Innovation and Initial Public Offering: Evidence from China

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Abstract

A successful innovation can result in new product releases that drive up business profits and create barriers to entry. However, due to the inherent risk of firm innovation, whether firms can ultimately benefit from increased innovation output is an empirical question. Our paper shows the likelihood of a successful mainland IPO for a sample of VC-backed entrepreneurial firms in China will increase as post investment innovation output increases. Additionally, we provide empirical evidence that innovation only affects mainland listing likelihood and not the probability of being acquired. Lastly, we show that innovation only affects IPO success in China by assisting with firm growth and meeting the stringent regulatory requirements. Once the firms reach the IPO review process, firm innovation does not further affect IPO approval.

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Introduction

Despite its relative short history, the Chinese capital market has experienced rapid advancement and has become the 2nd largest in the world. According to the World Bank, over the past 20 years, China's domestic market capitalization rose from around 500 billion USD to 11 trillion USD in 2022, second only to the United States and double the value of the 3rd highest country Japan. In terms of global IPO issuance, the Chinese mainland exchanges ranked first worldwide with 424 IPOs, raising a total of 85.2 billion USD and accounting for 39% of global IPO issuance in 2022.[1] Given the significance and rapid growth of the Chinese capital market, one important question to investigate is whether firms with greater innovation capabilities have higher chances to IPO in mainland China.

How innovation impacts firm IPO likelihood is important for at least two reasons. Firstly, innovation is the foundation of quality economic growth (Solow, 1957; Kogan et al., 2017; Acemoglu et al., 2018). Economists such as Solow and Rosenberg have attributed technological innovation as the major and dominant force of economic expansion (Rosenberg, 2004). In recent years, innovation has become a key agenda of the Chinese government in achieving Chinese modernization. We explore the allocation efficiency of China's capital market in terms of providing opportunities for innovative entrepreneurial firms in the form of a mainland listing. If higher opportunities exists, the Chinese capital market is efficient in promoting high quality economic growth based on technological innovation.

Secondly, the current literature on innovation and IPO mainly focuses on the different innovation strategies before and after an IPO (Bernstein, 2015; Acharya and Xu, 2017). Evidence on whether innovation has value for private firms and its impact

[1] The data is disclosed in the PricewaterhouseCoopers report "China IPO Watch 2022."

on firm exit prospects are relatively blank. Due to the inherent risks of firm innovation, whether firms can ultimately benefit from increased innovation output is an empirical question. For individual firms, innovation can contribute to firm growth and profitability through novel products (Babina et al., 2024), increased productivity (Bartel et al., 2007), and resilience to competition (Hombert and Matray, 2018). In the United States, entrepreneurial firms that win the patent "lottery" during their first patent application exhibit greater employment growth, higher sales, and pursue more subsequent innovation (Farre-Mensa et al., 2020). However, failed commercialization of innovation and unsuccessful new product launches can result in financial deterioration. Innovation requires exceptional tolerance for failure due to its unpredictable and idiosyncratic natures that are impossible to predict (Holmstrom, 1989; Tian and Wang, 2014). Firms are careful at introducing new products at experimental basis (Braguinsky et al., 2021) and technological innovation can lead to over adoption of risky technologies, creating technology bubbles that may lead to overcapacity and losses (DeMarzo et al., 2007). Innovative activities also require sunk development costs, and unsuccessful commercialization and product development can result in significant write-offs and losses, ultimately driving a firm to bankruptcy. Fernandes and Paunov (2015) note that a new product introduction may not cover the cost of its R&D and can be imitated or replaced by competitors, leading to worse firm financials.

The Chinese IPO market provides a unique setting to explore innovation's effect on listing likelihood. In order to IPO in China, all firms must satisfy the stringent financial requirements outlined by the China Securities Regulatory Commission (CSRC) such as revenue, cash flow, and net income. After meeting the requirements, firms wait in a queue to be reviewed by the CSRC for final approval. Unlike the listing process in the United States, listing in mainland China has various political and regulatory uncertainties. Previous research illustrates that turnover of local politicians (Piotroski and Zhang, 2014) and politically connected executives (Liu, Tang, and Tian, 2013) can accelerate IPO approval in mainland China. Cong and Howell (2021) note that the IPO review is an opaque process, and innovation is not a mandatory criteria. Therefore, due to these uncertainties, it is especially important to understand the role innovation plays in the Chinese IPO process. The paper aims to provide fresh insight into the effect of innovation on the two stages of the mainland listing.

We test the impact of innovation on the firm's mainland listing likelihood by constructing a unique sample of 2,199 Chinese firms with first round of investment by top 100 VCs from 2000 to 2013. Following the work of Sørensen (2007), this leaves the firms with at least seven years to exit. Due to the unavailability of R&D data for private firms, we measure innovation output as the number of patents applied and granted. We use hand-collected data from the Chinese State Intellectual Property Office (CSIPO), which is the standard for acquiring innovation information for firms in China. For our baseline analysis, our dependent variable is a dummy variable that indicates whether the firm eventually IPOs in mainland China. Using OLS and logistic models, we find that firms that have a high three-year average post investment innovation output have a higher chance of a successful mainland IPO. This is consistent for all specifications. Controlling for VC and deal level factors, a unit increase in log patent application and log patent granted can increase the odds of IPO 60% and 65%, respectively.

To eliminate endogeneity issues in our baseline tests, we introduce two instrumental variables. First, we use the implementation of local patent dispute jurisdiction as an IV for innovation. In 1985, the Chinese Supreme Court issued a "Notice on Several Issues Concerning the Implementation of Patent Trials", which handed out patent dispute jurisdiction of each province and autonomous region to the courts of their respective capital cities. Patent disputes in other cities in the province must be handled by the provincial capital city courts. Gradually, local patent dispute jurisdiction was given to non-capital cities by the Chinese Supreme Court as patent cases surged and judicial personnel became familiar with patent disputes. The staggered implementation of local patent dispute increases local IPR protection thereby stimulating local firm innovation. This creates an effective instrument for our study since the implementation of local jurisdiction only affects firm IPO likelihood through its effect on local firm innovation. The first stage and second stages of the 2SLS are consistent with our hypothesis.

For the second IV, we use an inventor founder dummy variable. An inventor founder is defined by whether the founder of the company is an inventor for a patent applied by the company. Since the technical founders have technological expertise, they can have research-related insights and be better at picking innovative projects. Islam and Zein (2020) find that inventor CEOs have a positive impact on patent quantity and quality. We show that an inventor founder has a similar positive effect on firm innovation in the first stage of 2SLS. During the second stage, firm innovation positively and significantly impacts the success of going public in mainland China.

For our robustness tests, we show that innovation is positive and statistically significant for increasing the likelihood of IPO across all mainland listing boards. This finding indicates that it is not because of the newly established STAR and ChiNext markets, which place a greater emphasis on technology and innovation, that make our results significant. Secondly, our baseline results use a three-year average innovation time frame to test the probability of IPO. In our robustness test, we incorporate averages of two-year, four-year, and five-year patent application and patent granted data. The results show that they are all positive and statistically significant. Furthermore, we used a multinomial logit regression to show how innovation affects other exits such as being acquired and listing overseas. Our results indicate that innovation increases IPO likelihood in mainland China and decreases the chances of no exits at a 1% significant level. This provides empirical evidence that firms with high innovation choose to exit through an IPO and innovation improves firm exit probabilities. Lastly, we illustrate that not only patent quantity, but also patent quality affects the chances of a mainland IPO.

