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Does the Stock Market Boost Firm Innovation? Evidence from Chinese Firms

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Abstract

The paper analyses the effect of the stock market on firm innovation through the lens of initial public offering (IPO) using uniquely matched Chinese firm-level data. We find that IPOs lead to an increase in both the quantity and quality of firm innovation activity. In addition, IPOs expand a firm's scope of innovation beyond its core business. The impact of IPOs on firm innovation varies across financial constraints, corporate governance, and ownership structures. Our results further illustrate that IPOs induce a firm to increase the number of inventors and enable better retention of existing inventors after the IPO. Finally, we show that the enhanced innovation activity resulting from IPOs increases a firm's Tobin's Q in the long run.

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Keywords: IPO, Innovation, Financial Constraint, Corporate Governance, State Ownership, China

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I. INTRODUCTION

Does the stock market affect a firm's innovation activity? This is an important question from both macro and micro perspectives. At the macro level, technological innovation is vital for a country's economic growth (Schumpeter, 1943; Solow, 1957; Aghion and Howitt, 1992). At the micro level, innovation capacity determines a firm's long-term competitive advantage (Porter, 1992).

On the one hand, a stock market is important for firms to raise capital. An initial public offering (IPO) can help increase a firm's innovation activity by providing access to a funding source of lower cost than debt financing (Hall and Lerner, 2010). Moreover, as Holmstrong (1989) points out, the payoff of innovation is heavily skewed and risky due to its long-term, idiosyncratic nature. As a result, debt is a less efficient way of financing innovation compared to equity. For these reasons, an IPO could lead to more innovation activities by giving access to equity financing.

On the other hand, corporate finance literature widely documents that agency problems weaken the efficiency of a firm's business operations (e.g., investment and M&A) after an IPO (Berle and Means, 1932; Jensen and Meckling, 1976). Similar analysis also applies to innovation activities. Innovation is often risky and could cost a manager his or her job. Career concerns may thus force a manager to choose less risky and therefore less innovative projects, which would eventually weaken the firm's innovation activity. In addition, innovation is a difficult and time-consuming task that may require more time and effort. An entrenched manager, therefore, could put less effort into innovation and enjoy a "quieter lifestyle," given the weaker institutional investor monitoring after the IPO. These two incentive channels would lead to less innovation.

With all these trade-offs, whether an IPO will increase or decrease a firm's innovation remains an empirical question. Using uniquely matched Chinese firm-level data, our paper aims to address this dilemma. To that end, we use data on annual patent applications from China's State Intellectual Property Office (SIPO) to capture firm innovation activities.

First, we use the number of patents that firms apply for each year to measure the *quantity* of innovation.

Second, we measure the quality of innovation by utilizing the Chinese patent categorization system. China's patent system divides patents into three categories: invention, design, and utility. Invention patents are considered major innovations, and go through rigorous and lengthy examination of substance similar to that of the United States (U.S.). Design and utility patents are viewed as minor innovations, thereby receiving much looser examination of substance and weaker protection compared to invention patents.[2] Prior literature, which

[2] See Fang, He, and Li (2016) for details of China's patent system.

mainly focuses on United States and European Union (EU) patent data, uses the patent citation number as a proxy for the quality of innovation (e.g., He and Tian, 2013). As citation data are not available for Chinese patents, we take advantage of the unique characteristics of the Chinese patent system and use the number of invention patent applications (alternatively the proportion of invention patents and the number of inventors per patent) to measure patent *quality*.

Last, the detailed information available on the patents' technology class allows us to explore a firm's innovation *scope*. We match patent application data with Chinese Industrial Survey (CIS) data, which contain detailed balance sheet information for *all* industrial firms (both listed and non-listed) that are either state-owned or non-state-owned with annual sales greater than RMB 5 million (around USD 800,000) (See Section 3.1 for details on the matching of the two datasets). Finally, we use the Chinese Stock Market & Accounting Research Database (CSMAR) to identify an IPO firm and its year of IPO.

Having these uniquely matched IPO datasets, we first run an ordinary least squares (OLS) regression using panel data as the baseline. Our results suggest that IPOs are positively associated with firm innovation, both quantity and quality. To be more specific, public listing is associated with an average 35.1 percent annual increase in total patent applications in the subsequent three years. A similar increase also holds for invention patent applications, indicating that IPOs are associated with an increase in quantity as well as quality.

An important concern in OLS analysis is that public listing could be endogenous, thus subjecting results to selection bias. For example, some factors could be simultaneously correlated with the firm's IPO decision and its innovation activity. As Jain and Kini (1994) point out, firms choose to go public at a specific stage in their life cycle, which could correspond to a certain level of firm innovation activities.

To mitigate these endogeneity concerns, we employ a *difference-in-differences* (DiD) approach that compares the innovation output of IPO firms or IPO subsidiaries (i.e. subsidiaries that were established before the IPO and continued to be subsidiaries during the three years following the IPO) to that of non-IPO firms and subsidiaries before and after the IPO conversion. To validate the DiD approach and ensure that IPO firms are compared to similar unlisted firms, we carefully match each IPO firm (and subsidiary) in the treatment group with a firm in the same industry but outside the treatment group by using the *propensity score matching* (PSM) algorithm along a broad range of firm characteristics. After undertaking a series of diagnostic tests to ensure the removal of observable differences between the two groups, we find that firms in the treatment group generate an average increase of 22.9 percent in annual patent applications following an IPO. The quality of the patent, as indicated by invention patent applications, appears to also increase by 12.9 percent. Other measurements of quality, such as the invention patent ratio and the number of inventors per patent, similarly indicate a rate increase in quality of innovation after the IPO.

To strengthen the identification process, we further use the two-step Heckman-type endogenous switching regression method to identify the causal relationship between IPO and innovation. This test generates quantitative results for innovation quantity and quality that are very similar to those of the DiD test, which corroborates our baseline findings.

We further examine the change in scope of innovation in the DiD framework by dividing a firm's patent applications into two categories—*related* and *unrelated*—based on whether a patent's technology area is related to the firm's core business or not. Theoretically, capital raised from an IPO could be used either to help a firm strengthen its competitive advantage in its core business or to facilitate its expansion into a new business. Our empirical evidence shows that IPO firms see an increase in innovation activity at both their core and new business.

The DiD estimation approach helps us mitigate the endogeneity problem in the OLS regression and shows that IPOs do indeed have a positive impact on innovation activity. To gain a better understanding of the factors that cause such positive effect on innovation, we further apply a *difference-in-difference-in-differences* (DiDiD) framework that helps determine how the IPO impact varies across firms' financial constraints, corporate governance, and ownership structures.

We further demonstrate that financial constraints play an important role in determining innovation performance after an IPO by addressing a firm's financial constraints from two perspectives.

First, we test whether the impact of an IPO on innovation depends on a firm's external financing needs. Following Rajan and Zingales (1998), we divide all two-digit industries into two groups: industries dependent on external finance (those above the median level of the external finance dependence index) and industries able to draw on internal finance (those below the median level of the external finance dependence index). Higher external finance needs imply that a firm is more likely to be subject to financial constraints. Our DiDiD regressions indicate that firms in industries dependent on external finance tend to experience higher increase rates in innovation (in terms of both quantity and quality) after an IPO compared to firms in industries with access to internal finance. This finding points to financial constraints playing an important role in a firm's increase in innovation after an IPO. The equity raised by an IPO helps relax a firm's financial constraints and enables it to meet its financing needs, which leads, in turn, to an increase in innovation activity.

Second, we look at the impact of collateral constraints on innovation. Following the literature (e.g., Kiyotaki and Moore, 1997), we use the ratio of fixed assets to total assets as a proxy for collateral constraints. A high ratio implies a higher collateral value; hence, less stringent financial constraints. We find evidence to support that an IPO firm with a lower fixed-assets ratio (characterized by stricter collateral constraints) before an IPO tends to experience improved innovation after the IPO. This finding is consistent with the message from the test of external financing needs: the equity raised by an IPO helps relax financial constraints, thus leading to increasing innovation activity. These results help us better understand the positive impact of IPOs on firm innovation in China. With an under-developed financial system, firms in China often face severe financial constraints. Equity fundraising through IPOs offers them a valuable source of innovation and growth.

In addition to financial constraints, our results show that corporate governance structures also play an important role in the positive impact of IPOs on innovation. We find that IPOs have a stronger impact on firms granting stock to their managers. By aligning the interests of managers and shareholders, stock granting provides a stronger incentive to innovate so as to add long-term value for the firm. Moreover, we find that firms with the same person as CEO and president tend to innovate more after an IPO. Career Concern Theory argues that, given the high risk of failure associated with innovation, managers may avoid engaging in it not to risk their own job security. According to this theory, CEOs who are also the president of their firms are entrenched (likely to be founders or even controlling shareholders) and thus more willing to take risk. Our results lend support to the Career Concern Theory.

Moreover, we discovered that privately-owned enterprises (POEs) exhibit a greater increase in innovation after an IPO than state-owned enterprises (SOEs). Since POEs face more stringent financial constraints before an IPO and deal better with agency problems caused by IPOs than SOEs, this finding further corroborates the importance of alleviating financial constraints as well as the deep effect agency problems have on innovation activity after an IPO.

Given the substantive increase in firm innovation quantity and quality, and the expansion of innovation scope after an IPO, it is natural to wonder how it happens. Leveraging the inventor information in our patent data, we show that having more inventors and better retention of existing inventors might be the reasons underlying the enhanced innovation activity after a firm's IPO. Our DiD test indicates that IPO firms tend to hire more inventors than non-IPO firms. This implies that the accumulation of human capital played a role in the increased number of patent applications. In addition, our analysis of inventors further demonstrates that IPO firms (especially POEs) have much lower inventor departure rates than non-IPO firms, indicating that IPOs help firms retain their innovators. Finally, we do not find evidence that the increase in patent applications is due to a growth in the productivity of inventors after an IPO. Therefore, enhanced innovation seems to be associated with changes in the *extensive* margin (i.e., entry and exit) rather than the *intensive* margin (productivity per existing inventor).

Further, we explore the following bottom-line question: Does the enhanced innovation activity after an IPO help create firm value in the long run? Our answer is yes. This question is important because IPO firms may simply increase their patent applications for "window-dressing" purposes. We have two pieces of evidence against the "window-dressing" hypothesis: First, as mentioned above, the quality of the patent applications (measured by invention patent counts, the share of invention patents in total patents, and the number of inventors for each patent) increases after an IPO. Second, we find that firms that apply for more patents during the three years following an IPO see a larger Tobin's Q increase, indicating that patent applications are associated with long-term value creation. Moreover, we find that the increase in invention patents has a stronger impact on increasing Tobin's Q than other patent types. All the above support the argument that increased innovation activity after an IPO leads to firm value creation in the long run and disprove that window dressing may boost short-term valuation.[3]

The rest of the paper is organized as follows: Section 2 discusses the related literature. Section 3 describes the data sample and variable construction; it also reports summary statistics. Section 4 presents baseline results and addresses identification issues concerning innovation quantity, quality, and scope. Section 5 further explores the relationships among IPOs, inventors, and innovation activity. Section 6 investigates the impact of enhanced innovation after an IPO on a firm's value. Section 7 provides the robustness check of the causal relationship between IPOs and innovation through exploring the two-step Heckman-type endogenous switching regression. Section 8 concludes.

II. Review of the Existing Literature

Our paper contributes to three strands of literature. First, studies on the real impact of IPOs have documented a wide range of post-IPO firm performance changes, such as the decline in profitability—documented in Jain and Kini (1994); Pagano, Panetta, and Zingales (1998); and Pastor, Taylor, and Veronesi (2009)—and the reduction in productivity shown in Chemmanur, He, and Nandy (2009). This paper contributes to the literature by leveraging our data and proposing a new DiD strategy to estimate the IPO effect on firms' innovative activities in the Chinese context.

Additionally, the paper is closely related to contemporaneous research by Bernstein (2015), who examines a similar question in the context of US IPOs. Our analysis differs from Bernstein's (2015) in several ways: We have implemented a DiD methodology to tackle the identification problem to leverage our unique datasets, including the balance sheet information of *both* listed and non-listed manufacturing firms in China. In contrast, Bernstein (2015) draws on an instrumental variable methodology using US IPO firm data.[4]

[3] Carpenter, Lu, and Whitelaw (2016) argue that counter to common perception, stock prices in China are strongly linked to firm fundamentals. Our results here confirm that the Chinese stock market encourages innovation and creates real value from a different angle.

[4] As an IPO is not an exogenous event, to control for potential selection bias, Bernstein (2015) uses S&P500 index fluctuations during the book-building phase as an instrumental variable (IV) for IPO completion in the estimation.

