is a dummy variable equal to one for competitive industries and zero for non-competitive industries. We measure industry competitiveness using the Hoberg-Phillips Industry Concentration Measure (HPICM). An industry is classified as competitive if its HPICM falls into the bottom tercile of all industries and as non-competitive if its HPICM falls into the top tercile. $X_{i,k,t-1}$ includes $\ln(Sales)$, $Tangible$, $Cash$, Age , $Capex$, growth in sales, and ROA. The model is estimated separately for firms in EFD and IFD industries. The coefficients on the control variables are not reported. Two-step consistent standard errors are reported in brackets. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Panel A: EFD Industries					
	ln(R&D)	ln(Patent)	ln(Citations)	Originality	Generality
<i>Competitive</i> × <i>Public</i>	0.5292*** [0.0823]	0.0053 [0.0533]	0.0518 [0.0526]	0.0234 [0.0446]	-0.0458 [0.0571]
<i>N</i>	26,501	26,501	26,501	8,678	8,678
Panel B: IFD Industries					
	ln(R&D)	ln(Patent)	ln(Citations)	Originality	Generality
<i>Competitive</i> × <i>Public</i>	-0.1837*** [0.0397]	-0.0863* [0.0489]	-0.1075** [0.0518]	-0.2776* [0.1658]	-0.2077 [0.2651]
<i>N</i>	3,591	3,591	3,591	460	460

Table 7:
Analyst Coverage and Innovation

This table reports the estimation results for the differential effects of analyst coverage on the innovation of public firms in EFD and IFD industries. The following model is estimated: $Y_{i,k,t+3} = \alpha + \beta \ln(Coverage)_{i,k,t} + \theta EFD_{i,k} \times \ln(Coverage)_{i,k,t} + \gamma X_{i,k,t-1} + \lambda X_{i,k,t-1} \times EFD_{i,k} + \xi_i + \zeta_t + \varepsilon_{i,k,t}$, where the depend variable is the innovation outcome measure including the three-year-ahead natural logarithm of one plus number of patents, the natural logarithm of one plus truncation bias-adjusted citations, originality, and generality. The independent variable $\ln(Coverage)_{i,k,t}$ is the natural logarithm of one plus the average of the monthly numbers of earnings per share forecasts for firm i over fiscal year t from $I/B/E/S$. $EFD_{i,k}$ is external finance dependence dummy. $X_{i,k,t-1}$ is a set of firm characteristic variables that affect a firm's innovation outcome. ξ_i controls for firm fixed effects and ζ_t captures year fixed effects. The coefficients on the control variables are not reported. Standard errors clustered at the firm level are reported in brackets. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

	$\ln(Patent)_{t+3}$	$\ln(Citations)_{t+3}$	$Originality_{t+3}$	$Generality_{t+3}$
$\ln(Coverage)$	-0.0648** [0.0275]	-0.0906* [0.0501]	-0.0185 [0.0612]	-0.1570** [0.0787]
$EFD \times \ln(Coverage)$	0.1029*** [0.0352]	0.1073* [0.0614]	0.0104 [0.0623]	0.1430* [0.0811]
N	14,272	14,272	5,284	5,284

Table 8:
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. In the first step, we estimate 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 patents per dollar R&D investment ($\ln(1 + \text{patents}/R\&D)$). The independent variables include the *Public* dummy, a set of characteristic variables that affect a firm's innovation activities, including $\ln(\text{Sales})$, *Tangible*, *Cash*, *Age*, *Capex*, growth in sales, and *ROA*, as well as Year and industry fixed effects. In the last column, we estimate the treatment effect model with the second step model as $Y_{i,k,t} = \alpha + \beta \text{Public}_i + \delta \text{EFD}_{i,k} + \theta \text{Public}_i \times \text{EFD}_{i,k} + \gamma X_{i,k,t-1} + \lambda X_{i,k,t-1} \times \text{EFD}_{i,k} + \phi \text{Mills}_i + \varepsilon_{i,k,t}$, where $Y_{i,k,t}$ is innovation efficiency; $\text{EFD}_{i,k}$ is an industry external finance index. $X_{i,k,t-1}$ is the set of control variables. 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. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

	EFD Industries	IFD Industries	All
Public	0.0701*** [0.0129]	0.0066 [0.0164]	0.0176 [0.0142]
EFD			-0.0784 [0.0806]
EFD×Public			0.0669*** [0.0151]
Mills	-0.0265*** [0.0078]	-0.0007 [0.0101]	-0.0223*** [0.0068]
<i>N</i>	10,171	2,163	12,334