Due to the regulatory environment in the Chinese mainland listings, we theorize that innovation affects mainland listing by allowing the entrepreneurial firms to meet the stringent size and health requirements. We propose that the main mechanism for assisting innovative firms to become listed in mainland China is innovation's impact on company growth. We provide two pieces of evidence that support the growth theory. We find that more innovative firms are more likely to receive a second round of investment using the Cox proportional hazard model. A firm's innovation output increases the hazard rate, which is the probability that the firm will receive further financing. Secondly, we show innovation impacts firm growth through human capital. We propose that more innovative firms have a greater focus on talents; thus, they will hire more skilled workers compared to their counterparts. By constructing a unique dataset of job hiring data, we illustrate that innovation has a positive impact on job hiring, especially for skilled workers. Human capital is vital for firms to develop and appropriate new technology necessary for growth. Additional financing and human capital allow the firm to expand, increase profitability certainty and VC monitoring, and improve firm performance.

Lastly, we examine whether a firm's innovation output can influence the approval decision of the CSRC. After meeting the initial listing requirements, the application is further reviewed by the Stock Issuance Examination and Verification Committee of the CSRC. Factors affecting the review process and the final IPO approval are opaque (Cong and Howell, 2021). Since the aim of the review is to ensure the accuracy and health of the firm in terms of sustainability and growth, we hypothesize that the CSRC committee does not facilitate listing approval of highly innovative firms. Our results support they hypothesize. Overall, these findings indicate that innovation can help a firm meet the listing requirements imposed by the CSRC such as company size and health. However, once under review, the CSRC acts in an unbiased manner and does not internally favor firms with high innovation.

First, the paper adds to the literature on innovation and IPO. Firms can alter their innovation strategy as they become public. Bernstein (2015) notes that the quality of internal innovation declines after a firm goes public. Dambra and Gustafson (2021) show that mandatory disclosure and governance as result of going public reduces firm innovation. Cox et al. (2021) show that the cost of the IPO process for the firm has a significant impact on the firm's post-IPO innovation output. In China, improved stock price informativeness is associated with greater innovation (Tan et al., 2020). Once a firm becomes public, it can have different innovation strategies due to investment horizons, financial constraints, talent attraction, and disclosure requirements. This paper adds to this strand of literature by providing new insight in private firm innovation before IPO by separating firms that eventually IPO in mainland China and those that do not. By proposing a unique identification strategy, we show that firms that eventually become listed in mainland China have higher pre-IPO innovation compared to those that remain private or exit through other methods.

The second strand of literature the paper relates to is venture capital and innovation. Kortum and Lerner (2000) find that an increase in venture capital activity in a certain industry is associated with significantly higher innovation as measured by patents. Additionally, CVC-backed firms produce more patents than their independent venture capital counterparts (Chemmanur, Loutskina, and Tian, 2014). Furthermore, Tian and Wang (2014) find that more failure-tolerant VCs promote more innovation in target firms, particularly in firms that are deemed to have high failure risk. In terms of VC exits, Hall and Lerner (2010) note that previous research indicates that the most profitable exit for a venture capital firm is usually through an IPO. Firms decide to go public at the peak of their productivity cycle (Chemmanur, He, and Nandy, 2010) and following an innovation breakthrough (Ferreira, Manso, and Silva, 2014). Furthermore, Schwienbacher (2008) shows that the optimal exit strategy for highly innovative VC-backed firms is through IPO due to private benefits and product differentiation. These literature shows how VCs influence firm innovation and that different VC characteristics can significantly affect their portfolio firm's innovation activities. This paper builds upon these ideas and provides fresh insight on how these VC induced innovations can ultimately help the entrepreneurial firms in the form of a higher mainland listing likelihood. It shows that by providing financing and assisting with firm innovation, VCs can increase the probability of a successful exit for their portfolio firms.

The last strand of literature focuses on how private and public firms differ in their innovation. Arrow (1972) argues that firms in a freely competitive market will invest less than the optimal amount of innovation and research due to innovation's inherent risky nature. From the perspective of public equity, Acharya and Xu (2017) find that public firms that are dependent on external financing have superior innovation compared to their private counterparts; however, for firms dependent on internal financing, there is no difference. This indicates that innovation can be promoted by reducing financing constraints faced by external financing dependent firms. How financial constraints can limit innovation is also documented by Hall and Lerner (2010), especially for smaller and younger companies (Brown et al., 2009). Additionally, Aggarwal and Hsu (2013) find innovation quality is best promoted under private ownership and lowest under public ownership. Private firms are more exploratory in their patents (Gao et al., 2018). Most literature focuses on how private and public firms differ in their innovation strategies. This paper adds to this strand of literature by providing new insight into how private firm innovation affects the outcome of firm exits and the value innovation for private firms.

1. Institutional Background

1.1 Venture Capital in China

China has been successful in nurturing its domestic VC market in the past decades. Venture capital started in China in 1985 after the Chinese Communist Party (CCP) issued the "Decision to Reform the Science and Technology System." According to White et al. (2005), the first mainland China venture capital firm was formed in 1986 by the State Science and Technology Commission and the Ministry of Finance. The Chinese government aims to promote local scientific research and technological capacities through venture capital, especially for non-state backed firms. Zhang (2016) notes that non-state backed firms in China were among the most financially constrained firms in the world in 2000; state banks almost exclusively lent to firms with government backing and venture capital firms facilitated financing to non-state backed firms. The venture capital market in China gained significant momentum after the internet boom in the late 1990s with the listings of Netease, Sina and Sohu (Zhang, 2016). According to Crunchbase, in 2021, China had the second largest global markets for venture funding after the United States and accounted for nearly 48% of all funding in Asia. Many major differences exist between the VC market in the United States and China.

Two prevalent dissimilarities related to our study are how different type of funds operate in China and VCs' exit strategies in China.

Funds in China are categorized into RMB funds and foreign funds. The majority of foreign funds in China are financed in USD. Lin (2021) notes that RMB funds are governed by the Chinese laws whereas foreign funds are governed by the fundraising jurisdiction. Additionally, foreign funds are subject to the investment restrictions of PRC Negative List for the Access of Foreign Investment, which prohibits and restricts foreign investments in certain industries in China. RMB funds that are partially funded by foreign investors are subject to PRC Foreign Investment law. Sectors that the government deem related to national security such as telecommunications, education and media often place investment limits or outright forbid foreign investment.