Additionally, we find that an IPO can substantially enhance firm innovation activity in terms of quantity, quality, and scope, which is in sharp contrast to the findings of Bernstein (2015) stating that IPOs have no impact on firm innovation quantity and have a significantly negative impact on quality. Our paper complements Bernstein (2015) by using a different identification strategy and emphasizing the positive impact of IPOs on innovation in the Chinese context, where firms face different financial constraints and corporate governance structures compared to their counterparts in the U.S. Our findings suggest that IPO benefits outweigh the costs of firm innovation in China and, perhaps even in other comparable developing countries. Moreover, we believe that financial constraints might play a very important role in understanding the reason behind our findings. Firms in China often face much more severe financial constraints than firms in the U.S., which makes accessing the equity market of uppermost importance for innovation in China. This aspect explains our finding that Chinese firms have more financial resources for retaining inventors after an IPO. Although we also identify the existence of the agency problem in China, which according to Bernstein (2015) is the source of the major negative impact on innovation brought by IPOs in the U.S., the benefits of IPOs in relaxing financial constraints significantly outweigh the negative impact of the agency problem induced by IPOs, a factor that had not been explored in the prior literature.

Second, the paper is also related to publications on equity markets and innovation, including a growing strand of literature comparing the behavior of public and private firms along various dimensions such as investment sensitivity (e.g., Asker, Farre-Mensa, and Ljungqvist, 2010; Sheen, 2009), debt financing and borrowing costs (Saunders and Steffen, 2011; Brav, 2009), external financing needs (Acharya and Xu, 2016), dividend payouts (Michaely and Roberts, 2007), and CEO compensation (Gao, Lemmon, and Li, 2010). Atanassov, Nanda, and Seru (2007) argue that arm's length financing (equity and public debt) is positively related to innovation, while relationship-based bank financing is negatively related to innovation. Our paper advances this line of inquiry by providing new evidence showing the positive role that arm's length financing can play in innovation.

Third, this paper also contributes to a growing theoretical and empirical literature strand that explores the role of governance, capital structure, and ownership concentration in corporate innovation. For instance, literature on larger institutional ownership (discussed by Aghion, Van Reenen, and Zingales, 2013), corporate venture capital (Chemmanur et al., 2014), and hotrather-than-cold markets (Nanda and Rhodes-Kropf, 2013) all treat how altered managerial incentives motivate managers to focus more on long-term innovation activities. Our paper provides new evidence showing that career concerns and management incentives can play an important role in affecting firm innovation after IPOs.

III. DATA DESCRIPTION

3.1 Data and Sample Construction

A. Firm-Level Data

Our first dataset is the annual Chinese Industrial Survey (CIS) conducted by the National Bureau of Statistics of China from 1998 to 2007. These data provide the most comprehensive coverage of Chinese manufacturing firms, including all state-owned and non-state-owned firms with sales over RMB 5 million (around USD 800,000). The number of firms included in this database varies from over 165,000 in 1998 to 337,000 in 2007. Firms in the CIS span the entire country and all manufacturing industries. The CIS provides detailed information on firm registration (e.g., name, location, industry, age) and balance sheet variables such as capital, debt, ownership structure (POE vs. SOE), employment, sales, interest payments, and profit. It also offers a rare opportunity to gain access to high-quality firm-level data for non-listed firms, reason why it has been widely used in recent writings (e.g., Hsieh and Klenow, 2009; Brandt, Biesebroeck, and Zhang, 2012; Hsieh and Song 2015; Aghion et al., 2015).

B. Patent Filing Data

We use a firm's patent applications as a proxy for the firm's innovation activity. Our patent filing data are from the State Intellectual Property Office of China (SIPO) and contains detailed information on each patent, including the application identifier, the title of the patent, the application date, the type of patent (invention, utility, or design), the technology class of the patent, the names of the inventors, and the applying institution. The dataset covers all patent applications from 1985 to 2011, with the number of annual applications varying from 575 in 1985 to 1,108,534 in 2011. This dramatic increase in patent applications has led China to surpass the U.S. and become the topmost country in patent applications. Although doubts have been raised regarding the quality of China's innovation and intellectual property rights, recent studies have shown that China's patents do indeed have a real positive impact on firms' productivity growth (see Fang, He, and Li, 2016).

In China, patents are classified into three types: invention, utility, and design. In contrast to utility and design patents, invention patents are granted for major technological innovations. These undergo much more rigorous scrutiny: Inventors must submit a clear and comprehensive description of the invention as well as reference materials for the patent application and undergo "substantive examination" for novelty, inventiveness, and industrial applicability. It usually takes two to three years for an invention patent application to go through the entire process. Once granted, invention patents enjoy much stronger legal protection than utility and design patents. For all these reasons, invention patents are viewed as having the highest quality. Accordingly, we use the quantity of invention patent applications to measure innovation quality.

We match the patent application data with firm information from CIS data by using the firm's name. The accuracy of the match is checked by comparing the location information.[5] In our sample, 6.01 percent of firms applied for at least one patent during the period 1998–2007. According to a report by the National Bureau of Statistics of China, about 8.8 percent of manufacturing firms with annual sales above RMB 5 million applied for patents between 2004 and 2006. Given the long-term trend of increasing patent applications during the sample period, the quality of our matching is reasonably good. Additionally, we only retain firms that have at least five years of observations in the CIS data to minimize the noise of short-lived firms and abnormal observations. After further filtering out firms with key missing variables and obvious data errors—following literature such as that of Cai and Liu (2009)—we eventually obtain a final sample of 999,114 firm-year observations corresponding to 136,762 firms.

C. IPO Data

Our third dataset is the Chinese Stock Market & Accounting Research Database (CSMAR), through which we can identify IPO firms and their subsidiaries. Among the 620 IPOs issued from 1999 to 2006, we can directly match 148 manufacturing IPO firms in the CIS data and further identify another 208 as subsidiaries[6] that were established at least one year before the IPO and continued to be a subsidiary of the IPO over the subsequent three years. Among these 356 firms affected by IPOs, 190 had at least one patent application over between 1998 and 2007.

In summary, by linking the CIS, patent filing, and CSMAR data, we generate a comprehensive dataset that includes firm balance sheets, patent filings, and IPO information for the 1998–2007 period.

3.2 Variable Construction

We use the patent filing counts to quantify innovation activity. The distribution of patent applications in our final sample is right-skewed, similar to U.S. patent data, with its median at zero (See Table 1). Following the literature (e.g., He and Tian, 2013; Gu, Mao, and Tian, 2013), we winsorize these variables at the 99th percentile. We then use the natural logarithm of one plus patent counts, LnPat, as the main measure of innovation activity. As illustrated previously, since invention patents are widely regarded as being of higher quality compared to design and utility patents, we also use the natural logarithm of one plus invention patent applications (LnInv) as the quality measure of firm innovation.

[5] See Fang, He, and Li (2016) for details of the matching.

[6] We require that the matched firms have observations at least one year before and after the IPO in the CIS data.

In our regression analysis, we follow the innovation literature in controlling for a set of firm and industry characteristics that might affect a firm's future innovation output. In the baseline regression, the control variables are (i) firm size, measured by the natural logarithm of total assets, $Ln(AT)$; (ii) $FixAT\_AT$, measured by net fixed assets divided by total assets; (iii) $Admin\_AT$, measured by administration expenditure divided by total assets; (iv) $Interest\_AT$, measured by interest expenditure divided by total assets; (v) $Leverage$, measured by total liabilities divided by total assets; (vi) $Liquidity$, measured by the ratio of the difference between current assets and liabilities and total assets; (vii) ROA, measured by net income divided by total assets; (viii) $Ln(Age)$, measured by the natural logarithm of one plus the number of years after establishment; (ix) HI, measured by the Herfindahl index based on annual sales; (x) SOE, a state-owned enterprise dummy that takes the value of one for SOEs, zero otherwise; (xi) EX, an exporter dummy that is equal to one for exporters, zero otherwise; and (xii) $Stock$, patent stock measured by the total patent applications of the firm prior to the current year. To circumvent the potential nonlinear effects of product market competition (Aghion et al., 2005), we include the squared Herfindahl index in our baseline regressions. All variables are computed for firm i over its fiscal year t.

3.3 Summary Statistics

Following the literature, we winsorize all variables at the 1st and 99th percentiles of their distribution to mitigate the effect of outliers. Table 1 presents the summary statistics of the main variables used in the analysis of our final sample. On average, a firm in our sample files 0.18 patents per year, 0.03 of which are invention patents. In comparison, IPO firms and their subsidiaries are more active in innovation. These IPO-related firms file 2.21 patents per year, of which 0.68 correspond on average to invention patents. In our merged sample, the average firm has total assets of RMB 9.99 million (USD 1.5 million), a fixed-assets to total-assets ratio ($FixAT\_AT$) of 0.33, and a leverage ratio of 0.59. The firms in our sample are on average 12.64 years old.

IV. EMPIRICAL RESULTS

4.1 Time Series Pattern and Panel Regression Results

In Figure 1, we plot the average number of industry- and year-adjusted innovation output variables within a seven-year window around the IPO event. More specifically, we adjust total patent (invention patent) filing numbers by subtracting the average number of total patent (invention patent) filings of all firms in the same industry and year. The time series plots in both Panel A and Panel B demonstrate that total patent (including invention, utility, and design patents) and invention patent filings do not significantly increase over the three years leading up to firms' IPOs. In contrast, there is sharp jump in the number of both total patent filings and invention patent filings starting from the IPO year. The increase lasts through the three years following the IPO.

Inspired by the raw pattern of innovation output surrounding the IPO in the time series data as demonstrated in Figure 1, we use the IPO firms' firm-year observations for a seven-year window centered on the IPO event and estimate an OLS regression:

$$Pat_{it}(Inv_{it}) = \alpha + \beta_1 before_{it}^{-3} + \beta_2 before_{it}^{-2} + \beta_3 current_{it} + \beta_4 after_{it}^{1} + \beta_5 after_{it}^{2} + \beta_6 after_{it}^{3} + \varepsilon_{it} \quad (1)$$

where *i* denotes the firm and *t* denotes the year. The dependent variable is firm *i*'s total patent filing (invention patent filing) adjusted for the industry-year average in year *t*. The independent variable $before_{it}^{-3}$ is a dummy that equals one if the firm-year observation is three years before the IPO event, and zero otherwise. Similarly, $before_{it}^{-2}$ is a dummy that equals one if the firm-year observation is two years before the IPO event, and zero otherwise. $current_{it}$ is a dummy that equals one if the firm-year observation is in the IPO year, and zero otherwise. The dummy variables $after_{it}^{1}, after_{it}^{2}$, $after_{it}^{3}$ are equal to one when the observations are one year, two years, and three years after the IPO event respectively, and zero otherwise. As can be seen, the benchmark group comprises the observations one year before the IPO.

The results are reported in Table 2. We find that the coefficient estimates of $before_{it}^{-2}$ and $before_{it}^{-3}$ are statistically insignificant for both total patents and invention patents, showing that firm innovation output stays at the same level before the IPO. In contrast, the coefficients of $current, after_{it}^{1}, after_{it}^{2}$ and $after_{it}^{3}$ are all positive and statistically significant, indicating a jump in innovation activity, both in terms of quantity and quality, after the IPO. These findings confirm the time series trend shown in Panels A and B of Figure 1.

Next, to take advantage of our rich data set, we explore the impact of IPOs on firm innovation using a panel data regression approach. We estimate the following regression

$$\mathrm{Ln}Pat_{i,t+\mathrm{n}}(\mathrm{Ln}In_{i,t+n}) = \alpha + \beta list_{it} + \gamma X_{it} + year_t + industry_{ij} + \varepsilon_{it} \quad (2)$$

where $\mathrm{Ln}Pat_{i,t+\mathrm{n}}(\mathrm{Ln}Inv_{i,t+n})$ is the natural logarithm of one plus the total patent (invention patent) filing in year *t*+*n* for firm *i*, where *n* is equal to 1,2,3. The variable of interest, $list_{it}$, is equal to one if firm *i* or firm *i*'s parent firm undergoes an IPO in year *t*, and zero otherwise. X_{it} is a group of firm-level control variables, summarized in Table 1, which according to the literature (e.g., Gu, Mao, and Tian 2013) are relevant to a firm's innovation activities. $year_t$ and $industry_{ij}$ control for the year and industry-level fixed effects.

The results of the panel data regression are reported in Table 2 Panel B. The coefficient estimate of $list_{it}$ is positive and statistically significant at the 1 percent level for n=1,2,3. Based on the coefficients estimated in columns (1)–(3), going public is associated with an increase in average annual patent filings of 35.1 percent for the subsequent three years after the IPO, indicating an economically significant magnitude. Similar results also hold for the invention patent applications according to columns (4)–(6). Various robustness tests were conducted to corroborate our baseline OLS regression results. For instance, we employed quantile regressions with various specifications, and the coefficients for the list dummy variable are always positive and significant.

4.2 Difference-in-differences Test

A legitimate concern regarding panel data regression results is the endogeneity problem. It is possible that both the IPO decision and firm innovation are affected by firms' unobservable characteristics. For instance, a rapidly growing firm is more likely to go public, and at the same time, it has reached a growth stage whereby it wants to increase its innovation activity. Our identification strategy to alleviate the endogeneity concern is based on a difference-in-differences (DiD) approach. The CIS data, which provide detailed balance sheet information for non-publicly listed manufacturing firms, allow us to match the IPO firms with non-publicly listed firms that have similar firm characteristics to the IPO firms. We then compare the innovation output of the IPO firms to the innovation output of the matching firms, which do not go public but are otherwise comparable, before and after the IPO.

The DiD approach has important advantages. First, it can rule out omitted trends that are correlated with an IPO and innovation in both treatment and control groups. For instance, the prosperity of a certain industry can simultaneously increase the likelihood of an IPO and future innovation. The DiD approach rules out the possibility that industry prosperity, rather than the IPO itself, drives the change in innovation activity. Second, the DiD approach controls for constant unobservable differences between the treatment and control groups.

We construct the treatment and control groups of firms using the PSM algorithm. Specifically, the treatment group includes all IPO firms and their subsidiary firms for the period 1999–2006 with non-missing matching variables in the pre-IPO year (t-1) and the post-IPO year ($t+1$). We further require that the subsidiary firms must maintain their subsidiary status from IPO year t to year $t+3$ and they must be established no later than t-3.

We use the PSM algorithm to identify matches between IPO firms and firms that do not go public. In our PSM, we first estimate a probit model with 356 firms associated with IPOs and 772,734 firm-year observations without IPOs. The dependent variable Y_{it} equals one if firm i has an IPO at year t, and zero otherwise. In the probit model, we include all control variables from the baseline specification in equation (2), which are measured in the year immediately preceding the IPO. We also include patent growth during the three years before the IPO, g_pn, and the patent stock, $Stock$, in the probit model, to ensure that the parallel trend assumption—the key requirement for the DiD approach—is appropriately accommodated.

The probit regression results indicate that our model captures a significant amount of variation in the dependent variable. We report the probit model results in column (1) of Panel A in Table 3. As can be seen, the pseudo R^2 reaches 16.5 percent and the p-value from the Chi-squared test of the overall model fitness is well below 0.0001, indicating that our model specification works well. We then use the predicted probabilities, or propensity scores, to conduct a nearest-neighbor PSM procedure. Specifically, we match each IPO firm-year observation (i.e., treatment group) with a non-IPO firm-year observation that has the closest propensity score among the observations in that IPO year and belongs to the same industry as the IPO firm to form the control group. We eventually generate 355 pairs of matched firms.[7]

Before progressing to the DiD test, we conduct a number of diagnostic tests to check the validity of the parallel trend assumption, which is essential for the DiD approach. First, we rerun the probit model, restricting the observations to only the 710 matched firms after the pairing. The results are shown in column (2) of Panel A in Table 3. As can be seen, none of the coefficients of the independent variables are statistically significant. In particular, the coefficient of the pre-IPO patent application growth variable g_pn is insignificant, indicating that there is no observable difference in innovation trend between the IPO and non-IPO firms before the IPO event. Moreover, the pseudo R^2 falls dramatically from 16.52 percent to 0.66 percent after the matching and the p-value of the Chi-squared test is close to 1, indicating that the null hypothesis that all the coefficient estimates are zero cannot be rejected.

Furthermore, we conduct a series of univariate variable tests of firm characteristics between the treatment and control group firms one year before the IPO. The results are reported in Panel B of Table 3, with the p-value of the tests shown in the last column of the table. As can be seen, none of the differences in firm characteristics between the treatment and control groups are statistically significant after the matching. In particular, the insignificance of the pre-IPO patent application growth variable (g_pn) provides further evidence that the parallel trend assumption is likely to hold.

In summary, the above diagnostic tests provide strong evidence that our PSM process removes significant observable differences (other than the difference in IPO) between the treatment and control group firms, meaning that the change in innovation activity is more likely to be driven by IPOs in the DiD test.

[7] Of the 356 firms affected by the IPOs, only one firm could not be matched as it violated the common support condition.

To provide a visual demonstration of the trend in patent applications around the IPO for both the treatment and control group firms, we plot the time series of the variable LnPat (LnInv) during a seven-year window around the IPO event in Figure 2. As can be seen, the trend lines of the treatment and control groups move closely in parallel during the years leading up to the IPO event, which provides another piece of evidence for the parallel trend assumption. However, after the IPO event, we can see a significant increase in patent applications for the treatment group line. In sharp contrast, the control group line stays flat after the IPO.

To corroborate the visual evidence, we conduct formal DiD tests and report the results in Panels C and D of Table 3. Panel C shows the change in average annual total patent (invention patent) applications around an IPO. Specifically, the first column in Panel C reports the difference in average annual total patent (invention patent) applications during the three years before and after the IPO event for the treatment group. Similarly, we calculate the change in average annual total patent (invention patent) applications for the control group in the second column. These results indicate that the changes in both total patent and invention patent applications are positive and statistically significant for the treatment group. The changes, however, are insignificant for the control group. The third and fourth columns further report the DiD estimate results for the treatment and control groups, respectively. We find that the DiD tests for the total patent and invention patent filings are both positive and statistically significant at the 1 percent level. The DiD test results are not only statistically significant, but are also economically significant. On average, an IPO results in an increase of 1.56 (0.77) total patent (invention patent) applications annually over the three years after the IPO.

Panel D in Table 3 further demonstrates the innovation dynamics of the DiD results in a regression framework. The firm-year observations are gathered in a seven-year window centered on the IPO year. The regression model is as follows:

$$\ln Pat_{it}\ (\ln Inv_{it}) = \alpha + \beta_1 list_i * before_{it}^{-2\&-3} + \beta_2 list_i * current_{it} + \beta_3 list_i * after_{it}^1 + \beta_4 list_i * after_{it}^2 + \beta_5 list_i * after_{it}^3 + before_{it}^{-2} + before_{it}^{-1} + current_{it} + after_{it}^1 + after_{it}^2 + after_{it}^3 + year_t + firm_i + \varepsilon_{it} \quad (3)$$

where *i* denotes the firm and *t* denotes the time; $list_i$ is a dummy, equal to one if firm *i* belongs to the treatment group (IPO firms), and zero otherwise (non-IPO firms); $before_{it}^{-2\&-3}$, $current_{it}$, $after_{it}^1$, $after_{it}^2$ and $after_{it}^3$ are all dummy variables equal to one if the year *t* is three or two years before an IPO, the IPO year, and one year, two years, or three years after the IPO, respectively, and zero otherwise. Therefore, the omitted or benchmark group comprises the observations one year before the IPO. We also include the year and firm fixed effects in the regression.

The coefficient estimates of interest are $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$. If reverse causality holds, that is, the increase in innovation activities helps improve the quality of the firm, which then leads to an IPO, we should observe significant and positive coefficient estimates of β_1. However, in contrast, we find statistically insignificant and negative coefficient estimates of β_1 , which indicates that there is no systemically different trend in firm innovation activity between IPO firms and non-IPO firms before the IPO. The coefficient estimates of $\beta_3, \beta_4,$ and β_5 are all positive and statistically significant, suggesting that compared to the non-IPO firms, IPO firms experience a significant increase in their patent application activity after the IPO event. Overall, our findings suggest that IPOs help increase firm innovation activity and reverse causality does not hold.

To check the robustness of our results, we also repeat the PSM algorithm and construct the control group samples by choosing five (instead of one) most closely matched non-IPO firms for each IPO firm in the treatment group. In our unreported results, the DiD tests on the treatment group and the augmented control group generate quantitatively similar results as in Table 3.

4.3 Further Tests on Innovation Quality

To corroborate our findings concerning patent quality, we also explore other proxies of patent quality. Our first proxy is the number of inventors per patent. The idea is that if a patent involves more inventors, it is likely that the patent requires more research input and expertise from multiple areas. Therefore, the patent is technologically more sophisticated and thus is of higher quality. For this reason, the number of inventors per patent can be used as a proxy for the quality of a patent.

Taking the number of inventors per patent as the dependent variable, we conduct a similar patent level DiD regression test as in equation (3), using the same treatment and control group firms constructed by PSM. The results are shown in Panel A of Table 4. As can be seen, since the coefficient estimate of $list_i * before_{it}^{-2\&-3}$ is statistically insignificant, the parallel trend assumption for the treatment and control groups before the IPO holds. The coefficient estimates for $list_i * current_{it}$, $list_i * after_{it}^1$, and $list_i * after_{it}^2$ are all statistically significant, indicating that after the IPO, the IPO firms increase their human capital deployment for each patent more than the non-IPO firms. This result lends support to our hypothesis that IPOs lead to higher quality firm innovation.

In addition to using the number of inventors per patent as the proxy for patent quality, we also explore the ratio of invention patents over total patents as another proxy for the quality of innovation. We carry out the same univariate DiD test as in Panel C of Table 3. Column (1) of Panel B in Table 4 reports the change in the average invention patent ratio for the IPO firms. We compute the change in the ratio by first subtracting the invention patent ratio over three years immediately preceding the IPO from the invention patent ratio counted over the three years immediately after the IPO for each treatment firm. The differences are then averaged across the treatment group. Similarly, we compute the average change in the invention patent ratio for the control group in column (2). Column

(3) reports the DiD estimates that are the difference between columns (1) and (2). Column (4) reports the p-value of testing the null hypothesis that the DiD estimates are zero. We find that the DiD estimate for the increase in the invention patent ratio is 0.043 after the IPO with a p-value equal to 6.8 percent. The DiD test result is economically significant given the fact that the average invention patent ratio for all firms before the IPO is only 0.09.

Both tests in this section indicate that firms not only increase the quantity but also the quality of innovation output after the IPO. These results are in sharp contrast to Bernstein's (2015) findings that the quality of firm innovation declines after an IPO in the US context. Bernstein (2015) suggests that this decline is due to the agency problem between managers and shareholders. The failure of innovation may result in the loss of the manager's job if shareholders attribute the failure to the manager, thereby pushing managers to cut back on those more innovative yet more risky research and development (R&D) projects. This type of agency problem, although important in the US, might be less relevant in China. Moreover, the financial resources gained through an IPO yield higher benefits for firms in China given that Chinese firms often face much more severe financial constraints. The benefit of financing through an IPO could then predominate over the negative impact brought about by an IPO in China. We will formally test the relevance of financial constraints and corporate governance later in Section 4.5.

4.4 The Scope of Innovation

Scope is another important dimension of innovation. On the one hand, focusing on innovation in the core business allows a firm to strengthen its competitive advantage over competitors; on the other hand, innovation extended to other industries, especially industries unrelated to the firm's current core businesses, can help the firm acquire new growth opportunities. Therefore, the choice of a firm's innovation scope after an IPO is an interesting empirical issue.

We study the scope of innovation by first classifying a firm's patents into two categories: patents that are related to a firm's main business (defined as related patents), and patents that are unrelated to a firm's main business (defined as unrelated patents). Specifically, we define a patent within a technology class that can be linked to a firm's Chinese Industry Classification (CIC) as a related patent, and otherwise as an unrelated patent. Practically, we first map each firm's CIC code to the international standard industrial classification (ISIC) code following Dean and Lovely (2010). Then, we use the concordance table provided by Schmoch et al. (2003) to link the ISIC code to the International Patent Classification (IPC), which classifies a patent's technology classes. The link is developed based on whether a patent's technology area is closely related to a certain industry. Our procedure eventually links a firm's industry to the directly related patent technology classes (IPCs). If a patent's IPC belongs to one of these IPCs, it is defined as a related patent, and otherwise unrelated.

Based on the above patent classification, we examine how firms allocate their innovation resources in core and non-core businesses after an IPO. We do so by investigating the changes in total patent applications and invention patent applications for both the related and unrelated patents surrounding an IPO in a DiD framework, using the same PSM sample of treatment and control group firms. Once again, we use a seven-year window centered on the IPO year and estimate the following regression model separately for the related and unrelated patent applications:

$$y_{it} = \alpha + \beta_1 list_i * before_{it}^{-2\&-3} + \beta_2 list_i * current_{it} + \beta_3 list_i * after_{it}^{1} + \beta_4 list_i * after_{it}^{2} + \beta_5 list_i * after_{it}^{3} + \beta_6 before_{it}^{-2} + before_{it}^{-1} + current_{it} + after_{it}^{1} + after_{it}^{2} + after_{it}^{3} + year_t + firm_i + \varepsilon_{it} \quad (4)$$

where we define the independent variables as in equation (3). The dependent variables we use in our tests are: 1) a dummy variable, $Dunrelated_{it}$, which is equal to one if firm *i* has unrelated patents in year *t*, and zero otherwise; 2) the number of technology classes to which firm i's unrelated patents belong, $UnrelatedClass_{it}$; 3) the natural logarithm of one plus related total patents, Ln $RelatedPat_{it}$; 4) the natural logarithm of one plus unrelated total patents, Ln $UnrelatedPat_{it}$; 5) the natural logarithm of one plus related invention patents, Ln $RelatedInv_{it}$; 6) the natural logarithm of one plus unrelated invention patents, Ln $Unrelatedv_{it}$.