According to Lin (2021), offshore variable interest entities (VIE) holding structures are usually set up by foreign funds for easier exit through overseas listing or sale. This structure circumvents China's restriction on foreign investment on domestic companies, especially for companies in the restricted industries. In order to IPO in mainland China, the CSRC requires clear ownership structure, which prohibits companies with VIE structure to list in the mainland market in the past. If companies with VIE structure want to list domestically, they need to undo the VIE structure, which is costly and time consuming. Due to these innate restrictions, companies that have VIE structure favor being acquired or list abroad. On the other hand, RMB funds tend to exit through the Chinese domestic market in the form of a mainland IPO or equity transfer.

Another characteristic of the Chinese VC market is state-backed venture capital firms. Lin (2021) states that for government backed VCs, compensation is not based on performance but on seniority. By not tying compensation to fund performance like market-based VC firms, this structure does not sufficiently incentivize managers.

Additionally, Wu, Xu, and Jiang (2023) find that state backed VCs can assist their portfolio firms in acquiring better access to bank loans. This can be attributed to China's regionalism as noted by Ahlstrom, Bruton, and Yeh (2007). They find that each region, province, industry or even locality requires different resources to raise and fund portfolio firms such as taxes, tariffs, and subsidies. Government backed venture capital firms usually have better influence or *guanxi* compared to private venture capital firms in these areas. Hussain, Li, and Scott (2017) show that while state-backed VCs can reduce the equity gap for small and mid-size enterprises and technology-based small firms that align with government objectives, they also encourage unsustainable projects and crowd out private capital, resulting in welfare losses for the country.

1.2 IPO Process in China

The IPO process in China has always been governed by the CSRC. Su and Yu (2015) describe that the Chinese IPO regulatory system has evolved from a quota-managed Administrative Review and Approval System to a sponsor-based approval system. In a quota managed system, the securities authorities determine the total listing quota based on national planning and policies and then allocate the quota to local governments, which then select companies for review by the CSRC. In a sponsor-based approval system, the sponsors and sponsor representatives first tutor the companies aiming to list in China and conduct firm due diligence. The sponsors, usually the underwriters, ensure that all documents submitted to the CSRC are true and without misleading statements or omitted information. Unlike most other countries, besides fulfilling a registration and disclosure requirements, firms aiming to list in mainland China must meet the basic listing requirements for the boards they wish to apply. These listing requirements include minimum thresholds in company health such as revenue, net profit, and cash flows. For example, the financial requirements for listing on the Main Boards of

Shanghai and Shenzhen Stock Exchanges include (1) positive net income for the past three fiscal years and a cumulative net income of at least 30 million RMB for the past three fiscal years, (2) aggregate net cash flows from operating activities of at least 50 million RMB or aggregate operating revenue of at least 300 million RMB in the past three fiscal years, (3) proportion of intangible assets (excluding rights such as land use rights, mining rights and other rights) over net assets is less than 20% at the last accounting period, and (4) no unrecovered losses at the last accounting period.

Under the approval-based system, when firms are in queue, the Stock Issuance Examination and Verification Committee of the CSRC examines the application and decides whether to grant approval.[2] During the IPO review process, the role of the committee is to make sure the firms meet the listing requirements and are healthy in nature. Even when firms meet the basic requirements, they can still be rejected by the committee due to other factors such as profitability sustainability, authenticity of financial data, accurate information disclosure, and company independence. Besides the official performance, company structure and company governance guidelines provided by the CSRC, other criteria for deciding approval or rejection are not made public such as politics (Fan, Wong, and Zhang, 2007; Piotroski and Zhang, 2014). Cong and Howell (2021) note a rejection rate of 20%-30% by the committee. If a firm is rejected by the committee, it can submit a new IPO application after it resolves the reasons for rejection. Once approved by the CSRC, the firm submits the application to the relevant exchange, goes on a road show to attract investors, and chooses a share subscription day. Shi, Sun, and Zhang (2018) find that there is an average of 24 working days between the subscription day and the listing day. When deemed necessary, the

[2] The Shanghai Stock Exchange Science and Technology Innovation Board (STAR Market) is the first registration-based listing board in China and began operations in July 2019. Since the STAR Market is based on registration and disclosure, the CSRC plays a limited role and has less impact during the approval process. However, the CSRC still needs to grant final approval before listing.

CSRC can also slow down or even temporarily suspend IPO reviews (Cong and Howell, 2021; Lee, Qu, and Shen, 2023). In the Chinese regulatory environment, a firm typically takes multiple years to list.

3. Data

3.1 Sample Selection

We focus on a sample of VC backed firms identified from the Zero2IPO Research (PEdata), the leading VC/PE data provider in China. First, we choose firms backed by VCs because these firms have a common aim to exit through either IPO or acquisition (Gompers and Lerner, 1999). VC firms push their target firms for an exit that maximizes their returns. Secondly, firms with VC funding are associated with higher exit potential, especially for those that are invested by more experienced VCs (Sørensen, 2007). The selection process of the VCs favors firms with healthier financials and better prospects. After investment, VCs can assist firms with their technical knowledge (Chemmanur, Loutskina and Tian, 2014) and financial expertise such as professionalization of start-up companies (Hellmann and Puri, 2002). Thus, we choose to examine VC-backed firms due to these intrinsic characteristics and set a comparable basis for the firms.

We follow the method of Sørensen (2007) and choose the top 100 VCs to ensure that investors in the final sample are active VCs and avoids small investors who might act in an idiosyncratic manner. We use investment data from the most experienced 100 VCs that invested in Chinese domestic companies measured in cumulative investments as of 2020. During the period, the top 100 VCs have cumulative investments ranging from 217 to 1,530 with a total of 41,178 investments, accounting for 42.3% of VC investments made by the top 1,000 VCs. In terms of total exits, the top 100 VCs have a cumulative total of 6,700, accounting for 44.7% of VC exits made by the top 1,000

VCs. Of the 100 VCs, 68 are domestic VCs that do not have any foreign investors in their ownership structure and 30 have some government investment in their ownership structure.

We first pool all top 100 VCs' investments together, accumulating a total of 43,629 investments. These investments include multiple accounts of investments for the same round of a target company if there is a syndicate and multiple accounts of investments for the same target company if there are multiple financing rounds. We then remove firms from our sample if, (1) the investment is made before 2000 and after 2013; (2) the firm is a financial firm following previous studies on company innovation; (3) firms with headquarters based outside of mainland China. After accounting for the abovementioned criteria, we are left with 9,993 entries. To account for multiple counting of investments, we only keep the earliest investment round for each company. After removing duplications, we have a total of 4,946 investments.

To further ensure a homogenous impact of VCs, we keep the portfolio companies if, (1) the companies receive the VC's investment as their first round of financing; (2) the VC's investment is at least one million RMB; and (3) the VC is the lead investor if there is a syndicate. The choice of first-round venture capital financing is consistent with prior studies because it has more influence on a firm's future direction than the later rounds (Nanda and Rhodes-Kropf, 2013). The one million or higher RMB investment criteria ensures that the VC has high involvement due to the large investment amounts. After the preliminary screening, we manually read the financing history of the firms and identify those that meet our above-mentioned criteria. If PEdata does not provide the information of lead investor in a syndicate, we search the news or identify the lead investor as the one with the largest investment amount. Ultimately, the sample is restricted to first-round investments made during 2000 to 2013. It leaves the portfolio companies 7 years to ultimately become listed. Lastly, we remove firms that IPO in mainland China within three years after the first investment year.[3] In the end, we are able to construct a sample of 2,199 companies which have a first round of investment by a top VC in China between 2000 and 2013.