We report the results in Table 5. The coefficient estimations of β_1 for the six regressions are all statistically insignificant, suggesting that the parallel trend assumption underlying the DiD test is likely to hold. The coefficient estimates of $\beta_3, \beta_{4,}$ and β_5, on the other hand, are positive and statistically significant for all tests except for β_3 in the unrelated class. The results in column (1) suggest that IPO firms are more likely to innovate beyond their core business than those matched unlisted firms after the IPO. In addition, IPO firms innovate in more unrelated technology classes according to the test in column (2). The results in columns (3)–(6) further indicate that an IPO boosts innovation quantity and quality in both the core and non-core businesses of the firms. In China, an IPO firm is able to obtain sufficient financial resources and will thus have plenty of opportunities to access new business. Our results confirm that IPO firms not only consolidate their advantage in their existing core businesses by increasing innovation (both quantity and quality), but also expand their innovation efforts by entering into non-core businesses.

4.5 Cross-Sectional Analysis

The impact of IPOs on firm innovation activity varies according to different firm characteristics. Exploring how our results vary according to these characteristics could help us understand the underlying mechanism influencing the positive impact of an IPO on innovation.

In this section, we explore the cross-sectional differences of IPOs using the same PSM sample in a seven-year window centered on the IPO year. We apply a difference-in-difference-in-difference (DiDiD) framework, estimating the following regression model:

$$\text{Ln}\, Pat_{it}\ (\text{Ln}\, Inv_{it}) = \alpha + \beta_1 list_i * \text{After}_{it}^{1\&2\&3} * X_i + \beta_2 list_i * After_{it}^{1\&2\&3} + \text{After}_{it}^{1\&2\&3} * X_i + \text{After}_{it}^{1\&2\&3} + firm_i + year_t + \varepsilon_{it} \quad (5)$$

where $\text{After}_{it}^{1\&2\&3}$ is equal to one if the observation is either one year, two years, or three years after an IPO for a given firm, and zero otherwise. X_i are relevant firm dummy variables. In our case, X_i could be a corporate ownership indicator, *SOE*, which is equal to one if the treatment group firm is a state-owned enterprise, and zero otherwise, or a dummy variable, *EXEHLD*, indicating whether the management team holds firm stock (one if management holds, zero if not) after the IPO, or a dummy variable, *Duality$_i$*, indicating if the same person is CEO and the president (one if so, zero otherwise) after the IPO, or a dummy variable, $Fixed$, equal to one if a firm's fixed assets ratio *(FixAT_AT*) is above the median level one year prior to the IPO, or a dummy variable, *External_dependence*, equal to one if a firm's industry belongs to the high external financing dependent group.

4.5.1 Financial Constraints

We begin our cross-sectional analysis by testing the role of financial constraints in determining firms' innovation performance after an IPO. We address a firm's financial constraints from two perspectives. First, we study a firm's external financing needs. With higher external financing needs, a firm is more likely to be subject to financial constraints. An IPO could benefit firms dependent on external finance by relaxing their financial constraints. Therefore, IPOs might help these firms disproportionally in enhancing their innovation.

We define a firm's external finance dependence as the firm's capital expenditures minus its cash flow from operations divided by capital expenditures (see Rajan and Zingales (1998)). Due to data availability, unfortunately firm-level cash flow is not available for the CIS data. Following Rajan and Zingales (1998), we then divide all two-digit industries into two groups: external finance industries (those industries above the median level on the external finance dependence index), and internal finance industries (those industries below the median level on the external finance dependence index). Table A2 tabulates the external finance / internal finance industries.

We run the DiDiD regression equation (5) for our PSM sample and report the results in columns (1)–(2) in Panel A of Table 6.[8] *External_dependence* is a dummy that is equal to one if an industry belongs to the high external financing-dependent group, and zero

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[8] For reasons of space, in all the panels in Table 6 we only report the coefficient estimates for the key variables $list_{it} * After_{it}^{1\&2\&3}$ and $list_{it} * After_{it}^{1\&2\&3} * X_i$. All other explanatory variables are suppressed.

otherwise. The coefficient estimates of the triple interaction term are positive and statistically significant. These results show that firms in external finance-dependent industries tend to increase their innovation more (both in terms of quantity and quality) after the IPO than their counterparts in internal finance-dependent industries. This piece of evidence sheds light on the financial constraint channel through which IPO helps to enhance firms' innovation.

External finance needs represent demand for external financing. An external finance-dependent firm might still be able to borrow enough to meet its demand and hence might not be subject to severe financial constraints. Therefore, as a second test of the financial constraint channel, we examine collateral constraints. Following the literature (e.g., Kiyotaki and Moore, 1997), we construct a variable, *Fixed*, as a proxy for the tightness of firms' financial constraints. *Fixed* is equal to one if a firm's fixed assets/total assets ratio is larger than the median level among all firms before the IPO, and zero otherwise. The idea is that a firm with more fixed assets has more collateral, and therefore it is easier for the firm to borrow from banks or issue bonds in capital markets. A lower fixed assets/total assets ratio thus represents tighter financial constraints.

We run the DiDiD regression equation (5) with the *Fixed* dummy and report our results in columns (3)–(4) of Panel A in Table 6. The coefficient estimates of the triple interaction term are negative and statistically significant. This result shows that firms facing tighter collateral constraints (lower fixed assets ratio) before the IPO exhibit a larger increase in innovation activity after the IPO, both in terms of quantity and quality. This finding confirms the message from the test of external finance needs: An IPO helps a firm to relax the financial constraints it faces via equity fundraising, which boosts the firm's innovation.[9]

4.5.2 Governance and Ownership Structure

In this section, we test whether corporate governance and ownership structure also play an important role in the IPO's positive impact on innovation.

We first run the DiDiD regression equation (5) with two dummies for corporate governance. In columns (1)–(2) of Panel B in Table 6, the dummy X_i is the indicator for the management team holding firm stock, $EXEHLD$ (1 for holding, 0 otherwise). The coefficient estimate of $list_{it} * \text{After}_{it}^{1\&2\&3} * EXEHLD_i$ is positive and statistically significant for both total patents and invention patents, indicating that firms that grant stock to their management team tend to witness a larger increase in innovation activity (both in terms of quantity and quality) after the IPO event. As management team stock holding aligns the interests of managers and shareholders, it provides incentives for managers to

[9] In our sample, the correlation between the *Fixed* dummy and the *External_dependence* dummy is -0.16. Therefore, a firm with a low fixed assets/total assets ratio (tight financial constraints) tends to have high external finance dependence.

engage in more innovation activities to boost the firm's long-term value. Our result thus demonstrates the importance of the management incentive structure in encouraging innovation activity after the IPO.

In addition, according to columns (3)–(4) of Panel B in Table 6, we find that firms with the same person as CEO and board president tend to have a larger increase in total patents and invention patents after the IPO event. This is indicated by the positive and statistically significant coefficient estimate of $list_{it} * After_{it}^{1\&2\&3} * Duality_i$, where $Duality_i$ is equal to one if the same person is both CEO and president, and zero otherwise. As having the same person as CEO and president is a strong indicator of management entrenchment (i.e., greater tolerance of the risk associated with innovation), our results show that the career concerns of top management could also affect innovation output after the IPO event.

Overall, our results demonstrate that corporate governance could play an important role in pursuing innovation after an IPO.

Moreover, we explore the impact of ownership structure on innovation output after an IPO. The results are reported in columns (5)–(6) of Panel B in Table 6. We find that POEs experience a much larger increase in innovation activities after an IPO than SOEs.[10] On average, a POE firm applies for 25.7 percent more total patents and 19.8 percent more invention patents than a SOE firm after an IPO. There are several reasons why this happens. First, top managers in SOEs often have weaker incentives to innovate compared to their counterparts in POEs. For example, SOEs less frequently grant stocks to the management team (in our PSM sample, 25.8 percent of POEs have $EXEHLD = 1$, while only 5.1% do so in SOEs). Second, SOEs are much more likely to have different persons as president and CEO (in our sample, 55.1 percent of POE firms have $Duality = 1$, while this ratio is 22.0 percent among SOEs). Both cases imply that top managers in SOEs are more likely to be subject to career concerns, which tends to reduce their incentives for innovation after IPOs. Third, SOEs face less stringent financial constraints, as most banks in China are controlled by the state and they have an obligation to grant SOEs favorable access to credit. Therefore, the gain in innovation after an IPO through relaxing financial constraints is smaller for SOEs than POEs.

The results above explain why our findings are in sharp contrast to Bernstein's (2015) finding using US data. Bernstein (2015) emphasizes the negative impact of IPOs on firm innovation due to the agency problem. On the one hand, our finding concerning corporate governance structure confirms the insights in Bernstein (2015): The career concerns of top management tend to reduce firms' innovation incentives after an IPO. On the other hand, our finding that the alleviation of financial constraints after an IPO increases firms'

[10] In an unreported exercise, we also separately conduct the DiD test as in equation (3) for SOE and POE subsamples, respectively. We find a significant positive impact of an IPO on innovation for POEs, but an insignificant IPO effect for SOEs.

innovation is the key to understanding the discrepancy between our finding and that of Bernstein (2015). Our results show the positive influence of IPOs on firms' innovation, which is more important in China's context as well as in other developing countries with underdeveloped financial systems.

V. HUMAN CAPITAL AND INNOVATION

Our previous results demonstrate that IPOs lead to an increase in innovation quantity, quality, and scope. It is natural to ask: How does this happen? What exactly drives this enhanced innovation activity? Annual investment in research, such as R&D costs, could be an important factor behind such an increase in innovation. As R&D information is limited in our data, we use the inventor number as a proxy for innovation input.[11] By leveraging our patent dataset, which contains detailed inventor information, we calculate the number of inventors who produce patents for each firm-year observation.

As an IPO brings a firm more resources through external financing, it could be easier for an IPO firm to hire more inventors and retain existing inventors. To explore the hypothesis that firms have more inventors after IPOs, we use the same DiD test framework as in equation (3) and the same PSM sample of treatment and control group firms. The sample is restricted to the three-year window before and after the IPO for both the treatment and matched control group firms as before. Panel A in Table 7 reports the results. The first column documents the average change in the number of inventors for the treatment group. We compute the changes by first subtracting the total number of inventors over the three-year window before the IPO from the total number of inventors over the three-year window after the IPO for each treatment group firm. The differences are then averaged across the treatment group. By the same token, we compute the average change in the number of inventors for the control group and report the results in the second column. In the third and fourth columns, we report the DiD estimates that are the differences between column (1) and column (2), and the corresponding p-value of the test. We find that an IPO helps a firm increase the number of inventors by 3.016 over three years, which is statistically significant at the 1 percent level. Compared to the average number of inventors in the treatment group firm before the IPO, which is 3.75, an IPO helps a firm increase its inventor count by 80 percent on average.

In addition to testing the hypothesis using the number of inventors, we also conduct a similar DiD test on the total patent (invention patent) applications per inventor. The results are also shown in Panel A of Table 7. For both cases, we find statistically insignificant results, indicating that neither the productivity nor the quality of inventors change much after the IPO. All this evidence indicates that the increase in patents, both invention and

[11] We only have two years (2005 and 2006) of R&D data available in the CIS dataset. Publicly listed firms in CSMAR have only reported R&D expenditures since 2006. Therefore, R&D data are limited in our matched data sample.

non-invention, is driven mainly by the increase in the number of inventors (extensive margin), rather than the increase in individual inventors' productivity (intensive margin).

An increase in the number of inventors could arise from hiring more inventors and/or retaining a firm's best talent. To investigate this mechanism, we carry out an analyst-level analysis. Following existing studies (e.g., Bernstein 2015),[12] we identify two groups of inventors. The first group is "stayers": inventors who produce at least one patent in a firm over three years before and three years after the firm's IPO, respectively. The second group of inventors is "leavers": inventors who produce at least one patent in a firm over the three years before the firm's IPO and at least one patent in a different firm over the three years after the IPO.

If retaining inventors is a way in which IPO firms can better manage their human capital, we would expect to observe that inventors are less likely to leave the firm after an IPO. By combining both "stayers" and "leavers" in our sample, we intend to focus on inventors who produce patents before the IPO, and examine the likelihood that these inventors leave the firm. We run the following model:

$$Leaver_{il} = \alpha + \beta Treat_{il} + \gamma X_{i,-1} + list\_year_{it} + industry_{ij} + \varepsilon_i \qquad (6)$$

where l denotes the inventor, i denotes the firm, j denotes the industry and t denotes time; $Leaver_{il}$ is a dummy variable equal to one if an inventor of firm i belongs to the "leavers," and zero otherwise; $Treat_{il}$ is a dummy variable indicating if inventor l works for a treatment group firm i before the IPO (one if yes, and zero otherwise); $X_{i,-1}$ represents firm-level control variables one year before the IPO; $list\_year_{it}$ and $industry_{ij}$ control for list year and industry fixed effects.

The results in the first column of Panel B in Table 7 show that inventors in IPO firms are 69.2 percent less likely to leave the firm during the three years after the IPO, with the coefficient being statistically significant at the 1 percent level. This result confirms our hypothesis that a firm's capacity to retain its talent improves substantially after the IPO. This could contribute to the increase in the number of inventors we observe after an IPO. Moreover, Panel B of Table 7 also shows that inventors in SOEs are 62.1 percent more likely to leave their firms than their counterparts in POEs. This partially explains why SOEs do worse than POEs in terms of innovation activity after their IPOs.

[12] In China's patent application data, there is no identification number granted to each individual inventor as there is in the US patent data. Therefore, we use the name of the inventor and the patent's technology field (IPC) to identify each individual inventor. For instance, if an inventor named A has previously filed a patent for wireless communications technology, and if a new patent is filed that is also related to wireless communications technology with an inventor named A, we consider that it is the same inventor who has filed the new patent. However, if the patent is in chemicals, we consider the new patent to have been filed by a different inventor who is also named A.

To further control for the quality of leavers, we add the number of patent applications invented by the person before the previous firm's IPO, *Pre_productivity,* as an additional control in regression equation (6). The results are reported in the second column of Panel B in Table 7. The results are very similar to those of our baseline in the first column.

VI. ECONOMIC IMPLICATIONS OF INNOVATION ACTIVITY

Our results so far suggest that IPOs can trigger more active innovation in firms. It is time to ask the "bottom line" question: Is the enhanced innovation activity value creating or value destroying for the firm? On the one hand, empirical studies indicate that innovation is positively associated with firm value (Hall, Jaffe, and Trajtenberg, 2005). On the other hand, there is literature arguing that overinvestment in innovation could be damaging for firm value. For instance, Hirshleifer, Low, and Teoh (2012) argue that overconfident managers, who chase short-term profits, could overinvest in innovation that may not serve the best interests of shareholders. In our setting, it could be the case that managers simply use patent applications as a "window-dressing" tool to cajole investors and boost firm valuation in the short run. It therefore does not have a long-run impact on the firm value. Which story is true? Our uniquely matched data can provide a partial answer.

To address the "bottom-line" question regarding the economic consequences of innovation, we focus only on the IPO firms, and aggregate all subsidiary firms' patent applications at the parent firm level. Following the literature, we use Tobin's Q to measure firm value. Tobin's Q is measured as the sum of the market value of equity and the book value of debt, divided by the book value of total assets. Because it usually takes time for the real impact of innovation to be reflected in firm equity valuation, to avoid short-term market noise, we employ $\Delta Q_{i,3\rightarrow 6}$, i.e., the change in Tobin's Q from the end of the third year after the IPO to the end of the sixth year after the IPO, thus measuring the increase in firm value in the long run. We then estimate the following model:

$$\Delta Q_{i,3\rightarrow 6} = \alpha + \beta Pat_{i[1,3]}(Inv_{i[1,3]}) + \gamma X_{i,3} + list\_year_{it} + \varepsilon_i \tag{7}$$

where i denotes the firm and t denotes time. $Pat_{i[1,3]}$ $(Inv_{i[1,3]})$ is firm i's total patent (invention patent) filing over the three years after the IPO. $X_{i,3}$ represents a group of firm-level control variables measured at the end of the third year after the IPO, including Tobin's Q, ROA (net income divided by total assets), $leverage$ (book value of total debt divided by total assets), total $asset$, and the ratio of fixed assets to total assets. In addition, we also control for the firm's stock returns over the three years after the IPO. Finally, $list\_year_{it}$ captures the list year fixed effect.

We report the results in Table 8. As can be seen, the coefficient estimate for $pat_{i[1,3]}$ in column (1) is positive and statistically significant, indicating that firms filing for more patents over the three years after the IPO tend to experience a higher increase in their Tobin's Q in the long run. This result shows that innovation activity after the IPO does indeed create real value for the firm in the long run.[13] In addition, we find that the coefficient estimate for $Inv_{i[1,3]}$ in column (2) is also positive and statistically significant, indicating that invention patent applications after the IPO are also associated with long-term value creation for the firm. Moreover, by comparing the coefficient estimates of $pat_{i[1,3]}$ and $Inv_{i[1,3]}$, it can be seen that invention patent filing (higher quality innovation activity) has a much stronger impact on firm value creation. Combined with our previous results that IPOs increase both the quantity and quality of firm innovation, it can be argued that IPOs create *real value* for the firm through boosting firm innovation activity in China. Moreover, the impact comes predominantly from the enhanced quality of innovation after the IPO. Our results therefore show evidence against the "window-dressing" hypothesis and support the view that the Chinese stock market does indeed create real value for firms (see Carpenter, Lu, and Whitelaw 2016).

VII. ROBUSTNESS CHECK: HECKMAN-STYLE TWO-STAGE MODEL

In this section, we adopt a two-step Heckman-type endogenous switching regression model to corroborate the causal relationship between IPOs and firm innovation established by the DiD test in Section 4.2. This methodology is discussed in detail in Heckman (1979) and Maddala (1983). It is a generalized version of the original Heckman model designed to tackle the endogeneity issue by introducing the inverse Mills ratios. The method has been widely used in the literature, such as Fang (2005) and Chemmanur, Krishnan, and Nandy (2011).

The Heckman methodology helps tackle the endogeneity of IPOs through a counterfactual analysis, namely, testing the "what-if" type of question: What could the innovation performance of an IPO firm have been had it not gone IPO? The estimation is carried out in two steps. The first step is to estimate the same probit model as in our previous propensity score matching (see Section 4.2) and calculate the inverse Mills ratios for IPO firms and non-IPO firms, respectively (Chemmanur, Krishnan and Nandy, 2011). The inverse Mills ratio is a measure of unobserved factors that affects both types of firms' IPO decision and the post-IPO innovation performance. In the second step, the growth of patent applications is regressed against the inverse Mills ratios and other control variables separately for IPO and non-IPO firms. And the predicted values of patent growth from the second step are used to conduct the counterfactual analysis.

The results of the switching regression analysis are reported in Table 9. Panel A shows the second step regressions of IPO and non-IPO firms augmented with the inverse Mills ratio

[13] Notice that the leverage ratio has a much larger and more significant effect (1.7-1.9) than innovation activity (0.005-0.014) in the regressions (Table 8), which indicates an indirect channel might be at play here: firms can obtain higher funding from banks or debt issuances after the IPOs, and the higher funding relaxes firms' financial constraint and further facilitates innovation activities. The indirect channel seems much larger than the direct effect from a innovation itself.

to control for the endogenous selection bias. The coefficients of the inverse Mills ratio are positive and statistically significant in all tests, suggesting that there are endogenous and unobserved factors affecting both types of firms' IPO and innovation. Therefore, properly controlling for these factors is needed to attribute the residual patent application growth to the pure IPO effect. Panel B presents the results of the counterfactual analysis of IPO versus non-IPO firms. We obtain the counterfactual values of patent application growth for IPO firms as the predicted values of the non-IPO firm regression and the corresponding inverse Mills ratio (using IPO firm data). The results in Panel B suggest that IPO firms achieve a higher total patent (invention patent) application growth, which is about 27.1% (14.2%) higher than what the same firms would have achieved had they not gone IPO, indicating a significant IPO effect. The magnitude of the improvement in innovation due to IPOs is very close to our earlier results presented in the Panel D of table 3.

VIII. CONCLUSIONS

In this paper, we empirically investigate the real impact of IPOs on firm innovation activity using uniquely matched firm-level data in China, linking patent filing and stock market information. To help mitigate endogeneity and establish causality, we use a DiD approach, together with the PSM algorithm to construct treatment and control groups. We find a significantly positive causal effect of IPOs on firms' patent applications, both in terms of quantity and quality. The causal effect is robust when we use a two-step Heckman-type endogenous switching regression model as an alternative identification model to control for endogenous selection bias caused by the IPO decision. We also found that, after an IPO, firms strengthen core-business innovation while expanding innovation into their non-core businesses.

Our findings confirm that the impact of IPOs on innovation varies across firms' financial constraints, corporate governance structures, and ownership. In particular, privately owned firms facing tighter financial constraints—with governance structures better aligning the interests of managers and stockholders— see a larger increase in innovation after an IPO.

We believe that our findings concerning the positive impact of IPOs on relaxing financial constraints is the key to understanding why firms increase the quality and quantity of innovation after IPOs in China.

Moreover, by using the inventor information in the Chinese patent data, we established that IPOs not only help a firm afford retention of existing inventors but also attract more external inventors, which could be an important factor driving the enhanced innovation activity. Finally, we find that the increase in innovation activity creates value in the long run, which supports our claim that innovation, through IPOs, has a *real* impact on Chinese firms.

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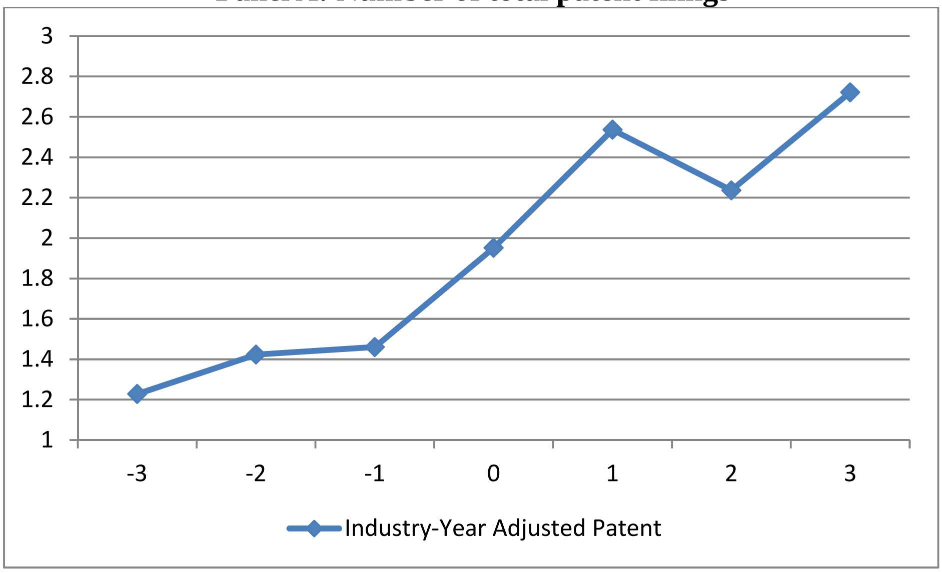
Figure 1: Industry and year-adjusted innovation output around IPOs

This figure presents firms' average number of industry- and year-adjusted patent applications around the IPO year. We adjust each firm's patent applications by subtracting the average number of patent applications of all firms in the same two-digit industry and year. Panel A shows that the time trend for total patent counts (including invention, design, and utility patents) and Panel B shows the time trend for invention patent counts only. The x-axis indicates the number of years before or after the IPO.

Panel A: Number of total patent filings



Panel B: Number of invention patent filings

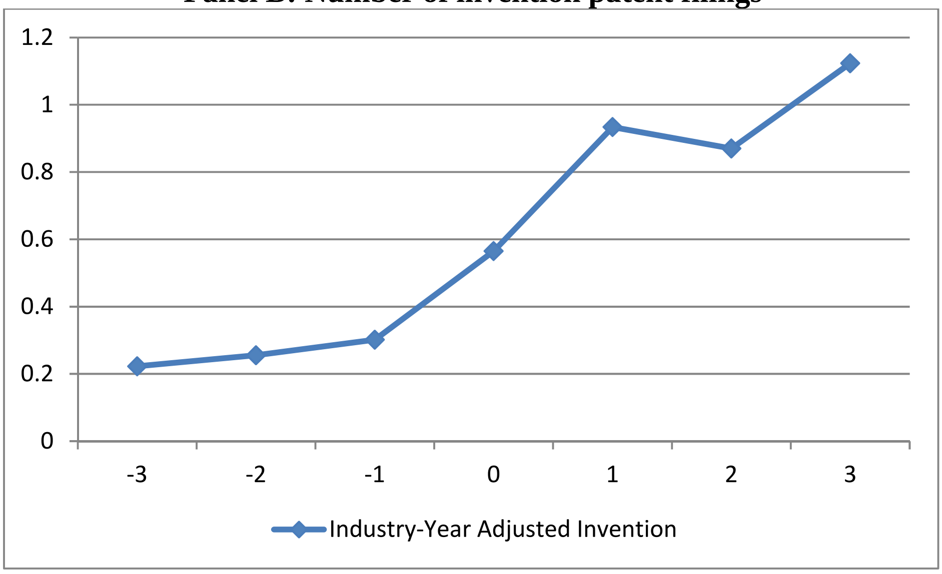
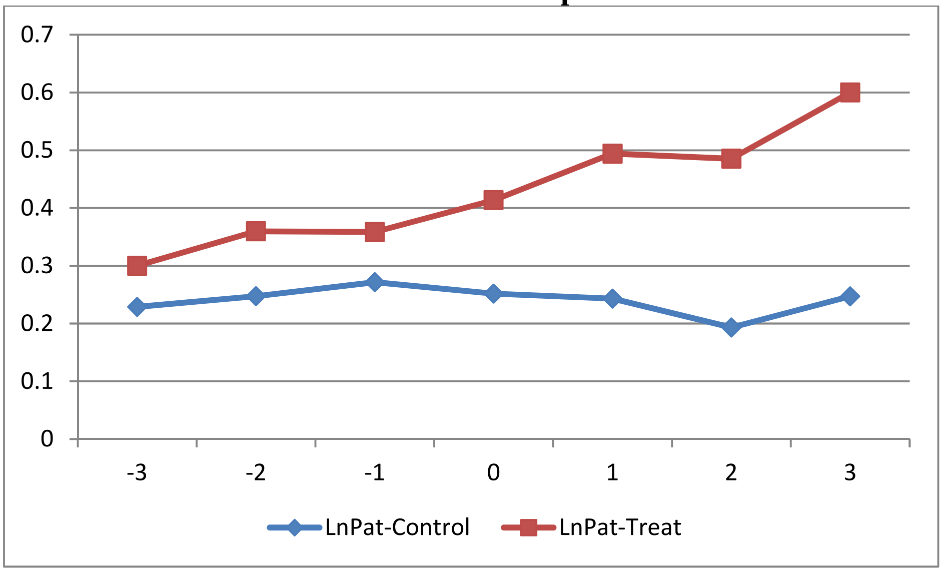


Figure 2: Innovation outputs around IPOs for treatment and control firms

This figure presents the mean values of innovation outputs around the IPO event. Panel A shows the time trend for the natural logarithm of one plus patent counts and Panel B shows the time trend for the natural logarithm of one plus invention counts. The square line is for treatment firms that implemented an IPO in a sample year. The diamond line is for PSM non-list firms (control group). The x-axis indicates the years before or after the IPO.