The company exit data is also provided by PEdata. For each investment, it shows where the company becomes listed if the company ultimately goes public and acquisition details if the company is ultimately acquired. Additionally, we manually check the IPO timing and location of the target firms using the Wind Database, the leading financial information and services provider in China. Our main dependent variable IPO equals 1 if the company goes public via IPO in mainland China and zero otherwise. We drop all firms with IPOs outside of mainland since we focus specifically on how innovation affects IPOs in mainland China. Results are robust when we account for IPO overseas.

3.2 Measuring Firm Innovation

Due to the unavailability of R&D data for unlisted firms, innovation is measured by patenting activities. For each of the firms, we hand-collect patent information from the Chinese State Intellectual Property Office (CSIPO), which is the patent office of the People's Republic of China (PRC). The patent application is measured by the number of patents the firm applied for during the specific year. Previous research indicates that patent applications are close proxies to the actual timing of innovation (Griliches, Pakes, and Hall, 1987). Patent granted is measured by how many of these patents applied in the specific year eventually become granted. This measure considers the quality of the

[3] Due to the uncertain and drawn-out regulatory approval process in China, a firm takes multiple years for an IPO application to be approved and the preparation period is usually one to three years (e.g., Cong and Howell, 2021). Thus, if the entrepreneurial firm became listed in China within three years after the initial investment, this indicates that the company is already preparing or filed for an IPO. Results are similar if we keep these firms.

patents applied while still being closer to the actual timing of innovation. (Chemmanur, Loutskina, and Tian, 2014). In the main analysis, we define PatApp (PatGrnd) as the natural logarithm of one plus the average annual number of patent applications (granted) over the three years after the first round of investment. We also try alternative time cutoff after the first round of investment and obtain similar results.

3.3 Summary statistics

Table 1 provides a summary of our variables. IPO has a mean of 0.12, indicating that 12% of our sample firms eventually goes public in mainland China. This is in line with findings by Nanda and Rhodes-Kropf (2013), showing an IPO success rate of 11% for VC backed firms in the United States. Patent application and patent granted both exhibit a positive skewness. Patent application has a mean of 3.73 as measured by the three-year average post investment patent applications. Patent granted has a mean of 2.95 as measured by the three-year average post investment patent granted. For invention patents, the average invention patent applications and invention patent granted is 1.72 and 0.94, respectively.

To investigate the impact of innovation on IPO, we construct and control for variables that are potentially linked to IPO. We categorize the variables into three distinct groups: deal level, VC level, and company level. A detailed description of each variable can be found in the Appendix Table. At the deal level, on average 26.6% of the investments are made by a syndicate of VCs. There are 584 firms that had an investment made by a syndicate. Conditional on having a syndicate, the average syndicate number has a mean value of 2.52. On average, 51.3% of the first-round investments have a follow-up investment in the future and 25.6% of the first-round investments have a follow-up investment by the same lead VC. RMB investments account for 75.8% of our sample. Lead VC investment amount for the first-round investment as an average of 50.7 million RMB and a median of 22.0 million RMB. Same province variable has an average of 0.34, indicating that in 34% of the first-round investments, the lead VC and the target company are based in the same province.

Table 1 also presents the characteristics of the lead VC in the investment. VC experience has a mean of 109.3, indicating that on average the lead VC has invested in roughly 109 companies up to the investment year of the target company. VC experience is right skewed with the median number of 64. VC successful exit has a mean of 15.7, showing that the lead VC has 15.7 successful exits characterized by IPO, equity transfer or buyout cumulative up to investment year. VC successful exit is right skewed with a median of 8.0 and standard deviation of 22.2. If any level of the VC ownership structure has government funding, then the VC is characterized as state backed. In our sample, 43.9% of the first-round investments are invested by lead VCs with some form of government funding. Domestic VCs are VCs that do not have any foreign investors in their ownership structure. 69.2% of our investments are made by purely domestic VCs. This is similar to the findings of Fu et al. (2019), which has domestic VC investments accounting for 63% of first round investments in China. There are a total of three corporate VCs in our sample: Intel Capital, Alibaba, and Tencent. They account for 1.7% of our total investments. The average age of the lead VC at investment year is 9.6 years with a median of 9.0 years.

For company level characteristics, the variable Stage in Table 1 shows that 55.5% of the first-round financing is acquired by growth or late-stage companies. This is comparable to the dataset provided by Fu et al. (2019) with 59.1% of first round investments in growth or late-stage companies. The variable CompanyAge has a mean of 5.3 years with a median of 4 years. This indicates that at the time of initial investment, portfolio firms have been established on average for 5.3 years.

Table 2 presents the correlation coefficients of the independent variables and provides further insight into the characteristics of the sample. The lower triangle shows the Pearson's correlation coefficients, and the upper, shaded triangle shows the Spearman's rank correlations. Both correlation coefficients show similar results. As expected, PatApp and PatGrnd have a high correlation of 98%. Stage and CompanyAge have a correlation of about 26% and 25% with PatApp, respectively. This indicates that later staged and longer established firms are correlated with more patent application. Economically, younger and smaller firms have less capital (Beck and Demirgüç-Kunt, 2006) to spend on research and development compared to more mature firms. Smaller firms are also disadvantaged in innovation due to weaker intellectual property rights protection (Lanjouw and Schankerman, 2004). Other variables have low or almost zero correlation with a firm's patent application. It suggests that the characteristics of deal and the lead VCs are not the prominent determinants of firm innovation. In Column (2), the number of patents granted exhibits similar results as patent application. Only Stage and CompanyAge have correlation coefficients in the twenties, while other variables have low or almost zero correlation. In Column (3), Stage is highly correlated with CompanyAge. This makes economic sense since longer established firms are more mature and more likely to be late staged. RMB, StateVC, and DomVC have 29%, 24% and 23% correlation with Stage, respectively. This indicates that later staged firms attract more RMB, government and domestic financing. In Column (4), syndicate and syndicate number are highly correlated. In Column (6), InvestCont and InvestLead are highly correlated. This indicates that lead VCs are likely to invest in future rounds in our sample if there are additional rounds. In Column (8), RMB is highly correlated with DomVC and state-backed VC. This aligns with the findings of Lin (2021). Compared to foreign funds, domestic and state-backed VCs prefer to use RMB and aim to exit in mainland China. In Column (11), LeadExp is highly correlated with LeadExitSuc, which indicates that the accumulated number of firms invested up to initial investment year has a high correlation with the accumulative number of successful exits a VC has up to initial investment year. This finding corroborates with the results of Sørensen (2007), which shows that companies funded by more experienced VCs are more likely to go public. In Column (13), we see that state-backed VCs are highly correlated with domestic VCs. In our sample, all of our state-backed VCs are domestic VCs.

4. Regression Results

4.1 Baseline Analysis

We propose that innovation affects the mainland listing likelihood of venture backed entrepreneurial firms. Before presenting evidence from our regression analyses, we first examine the IPO frequencies of the firms within VCs according to their innovation ranking. In Panel A of Table 3, we sort firms into high and low groups within each lead VC according to the within-VC median patent numbers. Since we focus on the top 100 VCs, we get 100 high groups and 100 low groups. We pool the 100 high groups together and calculate the average patent applied, average patent granted, and IPO frequency; we pool the 100 low groups together and calculate average patent applied, average patent granted, and IPO frequency. Finally, we show the difference between the two categories of firms. Results indicate that firms in the high innovation category have an IPO frequency of 0.203 whereas firms in the low innovation category have an IPO frequency of 0.073. We find that firms in the high innovation category are almost three times more likely to IPO in mainland China compared to firms in the low innovation category.

In Panel B, we sort firms into high and low groups within each lead VC according to the within-VC median patent numbers. For each high and low group, we calculate the total number of patents and IPO counts. Then for each lead VC, we calculate the difference of total patent number and IPO counts between the high and low groups. We report the mean, 25 percentile, 50 percentile, and 75 percentile for the differences. We see that the average of the differences of total number of patents applied is 110.722, which is larger than the mean of the differences of total number of patents granted (87.583). The 75 percentile of differences of total number of patents applied is 124.833, which is larger than the 75 percentile of differences of total number of patents granted (93.333). This indicates that patents applied show a larger variation between high and low groups than patents granted. The mean for the differences in IPO counts is 2.319. This implies for total IPO counts, firms in high innovation groups go public 2.319 times more than firms in low innovation groups. The T-statistics for the differences are all significant.

In Panel C, we use the same method as in Panel B, but use the mean number of patents and IPO frequency instead of the total number. Similarly, for each lead VC, we calculate the difference of the mean number of patents and mean IPO frequency between the high and low groups. The mean difference in IPO frequencies is 0.069, which suggests a higher mainland IPO likelihood for firms in the high innovation group compared to the low group. The finding supports the results of Panel B, and the t-statistic is statistically significant. Overall, we find evidence that supports firms with higher innovation within a VC portfolio have higher mainland IPO count and frequency compared to their lesser innovative peers. A detailed breakdown of IPO frequencies for each individual VC can be found in the Online Appendix.

Next, we first run ordinary least squares (OLS) and logit regressions to examine the relationship between a firm's innovation and its IPO success in mainland China.[4] All regressions are clustered at lead VC level. The baseline results use two measures of innovation: the natural logarithm of one plus the 3-year averaged patent application and patent granted data after initial investment year. The dependent variable IPO_i takes the value of 1 if the firm i eventually becomes listed in the mainland stock market. Firm, VC, and deal level controls are discussed in the data summary and a detailed description can be found in the Appendix Table. Specifically, we estimate the following regression:

$$IPO_i = \beta_0 + \beta_1 Innovation_i + \beta_2 Controls_i + Investment\ \ year_t + Industry_j + \varepsilon \quad (1)$$

Table 4 reports both the OLS and logit regression for the baseline result. We can see that our two main innovation variables are positive and statistically significant in all settings. This indicates that high innovation after initial investment is associated with a higher chance of a successful IPO in mainland China. Column (5) and (6) indicate that a unit increase in log patent application can increase the odds of IPO by 71% and 60% respectively. Column (7) and (8) indicate that a unit increase in log patent granted can increase the odds of IPO by 77% and 65%.[5] Comparing the specification with and without control, we see that the coefficients for the innovation variables are similar, indicating that the change in IPO success rate is not systematically correlated with our deal, VC, and firm level characteristics. Overall, this suggests that firms with higher post-investment innovation have a higher mainland IPO success rate.

In Table 4, by looking at the control variables, we see that syndicate is significant for the logit regression in Columns (6) and (8). Additionally, syndicate number is

[4] As mentioned previously, we drop all overseas IPO firms and firms that IPO within three years since the first investment year from our sample in the baseline regression to clearly distinguish the effect of innovation for private firms on their IPO success in mainland China.

[5] For interpretation of odds ratio for logistic regression, we use the formula (exp(β)-1). β is the coefficients of the independent variables for the logistic regression.

positive and statistically significant for the baseline result in the OLS regression in Columns (2) and (4). The results indicate that syndication and increasing the number of venture capitalist firms involved in the first round of financing can increase the chances for IPO. This finding supports the results of Tian (2012), which shows that when syndicates invest in a company, the company has a higher chance for a successful exit. The variables FutInvest and FutLeadInvest are significant in all specifications, indicating that entrepreneurial firms that receive additional rounds of financing and those that receive future financing from the lead investor will have a higher chance of IPO in mainland China. Staged financing and contracts allow VCs to abandon the investment if unsuccessful and continue to invest if the investment is deemed successful or meet certain milestones (Admati and Pfleiderer, 1994; Gompers, 1995; Tian, 2011). In this case, continued investment by VCs is linked with company success and has a positive correlation with the firm's future IPO success rate. Whether the investment is made using RMB or alternative currency also has an impact on its chances for listing in mainland China. As previously discussed, if financing for the first round is in a non-RMB currency, then the target company usually has a VIE structure, which indicates its propensity to IPO in mainland China is extremely low compared to companies that receive RMB funding. Corporate VC in our baseline regression is significant for both OLS and logit models. This implies that firms are more likely to survive and be successful enough to IPO when financed by corporate VCs since CVCs can offer the entrepreneurial firm with superior technological expertise and have greater tolerance for failure (Chemmanur, Loutskina, and Tian, 2014). Lastly, company age is also positively related to IPO success. Other variables have no significant impact in our sample.

4.2 Endogeneity

In our baseline setting, we cannot induce direct causation due to the possibility of omitted variable bias. Univariate results can be driven by time trends, firm characteristics, and VC characteristics. For example, our findings can be the result of unobserved VC characteristics such as resources and talents. VCs with better resources and talents can help the entrepreneurial firms with both increasing innovation output and its IPO success. To alleviate the problem of endogeneity, we utilize two instrumental variables to estimate the causal relationship between firm innovation and IPO likelihood in mainland China.

4.2.1 IV: Patent Dispute Jurisdiction

In China, patent cases for an entire province were originally handled by the provincial capital city's court. Gradually, other cities within the province were given local patent dispute jurisdiction over patent cases within their city. Increasing IPR protection is often associated with higher innovative output. Ang, Cheng, and Wu (2014) and Fang, Lerner, and Wu (2017) find that increasing intellectual property rights (IPR) protection increases firm innovation in China. Thus, this exogenous local jurisdiction implementation shock is a plausible instrument since it only affects the firm's IPO likelihood through its effect on innovation and is uncorrelated with any firm or VC characteristics.