Panel A: Number of patents



Panel B: Number of invention patent applications

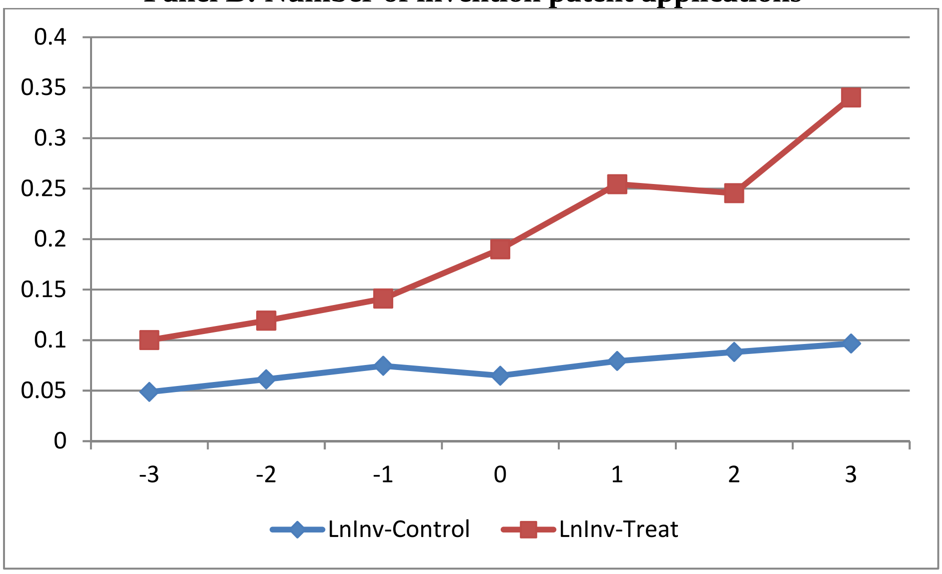


Table 1: Summary statistics

This table presents summary statistics for variables constructed using our merged data sample of listed and non-listed firms from 1998 to 2007. All variables are winsorized at the 1^{st} and 99^{th} percentiles of their distribution. The variable abbreviations are explained in the Table A1 of the Appendix.

	N	Mean	S.D.	P25	Median	P75
Pat	999114	0.18	1.91	0.00	0.00	0.00
Invention	999114	0.03	0.62	0.00	0.00	0.00
Ln(AT)	999114	10.04	1.37	9.06	9.87	10.87
FixAT_AT	999114	0.33	0.20	0.17	0.30	0.45
Interest_AT	999114	0.01	0.02	0.00	0.01	0.02
Admin_AT	999114	0.08	0.08	0.03	0.06	0.10
Ln(Age)	999114	2.22	0.80	1.79	2.20	2.71
Leverage	999114	0.59	0.27	0.40	0.60	0.78
Liquidity	999114	0.06	0.29	-0.11	0.06	0.24
ROA	999114	0.08	0.15	0.00	0.03	0.10
HI	999114	0.05	0.07	0.01	0.02	0.05
HI^2	999114	0.01	0.05	0.00	0.00	0.00
SOE	999114	0.12	0.33	0.00	0.00	0.00
EX	999114	0.34	0.47	0.00	0.00	1.00
Ln(Stock)	999114	0.18	0.58	0.00	0.00	0.00

Table 2 Panel A: Raw patterns for innovation dynamics surrounding IPOs

This table reports the OLS regression results estimating the innovation dynamics surrounding IPOs. Using a sample of all listed firms, we retain firm-year observations for a seven-year window centered on the IPO year, and we estimate the pooled OLS regression of the following model:

$$Pat_{it}(Inv_{it}) = \alpha + \beta_1 before_{it}^{-3} + \beta_2 before_{it}^{-2} + \beta_3 current_{it} + \beta_4 after_{it}^{1} + \beta_5 after_{it}^{2} + \beta_6 after_{it}^{3} + \varepsilon_{it}$$

The dependent variable is either Pat_{it}, firm *i*'s industry- and year-adjusted total patents filed in year *t*, or Inv_{it}, firm *i*'s industry- and year-adjusted invention patents filed in year *t*. We adjust innovation output variables by subtracting the average values of innovation outputs for all firms (excluding the listed firms) in the same two-digit industry and year. $before_{it}^{-3}$ ($before_{it}^{-2}$) is a dummy that equals one if a firm-year observation is from 3 (2) years before the IPO year, and zero otherwise. $current_{it}$ is a dummy that equals one if a firm-year observation is in its IPO year, and zero otherwise. $after_{it}^{1}$ ($after_{it}^{2}$, $after_{it}^{3}$) is a dummy that equals one if a firm-year observation is 1 (2, 3) year after the IPO year, and zero otherwise. Therefore, the omitted group (benchmark) comprises the observations 1 year before the IPO year. Standard errors clustered by industry are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Pat	(2) Inv
$before^3$	-0.262	-0.086
	(0.313)	(0.102)
$before^2$	-0.054	-0.045
	(0.218)	(0.069)
current	0.433*	0.246*
	(0.220)	(0.123)
$after^1$	1.012**	0.610***
	(0.423)	(0.212)
$after^2$	0.757**	0.561***
	(0.292)	(0.197)
$after^3$	1.255**	0.820**
	(0.532)	(0.315)
Constant	1.465***	0.302***
	(0.369)	(0.061)
Observations	2,118	2,118
R-squared	0.005	0.012

Table 2 Panel B: OLS regression of innovation outcomes on IPOs

This table reports the OLS results estimating the effect of an IPO on innovation output variables. We estimate the pooled OLS regression of the following model:

$$\text{LnPat}_{it+\text{n}}(\text{LnInv}_{it+\text{n}}) = \alpha + \beta list_{it} + \gamma X_{it} + year_t + industry_{ij} + \varepsilon_{it}$$

using a sample of all listed and non-listed firms from 1998 to 2007. The dependent variable LnPat_{it+n} is the natural logarithm of one plus the total number of patents applied for one (t+1), two (t+2), and three (t+3) years after year *t*, and the results are reported in columns (1)–(3), respectively. The dependent variable LnInv_{it+n} is the natural logarithm of one plus the number of invention patents applied for one (t+1), two (t+2), and three (t+3) years after year *t*, and the results are reported in columns (4)–(6), respectively. list_{it} is a dummy variable that equals one if an IPO occurs in year *t* for firm *i*, and zero otherwise. Year fixed effects, year_{it}, and industry fixed effects, industry_{it}, are included in all regressions. All other variables are as defined in the Appendix. Standard errors clustered by industry are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) LnPat_+1	(2) LnPat_+2	(3) LnPat_+3	(4) LnInv_+1	(5) LnInv_+2	(6) LnInv_+3
List	**0.336*** **	**0.312*** **	**0.406*** **	**0.205*** **	**0.183*** **	**0.263*** **
	(0.071)	**(0.053)**	**(0.093)**	**(0.041)**	**(0.038)**	**(0.076)**
Ln(AT)	0.048***	0.050***	0.052***	0.016***	0.017***	0.019***
	(0.007)	(0.007)	(0.008)	(0.003)	(0.003)	(0.003)
FixAT_AT	-0.066***	-0.071***	-0.079***	-0.017***	-0.022***	-0.025***
	(0.013)	(0.014)	(0.015)	(0.004)	(0.005)	(0.006)
Admin_a	0.214***	0.223***	0.235***	0.062***	0.066***	0.074***
	(0.035)	(0.037)	(0.039)	(0.014)	(0.015)	(0.016)
Ln(Age)	-0.004**	-0.005***	-0.005***	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
SOE	0.008	0.009	0.010	0.006**	0.006**	0.006**
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
EX	0.025***	0.026***	0.026***	0.006***	0.007***	0.007**
	(0.006)	(0.007)	(0.007)	(0.002)	(0.002)	(0.003)
Leverage	-0.024***	-0.023***	-0.024***	-0.007***	-0.009***	-0.009***
	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)
Liquidity	-0.007*	-0.007*	-0.008*	0.001	-0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)
Interest_At	-0.033	-0.056*	-0.047	0.036**	0.030	0.029
	(0.032)	(0.033)	(0.037)	(0.017)	(0.019)	(0.019)
ROA	0.053***	0.068***	0.088***	0.020***	0.028***	0.038***
	(0.009)	(0.011)	(0.015)	(0.004)	(0.006)	(0.008)
HI	-0.034	-0.037	-0.050*	-0.003	-0.006	-0.009
	(0.026)	(0.027)	(0.029)	(0.011)	(0.013)	(0.013)
HI^2	0.066*	0.076**	0.081**	0.023	0.029	0.028
	(0.034)	(0.036)	(0.038)	(0.020)	(0.023)	(0.025)
Constant	-0.440***	-0.459***	-0.482***	-0.159***	-0.171***	-0.186***
	(0.065)	(0.069)	(0.072)	(0.028)	(0.031)	(0.032)
Observations	839,761	709,997	580,425	839,761	709,997	580,425
R-squared	0.064	0.065	0.067	0.039	0.040	0.043
Year fixed effects	Y	Y	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y	Y	Y
Firm fixed effects	N	N	N	N	N	N

Standard errors in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Table 3: Difference-in-differences (DiD) test results

This table reports diagnostic tests and the DiD results concerning how IPOs affect firm innovation. Our sample contains firms that experienced an IPO from 1999 to 2006 and non-listed firms. We match firms using a one-to-one nearest neighbor PSM, with replacement, on a host of observable characteristics, including all independent variables used in equation (2), for the year before the IPO, the growth in the number of patents, g_pn, computed over the three-year period before the IPO, two-digit industry dummies, and year fixed effects. Definitions of all other variables are listed in the Appendix. Our treatment group contains those listed firms' observations in their IPO year. Our control group includes all non-listed firm-year observations. Panel A reports parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. The dependent variable equals one for the firm-year belonging to the treatment group and zero for those belonging to the control group. The "Pre-Match" column contains the parameter estimates of the probit model estimated using the sample prior to matching. These estimates are then used to generate the propensity scores for matching. The "Post-Match" column contains the parameter estimates of the probit model estimated using the subsample of matched treatment–control pairs after matching. Robust standard errors are displayed in parentheses below each coefficient estimate. Panel B presents the univariate comparisons between the treatment and control firms' characteristics, and their corresponding p-values, testing the null hypothesis that the differences are zero. Panel C gives the DiD test results. *Patent* is the mean of firm *i*'s number of patents in the three-year window before or after the IPO. *Invention* is the average of firm *i*'s number of inventions in the three-year window before or after the IPO. Panel D reports the regression results estimating the innovation dynamics of the treatment and control firms surrounding an IPO. The dependent variable is either Ln Pat_{it}, the natural logarithm of one plus firm *i*'s number of patents in year *t*, or Ln Inv_{it}, the natural logarithm of one plus firm *i*'s number of inventions in year *t*. list_i is a dummy that equals one for treatment firms (listed firms) and zero for control firms (non-listed firms). $\text{before}_{it}^{2\&3}$ is a dummy that equals one if a firm-year observation is from 2 or 3 years before the IPO year (year 0), and zero otherwise. current_{it} is a dummy that equals one if a firm-year observation is in the IPO year (year 0), and zero otherwise. after_{it}^{1} (after_{it}^{2}, after_{it}^{3}) is a dummy that equals one if a firm-year observation is from 1 (2,3) year after the IPO year (year 0), and zero otherwise. Robust standard errors are displayed in parentheses under each coefficient estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Panel A: Pre-match propensity score regression and post-match diagnostic regression

VARIABLES	(1) Pre-match	(2) Post-match
Ln(AT)	0.256***	-0.046
	(0.013)	(0.043)
FixAT_AT	-0.373***	0.045
	(0.100)	(0.365)
Admin_AT	0.863***	0.141
	(0.178)	(0.992)
Ln(Age)	-0.185***	0.000
	(0.021)	(0.054)
SOE	0.243***	0.061
	(0.043)	(0.112)
EX	-0.081**	-0.007
	(0.036)	(0.113)
Leverage	-0.284***	0.048
	(0.086)	(0.333)
Liquidity	-0.006	-0.074
	(0.096)	(0.298)
Interes_AT	0.915	1.645
	(0.980)	(3.962)
ROA	0.644***	0.499
	(0.086)	(0.510)
HI	0.151	0.125
	(0.420)	(1.265)
HI^2	-0.599	-1.046
	(0.778)	(2.248)
Stock	0.098***	0.077
	(0.019)	(0.050)
g_pn	0.050	0.045
	(0.030)	(0.077)
Constant	-5.441***	0.408
	(0.183)	(0.627)
Observations	773,090	710
P-value of Chi-squared	0.0000	1.0000
Pseudo-R^2	0.1652	0.0066
Industry fixed effects	Y	Y
Year fixed effects	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Panel B: Post-match differences

	Control	Treat	Treat-Control	p-value
Ln(AT)	11.94	11.86	-0.08	0.45
FixAT_AT	0.29	0.29	0.00	0.85
Admin_AT	0.06	0.07	0.00	0.34
Ln(Age)	1.99	2.01	0.01	0.86
SOE	0.37	0.37	0.01	0.88
EX	0.42	0.42	0.00	1.00
Leverage	0.53	0.53	0.00	0.87
Liquidity	0.11	0.11	0.00	0.81
Interest_AT	0.01	0.01	0.00	0.63
ROA	0.08	0.09	0.01	0.36
HI	0.06	0.06	0.00	0.67
HI^2	0.01	0.01	0.00	0.53
Stock	0.57	0.69	0.12	0.16
g_pn	0.12	0.14	0.04	0.40

Table 3 Panel C: DID estimates

	Mean Treatment Difference (after-before)	Mean Control Difference (after-before)	Mean DID estimate (treat-control)	p-value for DID Estimate
Patent	1.577	0.014	1.563	0.001
(s.e.)	0.405	0.262	0.482	
Inv	0.858	0.086	0.772	0.000
(s.e.)	0.198	0.072	0.210	

Table 3 Panel D: DiD analysis for innovation dynamics

VARIABLES	(1) LnPat	(2) LnInv
$list_i * before_{it}^{2\&3}$	-0.043	-0.066
	(0.052)	(0.041)
$list_i * current$	0.075	0.043
	(0.050)	(0.031)
$list_i * after_{it}^{1}$	**0.164*** **	**0.093*** **
	(0.052)	**(0.033)**
$list_i * after_{it}^{2}$	**0.231*** **	**0.101*** **
	(0.054)	**(0.034)**
$list_i * after_{it}^{3}$	**0.291*** **	**0.192*** **
	(0.062)	**(0.042)**
$before_{it}^{2}$	0.080**	0.043*
	(0.038)	(0.023)
$before_{it}^{1}$	0.116***	0.062***
	(0.044)	(0.024)
Current	0.096**	0.047*
	(0.042)	(0.024)
$after_{it}^{1}$	**0.096** **	**0.068*** **
	(0.043)	**(0.024)**
$after_{it}^{2}$	**0.060**	**0.071** **
	(0.047)	**(0.029)**
$after_{it}^{3}$	**0.127** **	**0.078*** **
	(0.050)	**(0.028)**
Constant	0.173***	0.064**
	(0.044)	(0.025)
Observations	4,253	4,253
R-squared	0.655	0.576
Year fixed effects	Y	Y
Firm fixed effects	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Difference-in-differences (DiD) test results for innovation quality

This table reports the DiD test results concerning how an IPO affects innovation quality. We use the PSM sample and retain firm-year observations for both treatment and control groups for a seven-year window centered on the IPO year. Panel A illustrates a regression run with the dependent variable *inventor_per_patent*, which is equal to the average number of inventors per patent for firm *i* in year *t*. Panel B reports the univariate DiD test results for *Inv_ratio*, which is the ratio of invention patents over the total patent number over the three-year window before and after the IPO.

Table 4 Panel A: Inventor per patent regression

VARIABLES	(1) inventor_per_patent
$list_i * before_{it}^{2\&3}$	-0.102
	(0.083)
$list_i * current$	0.075
	(0.091)
$list_i * after_{it}^{1}$	**0.200***
	(0.106)
$list_i * after_{it}^{2}$	**0.299****
	(0.139)
$list_i * after_{it}^{3}$	**0.433****
	(0.180)
$before_{it}^{2}$	0.071
	(0.060)
$before_{it}^{1}$	0.064
	(0.077)
current	-0.035
	(0.077)
$after_{it}^{1}$	-0.107
	(0.087)
$after_{it}^{2}$	-0.077
	(0.110)
$after_{it}^{3}$	-0.282*
	(0.161)
Constant	2.251***
	(0.092)
Observations	9,088
R-squared	0.611
Year fixed effects	Y
Firm fixed effects	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Panel B: Univariate DiD estimates

	Mean Treatment Difference (after-before)	Mean Control Difference (after-before)	Mean DID estimate (treat-control)	p-value for DID estimates
Inv_ratio	0.077***	0.033**	**0.043***	**0.068**
(s.e.)	0.018	0.016	0.024	

Table 5: DiD analysis for innovation scope

This table reports the regression results examining the effect of an IPO on the expansion of innovation scope, and then estimating the related (unrelated) innovation dynamics of treatment and control firms surrounding an IPO. We use the PSM sample and retain firm-year observations for both treatment and control groups for a seven-year window centered on the IPO year. We estimate the following model:

$$y_{it} = \alpha + \beta_1 list_i * before_{it}^{2\&3} + \beta_2 list_i * current_{it} + \beta_3 list_i * after_{it}^1 + \beta_4 list_i * after_{it}^2 + \beta_5 list_i * after_{it}^3 + \beta_6 before_{it}^{2\&3} + before_{it}^1 + current_{it} + after_{it}^1 + after_{it}^2 + after_{it}^3 + year_t + firm_i + \varepsilon_{it}$$

The dependent variable y_{it} in the various specifications is as follows: $Dunrelated_{it}$, a dummy that equals one if firm *i* has unrelated patents in year *t* and zero otherwise; $UnrelatedClass_{it}$, the number of technology classes to which firm i's unrelated patents belong; $lnRelatedPat_{it}$, the natural logarithm of one plus firm *i*'s number of related patents in year *t*; $lnUnrelatedPat_{it}$, the natural logarithm of one plus firm *i*'s number of unrelated patents in year *t*; $lnRelatedInv_{it}$, the natural logarithm of one plus firm *i*'s number of related inventions in year *t*; $lnUnrelatedInv_{it}$, the natural logarithm of one plus firm *i*'s number of unrelated inventions in year *t*. The patent's technology class is defined based on its IPC. We describe this detailed procedure in Section 4.3. Related innovations are those related to a firm's core business and unrelated innovations are those unrelated to a firm's core business. $\mathrm{list_i}$ is a dummy that equals one for treatment firms (listed firms), and zero for control firms (non-listed firms). $\mathrm{before_{it}^{2,3}}$ is a dummy that equals one if a firm-year observation is from 2 or 3 years before the IPO year (year 0), and zero otherwise. $\mathrm{current_{it}}$ is a dummy that equals one if a firm-year observation is in the IPO year (year 0), and zero otherwise. $\mathrm{after_{it}^1}$ ($\mathrm{after_{it}^2}$, $\mathrm{after_{it}^3}$) is a dummy that equals one if a firm-year observation is from 1 (2,3) year after the IPO year (year 0), and zero otherwise. All specifications include year and firm fixed effects. Robust standard errors are displayed in parentheses under each coefficient estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Dunrelated	(2) UnrelatedClass	(3) LnrRelatedPat	(4) LnUnrelatedPat	(5) LnRelatedInv	(6) LnUnrelatedInv
$list_i * before^{23}$	-0.005	-0.069	-0.036	-0.035	-0.040	-0.034
	(0.023)	(0.062)	(0.033)	(0.034)	(0.026)	(0.023)
$list_i * current$	**0.031**	**0.076**	**0.016**	**0.047**	**0.028**	**0.031**
	(0.025)	**(0.060)**	**(0.032)**	**(0.034)**	**(0.025)**	**(0.024)**
$list_i * after_{it}^1$	**0.054****	**0.085**	**0.081****	**0.076****	**0.069*****	**0.049***
	(0.025)	**(0.063)**	**(0.032)**	**(0.034)**	**(0.027)**	**(0.025)**
$list_i * after^2$	**0.061****	**0.217*****	**0.110*****	**0.113*****	**0.066****	**0.086*****
	(0.026)	**(0.068)**	**(0.036)**	**(0.036)**	**(0.029)**	**(0.026)**
$list_i * after^3$	**0.115*****	**0.337*****	**0.143*****	**0.198*****	**0.091*****	**0.147*****
	(0.030)	**(0.074)**	**(0.041)**	**(0.039)**	**(0.033)**	**(0.031)**
$before^2$	0.045***	0.088*	0.042*	0.057**	0.033*	0.025
	(0.016)	(0.049)	(0.025)	(0.026)	(0.020)	(0.016)
$before^1$	0.060***	0.063	0.059**	0.060**	0.039**	0.034**
	(0.019)	(0.053)	(0.024)	(0.027)	(0.018)	(0.017)
$current$	0.063***	0.068	0.062**	0.064**	0.040**	0.024
	(0.018)	(0.052)	(0.025)	(0.027)	(0.019)	(0.017)
$after^1$	0.063***	0.105*	0.048**	0.068**	0.043**	0.052***
	(0.020)	(0.056)	(0.022)	(0.028)	(0.018)	(0.019)
$after^2$	0.044**	0.022	0.058**	0.039	0.053**	0.040*
	(0.021)	(0.057)	(0.028)	(0.032)	(0.024)	(0.021)
$after^3$	0.057***	0.038	0.078***	0.035	0.063***	0.035*
	(0.022)	(0.056)	(0.027)	(0.030)	(0.022)	(0.020)
Constant	0.052***	0.158***	0.044*	0.097***	0.029	0.046**
	(0.018)	(0.053)	(0.024)	(0.028)	(0.019)	(0.018)
Observations	4,253	4,253	4,253	4,253	4,253	4,253
R-squared	0.536	0.588	0.571	0.650	0.501	0.556
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Cross-section analysis of an IPO's impact on innovation output

This table reports the effects of an IPO on firm innovation output across firms with different characteristics. We use the PSM sample and retain firm-year observations for both the treatment and control groups for a seven-year window centered on the IPO year. We focus on comparing the three-year window after the IPO to the three-year window before the IPO, and we drop the IPO year. The estimation model is as follows.

$$\ln Pat_{it}\ (\ln Inv_{it}) = \alpha + \beta_1 list_i * \mathrm{After}_{it}^{1\&2\&3} * X_i + \beta_2 list_i * After_{it}^{1\&2\&3} + \mathrm{After}_{it}^{1\&2\&3} * X_i + \mathrm{After}_{it}^{1\&2\&3} + firm_i + year_t + \varepsilon_{it}$$

The dependent variable in the specifications is as follows: $ln\, Pat_{it}$, the natural logarithm of one plus firm *i*'s number of patents in year *t*; $ln\, Inv_{it}$, the natural logarithm of one plus firm *i*'s number of invention patents in year *t*. X_i are relevant firm dummy variables. X_i takes the following forms: a corporate ownership indicator, such as the dummy variable, *SOE*, which equals one if the treatment group firm is an SOE, and zero otherwise; a dummy variable, *EXEHLD*, indicating whether the management team holds firm stock (one if management holds such stock, zero if not) after the IPO; a dummy variable, *Duality*, indicating if the *CEO* and the president are the same person (one if so, zero otherwise) after the IPO; a dummy variable, *Fixed*, equal to one if a firm's fixed assets ratio (*FixAT_AT*) is above the median level one year prior to the IPO; a dummy variable, *External_dependence*, equal to one if an industry belongs to the high external financing dependent group, zero otherwise. $After_{it}^{1\&2\&3}$ is a dummy equal to one if a firm-year observation is after the IPO. $list_i$ is a dummy that equals one for the treatment group, zero otherwise. For brevity, we only report the coefficient estimates of variables $list_{it} * After_{it}^{1\&2\&3}$ and $list_i * \mathrm{After}_{it}^{1\&2\&3} * X_i$. All specifications include year and firm fixed effects. Robust standard errors are displayed in parentheses under each coefficient estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Panel A: Cross-sectional analysis of an IPO's impact on innovation output: financial constraints