In 1985, the Supreme People's Court of The People's Republic of China (Chinese Supreme Court) issued a notice that dictated that patent disputes in each province and autonomous region are handled by the courts of their respective capital city. In addition, the four special municipalities (Beijing, Shanghai, Tianjin, and Chongqing) and four special economic zones (Shenzhen, Zhuhai, Shantou, and Xiamen) have local jurisdiction over the local patent disputes. Due to the rapid expansion of the Chinese economy and an increase of patent disputes, local city jurisdiction of patent dispute cases is gradually handed out to local city courts by the Chinese Supreme Court. The patent dispute jurisdiction data is primarily collected from PKULaw, which is a database originating from Peking University's law department that hosts law legislations and documentations in China. We derive the majority of our data from the official Chinese Supreme Court documentation collected from the database.[6] Additionally, we supplement our data using government websites and news. A complete tabulation of local jurisdiction implementation can be found in the Online Appendix.

We utilize the two-stage least squares (2SLS) estimation to alleviate endogeneity issues. The variable *Jurisdiction* measures the difference between the year when local court receives the jurisdiction over patent dispute cases and initial investment year. From Panel A of Table 5, we see that during the first stage regression, *Jurisdiction* significantly and positively impacts patent application and patent granted for invested firms at the 1% level. This indicates that more recently established jurisdiction has a greater impact on local firm innovation as measured by patent application and patent granted. Local jurisdiction provides greater accessibility for local firms and makes patent disputes more efficient, which results in stronger IPR protection. As documented by Jia and Tian (2018), accessibility is important in fostering innovation. In China, Yue et al. (2015) note that local judicial protectionism disturbs outcomes of litigations and hinders firm innovation. Local judicial protectionism tends to favor longer established mature firms in the city and those that have greater local political connections. More recently implemented local patent dispute jurisdiction has greater judicial independence

[6] Chinese Supreme Court issued official replies such as "Reply of the Supreme People's Court on Designating Yantai Intermediate People's Court to Judge Certain Patent Dispute Cases." We collected official documentations of similar formats for the cities that were given local jurisdiction over patent dispute cases.

and has less time for local judicial protectionism to manifest. Thus, since our sample firms are startup entrepreneurial firms, a fairer judicial environment and less judicial disturbance is beneficial to its innovation output as shown in the first stage results.

For the second stage of the 2SLS, we see that patent application and patent granted significantly and positively affect the firm's likelihood of a mainland IPO, indicating that *Jurisdiction* is an effective instrument. We find that the coefficients in the 2SLS regression are larger than that of the OLS regression. By using 2SLS, we account for the endogeneity problem of the baseline regression and conclude that innovation does indeed have a positive causal relationship with a firm's listing probability in mainland China. These results are similar when adding VC province fixed effects.

4.2.2 IV: Inventor Founder

We propose another IV to mitigate the effect of omitted variable bias. Islam and Zein (2020) find that inventor CEOs positively impact the quality and quantity of patents through their innovation-related insights and ability to pick superior innovative projects. We use inventor founder instead of inventor CEO at the time of initial investment, which we show has similar effect on promoting innovation in the first stage of 2SLS. Despite strength in innovation, technical founders may not be as capable in daily operations and technology commercialization. Hellmann and Puri (2002) show that technical founders are often replaced with professional CEOs and management teams after initial investment by VCs, especially at an early stage of development. VCs also influence roles in marketing, sales and human resources, and the process of IPO is often managed by a professional team. While some founders leave from all positions, other founders may still want to be involved in the firm through leadership roles in technology, business development or board of directors. We propose that after VC investment, technical founders' main impact on IPO success is through their focus on technology and innovation driven business development strategies.

We define inventor founder as the controlling founder or chairman (if no shareholding stake is disclosed) at the time of the first VC investment. Additionally, to be classified as an inventor founder, the founder or chairman must be listed as an inventor for a patent applied for by the company. For listed companies, we can find founders through the company prospectus when companies file for an IPO. For private companies, the data is gathered from Tianyancha and Qichacha platforms, which are the two leading providers of corporate information in China based on publicly available government information.[7] As the top provider, Tianyancha contains over 240 million enterprises' information such as company background, legal lawsuits, operational risks, and partners with numerous banks, government agencies and investment banks in China. In China, whenever company management, legal representative or company shareholders change, they must notify the local Industry and Commerce Bureau and this information is updated in the National Enterprise Credit Information Publicity System. This setting allows us to identify the founders and see changes in management and shareholding for private companies. Lastly, we use the CSIPO database to validate whether the founder had filed patents in the past for the company.

Similarly, we use the 2SLS estimation to mitigate endogeneity issues. *InvFder* is a dummy which equals 1 if the founder has previously applied for an invention patent, and zero otherwise. All the control variables are the same from Equation (1). In Panel B of Table 5, Columns (1) and (2) report the first stage and second stage results of the 2SLS with PatApp and Columns (3) and (4) report the first stage and second stage

[7] The platforms gather information from official government sources such as the National Enterprise Credit Information Publicity System, Trademark office of China National Intellectual Property Administration and China Judgements Online.

results of the 2SLS with PatGrnd. From the first stage results of Panel B, we see that an inventor founder positively and significantly impacts a firm's total innovation. This makes economic sense since the founders place greater importance on innovation when they are actively involved and are knowledgeable in the field. This is similar to the findings of Islam and Zein (2020). They find CEOs familiar with technological innovation and had hands-on experience from previous patent generations can enhance the innovation output of the firms they lead, taking into account of other innate characteristics. For the second stage, we see that the results are positive and significant for IPO likelihood in mainland China. The coefficients are similar to the baseline results. The result corroborates the findings of the main analysis and suggests that there is a causal relationship between a firm's post investment innovation and its IPO success rate in China.

4.3 Robustness Tests

Our baseline and endogeneity results show a positive and casual relationship between post investment innovation output and mainland IPO likelihood. In this subsection, we provide additional robustness tests to further support the casual link.

4.3.1 Innovation and future IPO: Different listing boards and patent measures

Established in 1990, both the Shanghai Stock Exchange and Shenzhen Stock Exchange are often dubbed as the Main Boards of China. In October 2009, the ChiNext Market was established. It caters to smaller firms that have high growth potential. The goal of the ChiNext Market is to provide a new financing platform for smaller companies that cannot meet the listing requirements of the Main Board. The financial threshold for listing in the ChiNext Market is therefore much relaxed. In November of 2018, President Xi announced plans for a listing board that focuses on science and technology. In July 2019, the Shanghai Stock Exchange Science and Technology

Innovation Board (STAR Market) began operations and became the first registration-based listing board in China. The CSRC has limited regulatory power and the listing standards such as size and profitability are lifted. The purpose of the board is to support innovative firms, especially those that are aligned with national security and have science and technology breakthroughs.

For our first robustness test, we examine how firm innovation affects the listing probability for different boards. It is possible that our previous results are only significant due to the ChiNext and STAR markets, which focus primarily on fostering innovative and technologically advanced firms. If our main hypothesis holds, we expect innovation to positively affect all listing boards. For Panel A of Table 6, columns (1) and (2) exclude firms that IPO via STAR and ChiNext markets, and the dependent variable Main Boards takes on the value of 1 when the firm is listed through the Main Boards. We find that innovation still significantly and positively affects firm chances to list on the Main Boards. Columns (3) and (4) exclude firms that go public through the Main Board and the dependent variable STAR and ChiNext takes on the value of 1 when the firm is listed through the STAR and ChiNext markets. Similarly, innovation has a significant positive effect on the likelihood of going public for the STAR and ChiNext markets. Surprisingly, the coefficients are larger for the Main Boards compared to the STAR and ChiNext markets. The estimated coefficient of PatApp for Main Boards is 0.046 while the estimated coefficient of PatApp for Star and ChiNext is 0.024. This indicates that innovation positively affects listing likelihood for all boards in mainland China.