VARIABLES	(1) External Vs Internal LnPat	(2) External Vs Internal LnInv	(3) High fixed ratio Vs Low fixed ratio LnPat	(4) High fixed ratio Vs Low fixed ratio LnInv
$list{*}After^{1\&2\&3}$	0.139***	0.085**	0.293***	0.238***
	(0.052)	(0.036)	(0.045)	(0.039)
$list{*}After^{1\&2\&3} * External\_dependence$	**0.155****	**0.108****		
	(0.072)	(0.048)		
$list{*}After^{1\&2\&3} * Fixed$			**-0.098****	**-0.162*****
			(0.038)	(0.048)
Observations	3,543	3,543	3,543	3,543
R-squared	0.655	0.585	0.655	0.587
Year fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Panel B: Cross-sectional analysis of an IPO's impact on innovation output: governance and ownership

VARIABLES	(1) EXEHLD vs. non- EXEHLD LnPat	(2) EXEHLD vs. non- EXEHLD LnInv	(3) Duality vs. No duality LnPat	(4) Duality vs. No duality LnInv	(5) SOE vs. POE LnPat	(6) SOE vs. POE LnInv
$list{*}After^{1\&2\&3}$	0.232**	0.207***	0.343***	0.244***	0.341***	0.233***
	(0.095)	(0.063)	(0.075)	(0.052)	(0.047)	(0.031)
$list{*}After^{1\&2\&3} * EXEHLD$	**0.470*****	**0.280*****				
	(0.144)	(0.103)				
$list{*}After^{1\&2\&3} * Duality$			**0.526****	**0.477*****		
			(0.222)	(0.157)		
$list{*}After^{1\&2\&3} * SOE$					**-0.257*****	**-0.198*****
					(0.078)	(0.051)
Observations	1,464	1,464	1,464	1,464	3,543	3,543
R-squared	0.672	0.574	0.672	0.578	0.655	0.586
Year fixed effects	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Inventor mobility and innovative productivity

This table reports the effects of an IPO on inventors' mobility and innovative activity. We use the PSM sample and retain firm-year observations for both treatment and control groups for a seven-year window centered on the IPO year. Inventors are classified into three categories: stayers, leavers, and newcomers, as defined in the text. Panel A provides the DiD results for the yearly average of inventor numbers across firms, and per inventor total patent and invention patent. Inventor is the yearly average of firm *i*'s inventor number in the three-year window before or after the IPO, which is calculated by the total inventor number divided by the year of firm survival. Patent (Invention) is per inventor patents (inventions) of firm *i* in the three-year window before or after an IPO, which is measured by total patents (inventions) divided by the number of total inventors of firm *i*.

Panel B reports the effects of an IPO on inventors' departure. We estimate the probit model below:

$$Leaver_{il} = \alpha + \beta Treat_{il} + \gamma X_{i,-1} + list\_year_{it} + industry_{ij} + \varepsilon_i$$

We include stayers and leavers in our sample, where the dependent variable equals one if the inventor leaves firm, and zero otherwise. IPO is a dummy variable equal to one if a firm experiences an IPO, and zero otherwise. In all specifications, we control firm characteristics before an IPO and an inventor's total patents during the three years before an IPO as the inventor's productivity. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Table 7 Panel A: DiD estimates of inventor and innovative productivity

	Mean Treatment Difference (after-before)	Mean Control Difference (after-before)	Mean DID estimate (treat-control)	p-value for DID Estimate
Number of Inventors	3.461	0.445	3.016	0.001
(s.e.)	0.848	0.232	0.879	
per capita total patents	-0.145	-0.720	0.575	0.242
(s.e.)	0.247	0.424	0.491	
Per capita Invention patents	0.081	0.014	0.067	0.379
(s.e.)	0.072	0.024	0.076	

Table 7 Panel B: DiD analysis for inventor mobility

VARIABLES	leaver	Leaver
Treat	**-0.692*** **	**-0.719*** **
	(0.164)	**(0.166)**
Pre_productivity		-0.017
		(0.013)
Ln(At)	0.223*	0.224*
	(0.125)	(0.125)
FixAT_AT	0.881	0.843
	(0.862)	(0.864)
Admin_AT	-1.389	-1.428
	(1.697)	(1.698)
Ln(Age)	-0.116	-0.121
	(0.108)	(0.109)
SOE	0.621***	0.593***
	(0.194)	(0.195)
EX	-0.060	-0.039
	(0.216)	(0.217)
Leverage	-0.749	-0.748
	(0.811)	(0.814)
Liquidity	-0.216	-0.215
	(0.763)	(0.765)
Interest_AT	-20.971*	-20.181*
	(11.992)	(12.049)
ROA	-1.214	-1.309
	(1.316)	(1.321)
HI	3.306	2.838
	(3.747)	(3.777)
HI^2	-12.445	-11.327
	(11.232)	(11.340)
Constant	-8.320	-8.303
	(138.972)	(139.139)
Observations	600	600
List year fixed effects	Y	Y
Industry fixed effects	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: The real effect of innovation: innovation and firm value

This table reports the effect of innovation on firm value. We focus only on the IPO firms and aggregate all subsidiary firms' patent applications at the parent firm level. The accounting information is collected from CSMAR. We estimate the following model:

$$\Delta Q_{i,3\to 6} = \alpha + \beta Pat_{i[1,3]} Inv_{i[1,3],} + \gamma X_{i,3} + list\_year_{it} + \varepsilon_i$$

The dependent variable is $\Delta Q_{i,3\to 6}$, the change of Tobin's Q from the end of the third year after an IPO to the end of the sixth year after an IPO. $Pat_{i[1,3]}$ ($Inv_{i[1,3]}$) is firm i's total patent (invention patent) filing over the three years after an IPO. The firm characteristic variables in the regression are measured at the end of the third year after an IPO, and the definitions of these variables are in the Appendix. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) $\Delta \text{Ln}Q_{i,t+3\to t+6}$	(2) $\Delta \text{Ln}Q_{i,t+3\to t+6}$
$\boldsymbol{Pat_{i[1,3]}}$	**0.005***	
	(0.003)	
$\boldsymbol{Inv_{i[1,3]}}$		**0.014***
		(0.007)
$AccuRET_{i[1,3]}$	-0.073	-0.074
	(0.103)	(0.103)
$Q_{i,3}$	-0.123	-0.112
	(0.159)	(0.159)
$Ln(AT)_{i,3}$	-0.580***	-0.537***
	(0.181)	(0.178)
$FixAT\_AT_{i,3}$	-0.326	-0.497
	(0.768)	(0.752)
$Leverage_{i,3}$	1.864**	1.663**
	(0.756)	(0.758)
$ROA_{i,3}$	-2.528	-3.344
	(3.167)	(3.164)
Constant	10.824***	10.103***
	(3.792)	(3.750)
Observations	148	148
R-squared	0.514	0.514
List year fixed effects	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: The robustness check: Heckman-style two-stage model

This table presents the second stage results of the two-step Heckman-type estimation and the counterfactual analysis. The dependent variable in Panel A is the patent (invention) application growth, which is defined as the difference between the average patent (invention) application over the next 3 year and the patent (invention) application of the past year. The independent variables in this regression include inverse Mills ratios (generated in the first stage regression) and the firm control variables we introduce in prior analysis. Firm fixed effect and year fixed effect are also included in all regressions. Panel B reports the results of the counterfactual analysis based on the switching regression model of Panel A. It reports the actual patent application growth for IPO firms, patent application growth if IPO firms had not gone IPO, and the difference between actual and hypothetical patent application growth (patent application growth improvement). Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Panel A: Second stage results for endogenous switching regressions

VARIABLES	IPO firm LnPat_growth	Non-IPO firm LnPat_growth	IPO firm LnInv_growth	Non-IPO firm LnInv_growth
Inverse Mills Ratios	1.209***	0.225***	0.367***	0.038***
	(0.099)	(0.002)	(0.069)	(0.001)
Ln(AT)	0.192***	0.030***	0.056*	0.008***
	(0.049)	(0.001)	(0.034)	(0.000)
FixAT_AT	-0.305*	-0.006*	-0.297**	-0.003**
	(0.171)	(0.004)	(0.119)	(0.002)
Admin_AT	1.318**	0.049***	0.796**	0.018***
	(0.538)	(0.008)	(0.374)	(0.004)
Ln(Age)	-0.107***	-0.021***	-0.019	-0.004***
	(0.032)	(0.001)	(0.023)	(0.000)
SOE	0.128**	0.005**	0.094**	-0.002
	(0.058)	(0.002)	(0.041)	(0.001)
EX	-0.011	-0.000	-0.043	0.001
	(0.060)	(0.002)	(0.042)	(0.001)
Leverage	-0.084	-0.011***	-0.054	0.000
	(0.170)	(0.003)	(0.118)	(0.001)
Liquidity	0.042	0.007**	0.126	0.002
	(0.135)	(0.003)	(0.094)	(0.001)
Interest_AT	-1.680	0.046	-0.364	-0.000
	(1.924)	(0.030)	(1.339)	(0.014)
ROA	0.396*	0.036***	0.152	0.004**
	(0.222)	(0.004)	(0.155)	(0.002)
HI	0.465	0.032*	0.463	0.002
	(0.715)	(0.017)	(0.498)	(0.008)
HI^2	-0.755	-0.076***	-0.624	-0.000
	(0.892)	(0.022)	(0.621)	(0.010)
Constant	-5.876***	-1.126***	-1.699***	-0.213***
	(0.793)	(0.017)	(0.552)	(0.008)
Observations	2,217	700,459	2,217	700,459
R-squared	0.311	0.296	0.321	0.337
Year fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 Panel B: Actual and hypothetical patent and invention growth for IPO firms

	Actual LnPat_growth for IPO firms	LnPat_growth for IPO firms if they had not gone IPO	LnPat_growth improvement
Mean	0.184	-0.087	0.271 ***
(s.e.)	0.015	0.002	0.015
	Actual LnInv_growth for IPO firms	LnInv_growth for IPO firms if they had not gone IPO	Lninv_growth improvement
Mean	0.140	-0.002	0.142 ***
(s.e.)	0.011	0.000	0.011

Appendix

Table A1: Definition of variables

Innovation Measure	
Pat	Total number of patents applied for in a given year
Inv	Total number of invention patents applied for in a given year
Related patents	Number of patents that are related to a firm's core business, i.e., the number of patents that are mapped to a firm's field, defined mainly based on the two-digit CIC industry
Unrelated patents	Number of patents that are unrelated to a firm's core business, i.e., the number of patents that are not mapped to a firm's field, defined mainly based on the two-digit CIC industry
Firm Characteristics	
Ln(AT)	Natural logarithm of total assets
FixAT_AT	Net fixed assets divided by the book value of total assets
Admin_AT	Administration expenditure divided by the book value of total assets
Ln(Age)	Natural logarithm of the number of years since the firm's establishment
SOE	A dummy equal to 1 if a firm's registered capital held by the state exceeds 50% or the "controlling shareholder" identifies the state as its controlling holder
EX	A dummy equal to 1 if a firm exports
Leverage	Book value of total debt divided by the book value of total assets
Liquidity_AT	The difference of current assets and debt divided by total assets
Interest_AT	Interest expenditure divided by the book value of total assets
ROA	Operating profit divided by the book value of total assets
HI	Herfindahl index based on annual sales in the cell of two-digit CIC industry and province
Ln(Stock)	Natural logarithm of firm's stock; stock is the sum of the patents a firm has applied for before a given year (the given year included)
Growth of patent	Growth in the number of patents computed over the three-year period before an IPO, LnPat_t-LnPat_it-2; t is the IPO year
Tobin's Q	The sum of the firm's market value of equity plus the book value of its debt divided by the firm's total assets

Table A2: External financing across industries

External finance dependent industries	
13	Processing of Foods
14	Manufacture of Foods
15	Manufacture of Beverages
16	Manufacture of Tobacco
18	Manufacture of Apparel, Footwear, & Caps
19	Manufacture of Leather, Fur, & Feather
20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, & Straw Products
22	Manufacture of Paper & Paper Products
23	Printing, Reproduction of Recording Media
24	Manufacture of Articles for Culture, Education, & Sports Activities
26	Manufacture of Raw Chemical Materials
28	Manufacture of Chemical Fibers
29	Manufacture of Rubber
32	Smelting & Pressing of Ferrous Metals
33	Smelting & Pressing of Non-ferrous Metals
Internal finance dependent industries	
17	Manufacture of Textiles
21	Manufacture of Furniture
25	Processing of Petroleum, Coking, &Fuel
27	Manufacture of Medicines
30	Manufacture of Plastics
31	Manufacture of Non-metallic Mineral Goods
34	Manufacture of Metal Products
35	Manufacture of General Purpose Machinery
36	Manufacture of Special Purpose Machinery
37	Manufacture of Transport Equipment
39	Electrical Machinery & Equipment
40	Computers & Other Electronic Equipment
41	Manufacture of Measuring Instruments & Machinery for Cultural Activity & Office Work
42	Manufacture of Artwork