Next, we use different time lengths of innovation as a robustness test. Patent generation has a lag and initial research may take numerous years to bear fruit. In our baseline result, we drop firms that became public within 3 years after the investment year and use three-year average patent application and patent granted as the main innovation data. This ensures that during the three-year period after the investment year, all firms are private. For this robustness test, we use alternative innovation proxies to measure the effect of short-term, intermediate-term and long-term effect of post investment innovation on firm listing probability. If firm innovation positively affects listing chances, our alternative innovation proxies should also be positive and statistically significant.

In Panel B of Table 6, Columns (1) and (2) exhibit the two-year average patent application and patent granted data while dropping firms that IPO within two years. Columns (3) and (4) exhibit the four-year average patent application and patent granted data while dropping firms that IPO within four years. Columns (5) and (6) exhibit the five-year average patent application and patent granted data while dropping firms that IPO within five years. The coefficients for all the innovation proxies are positive and significant in all specifications. This indicates that short-, medium- and long-term innovation measures all increase the likelihood of a firm's IPO probability in mainland China.

For our main analysis, we control lead VC characteristics using lead VC level controls. We use lead VC level controls instead of lead VC fixed effect because the number of VCs was relatively large for our sample size. Additionally, lead VC fixed effects don't fully substitute for VC-related controls in our paper. Because our observations are cross section data with different initial investment years, the VC-related controls for each observation might occur in different years and have time variation. However, it is possible our VC level characteristics do not account for all the effects of the lead VC. To address this issue, we utilize the lead VC fixed effect for our robustness test. In Panel C, we include the lead VC fixed effects to our baseline results in Table 4 and accordingly drop the control variables related to VC characteristics. The results show that when adding lead VC fixed effect, all innovation measures positively and significantly affect IPO probability in all settings. The test provides further evidence on the causal relationship between post investment innovation and mainland IPO likelihood by addressing omitted VC-level controls.

4.3.2 Innovation and future IPO: Multinomial logit

Our previous results indicate a causal relationship between innovation and IPO success in mainland China. For this robustness test, we investigate the impact of post investment innovation on different types of exits. Schwienbacher (2008) argues that firms will pay a higher premium for low innovation firms because they see the firm as competition, while high innovation firms create products that the acquiring firm no longer sees as competition. Coupled with the private benefits of the entrepreneur, firms that have high innovation prefer to exit through an IPO. Phillips and Zhdanov (2013) illustrate that active acquisition market can promote small firms to innovate. Thus, it is possible that private firms will increase their innovation output with hopes of being acquired by larger firms instead of exiting through an IPO. We test this theory by separating firm outcomes into three distinct categories: no exit, mainland IPO, and acquired. We use a multinomial logit model for dealing with multiple discrete outcomes. This model predicts each outcome’s probability for categorically distributed variables, which in this case are the abovementioned three categories. The variable Exit equals 1 if the firm exit through a mainland IPO and equals 2 if the firm exit through being acquired. The no exit group serves as the benchmark for our test and takes on the value of 0 if the firm does not have an exit. These categories are mutually exclusive; thus, we can use the multinomial logit model to estimate the likelihood of each outcomes.

From Panel A of Table 7, we see that the coefficients in patent application for mainland IPO are positive and statistically significant. With one unit increase of the variable patent application, the log odds for a firm to go public in mainland rather than having no exit will increase by 0.52; the log odds for a firm to be acquired rather than having no exit will not change significantly. Partial effects are interpreted as while keeping other variables constant, with 1 unit of increase in PatApp, the probability of going public in mainland increases on average by 4.5% and reduces the probability of having no exit on average by 4.2%. Similarly, looking at Panel B, we see that with one unit increase in the variable patent granted, the log odds for a firm to go public in mainland rather than having no exit will increase by 0.55, while other variables remain insignificant. Looking at partial effects, we see that with 1 unit increase of PatGrnd, the probability of going public in mainland increases on average by 4.9% and reduces the probability of having no exit on average by 4.2%. Overall, Table 7 illustrates that innovation decreases the chances of no exit and increases the likelihood of a mainland IPO. Additionally, the results show that innovation does not increase the likelihood of being acquired.

4.3.3 Innovation and future IPO: Patent Quality

While China has experienced an explosion of patent applications, some researchers find that they are inflated by low-quality patents. (Dang and Motohashi, 2015; Chen and Zhang, 2019). In our baseline results, our main innovation variables capture the effect of patent quantity on listing likelihood in mainland China. In this robustness test, we explore patent quality’s effect on firm exit using a firm’s proportion of invention patents and different measures of citations. Invention patents, which cover new technical solutions, improvements, or processes, are more innovative compared to utility model and design patents. Additionally, more cited patents are viewed as having higher quality and innovativeness. We hypothesize that patent quality will also improve a firm's IPO likelihood in mainland China.

In Table 8, we propose different measures to account for innovation quality. First, in Panel A, we interact patent application and patent granted with the variable HighQ. HighQ takes the value of 1 if the proportion of invention granted over total granted is larger than the 75% quantile, and 0 otherwise. This variable HighQ is our first measure of patent quality. In Panel A, we see that the coefficient of the interaction term PatApp x HighQ takes on the value of 0.036 and is significant at the 5% level in column (1). The coefficient of the interaction term PatGrnd x HighQ takes on the value of 0.037 and is also significant at the 5% level in column (2). This indicates high quality innovation can improve the likelihood of a mainland IPO.

In Panel B, we introduce four innovation quality variables. Citation is the log of the citations for patents applied over the three years after the first investment round. AvgCitation measures the average number of citations per patent applied over the three years after the first round of investment. Citations suffer from truncation issues and citation intensities vary across industries. To address these problems, we generate two variables CorrCitation1 and CorrCitation2, which use the fixed effect method outlined by Hall, Jaffe, and Trajtenberg (2001). A detailed description can be found in the Appendix Table. From Panel B, we see that all four measures of citations are positive and statistically significant. This provides empirical evidence to support the hypothesis that innovation in terms of both quantity and quality can positively affect a firm's chances to become listed in mainland China.

5. Mechanism and Additional Evidence

Our baseline results reveal that post investment innovation increases the likelihood of a mainland listing and the finding is robust under various settings. In this section, we provide the underlying mechanisms and additional evidence to explain how firm innovation impacts listing likelihood in mainland China. We first propose that for entrepreneurial firms, innovation promotes firm growth and improves firm financials through future financing and human capital. These two channels provide the necessary financial assistance and technological capacity necessary for firms to grow healthily enough to meet the stringent listing requirements in China. Once the firm meets the listing requirements and is under review, innovation does not impact the IPO approval rate.

5.1 Innovation and future round of VC investment

As documented by prior research, staged financing can mitigate the agency problems between the VC and the entrepreneur by giving the VC the option of abandoning the project (Admati and Pfleiderer, 1994). Tian (2011) find that VC staging can positively impact the firm's propensity to go public if the firm is located far away from the VC. If firms fail to secure further financing after initial investment, it is viewed as an abandoned project and its likelihood of an IPO is lowered. Alternatively, when entrepreneurial firms receive additional rounds of financing, it can be a signal of success through meeting stage targets or milestones. Due to large information asymmetry between the VC and invested firms, technical advancement in terms of patents can often be viewed as a sign of achieving milestones. Giot and Schwienbacher (2007) note that achievement of milestones reduces uncertainty in venture profitability, which results in better firm financials. Additionally, as a signal of success, further financing increases VC monitoring by attracting new investors and deepening the involvement of existing investors. Bernstein et al. (2016) find that increasing VC monitoring is positively associated with IPO likelihood. Lastly, additional financing provides the firms with the capital and resources to expand and grow in order to meet the financial listing requirements of the CSRC.

Using our sample, we investigate how firm innovation impacts its success for receiving follow-up investments. Given the fact that we study firms backed by VCs, all of firms have received at least one round of investment within our sample year cohort. The question is whether and how innovation will affect the firm's chances of receiving a second round of investment. This provides a suitable condition to implement the Cox proportional hazards model. Using the Cox proportional hazards model, we examine the timing of the next round of VC investment conditional on receiving the first round. We perform a survival (or duration) analysis, which studies the occurrence and timing of events. We consider investment round adoption a failure event and use the following Cox proportional hazards model:

$$\lambda(t_i) = \lambda_0(t_i)\exp(-\beta' X_i) \tag{2}$$

The dependent variable $\lambda(t_i)$ is the hazard rate for firm *i* at time *t* or the probability that firm *i* will receive the second round of investment at time *t* with the "survival condition" that it does not receive second round investment at time *t*. $\lambda_0(t_i)$ is the base hazard rate, capturing the individual heterogeneity of firm i. Cox's partial likelihood method allows us to estimate the coefficient vector β as the chance of receiving second round of investment, without estimating $\lambda_0(t_i)$. X_i is a vector of independent variables including innovation as variable in interest, controls in the baseline regression, and fixed effects. The model allows us to examine how innovation influences the chance of receiving second round investment within a particular period. If a firm receives the second round of investment on time *t*, we classify it as an adopting firm and classify *t* as the time interval between the year of the initial investment and the time it receives the second round of investment. Conversely, if a firm has not received the second round of investment during a given sampling period, we classify it as a "censored" observation and set *t* as the time interval between the year of the initial investment and cut-off period. Although the firm has not received its second round of investment in time interval *t,* it may still have a chance to receive investment in a longer period; thus, we label it as "censored" observation.

Table 9 presents the results of the Cox proportional hazards model. The central concept in survival analysis is the hazard rate, which is the probability that a sample firm will receive its second round of investment on time *t*, contingent on a vector of covariates in our analysis. In our setting, a high hazard rate indicates the firm is more likely to receive a second round of investments. In Panel A, we set the cut-off period to 3.1 years after initial investment to test a firm's likelihood to receive a second round of investment within 3 years of their initial investment. Column (1) and Column (3) are the models we use to predict the hazard rate. Column (2) and Column (4) extend Column (1) and (3) with controls. PatApp and PatGrnd both positively affect the chances of receiving second round investments and are statistically significant in all settings. In Panel B and Panel C, we set the cut-off period to 4.1 years and 5.1 years, respectively. The results show that in all settings PatApp and PatGrnd are statistically significant and positively impact the chances of second round of financing. The results in Table 9 are consistent and confirm that innovation contributes to a higher hazard rate of receiving subsequent investments. This indicates firms with higher innovation outputs are more likely to receive a second round of investments, enabling the firms to expand and meet the listing requirements of the CSRC.

5.2 Innovation and job hiring

Human capital is viewed as a key component of a successful firm. Hall and Lerner (2010) note that more than half of firm R&D spending is on human capital. Human capital expands a firm's innovation capacity by integrating the know-hows, skills, and knowledge of individuals with company resources (Chemmanur et al., 2019). Innovation capacity is crucial for firms to sustain competitive advantage, introduce new products, and appropriate new technology for firm growth. Wang and Yu (2023) illustrate that human capital increases firm value, firm productivity, and capital-labor ratio, improving firm performance. The effect is more pronounced for higher educated workers. In this section, we examine the impact of innovation on human capital for our sample of firms. We collect firm hiring data from RESSET, a financial and economic data services provider for universities, governments, and financial institutions in China. The job listing data starts from 2016 and ends in 2020 when our sample period finishes. The data is compiled by gathering data from the top 5 job listing sites in China. If the specific job hiring data is listed on multiple sites, only one entry will be kept, and other entries removed. After collecting the job information data, we match the data with our sample and manually correct input errors such as spaces and parentheses. We only include hiring data from the parent company and not from its subsidiaries. In the end, we have a dataset that has yearly hiring data from 2016 to 2020 for our sample. The variable Job equals the natural logarithm of one plus all job listings for the specific company regardless of education level. The variable GradJob equals the natural logarithm of one plus number of job postings that require a master's degree or above.

In Panel A of Table 10, we first drop all firms with 0 patent application and divide patent application into quintiles. We can see an overall trend that the more patent applications result in more job postings. The variable Job is more than double in the highest quintile of patent application compared to the lowest quintile. The trend is more pronounced in GradJob, where we see a steady increase in graduate level hires for higher patent application companies. The variable GradJob in the highest quintile is more than triple the value compared to the lowest quintile. We also see similar trends in Panel B. Panel B drops all firms with 0 patent granted and divides patent granted into quintiles. The Job variable increases with higher number of patents granted. GradJob has a more noticeable growth trajectory with value increasing in each quintile. These preliminary results show that companies with a high average three-year innovation as measured in patent application and patent granted after investment year will have more job hiring than the less innovative firms.

In Panel C, we show the regression of job posting on our innovation variables. We see that in all columns, the coefficients for PatApp and PatGrnd are positive and statistically significant. This indicates that innovation after the initial investment year can promote job hiring within a firm. We also find that the variable IPO is positive and statistically significant in all settings. This implies that public firms hire more workers than their private counterparts. These results hold true for the entire working population and for the subsample of graduate level workers. The three-year average innovation after first investment can be viewed as the firm's early innovation success. As the company becomes successful, it will expand and hire more workers. Especially as the firm focuses more on innovation, its hiring of skilled workers who hold graduate level degrees will also increase.[8] As more skilled workers are hired, the firm's technological capacity and productivity will increase, allowing the firm to grow more rapidly compared to its peers. Thus, the increased human capital provides a mechanism for the firm to grow and improve firm financials in order to meet the CSRC listing requirements, enhancing its likelihood of a mainland listing.

5.3 Innovation and IPO Review

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8 Bias et al. (2021) document that IPO firms exhibit a significant growth in the size of their labor force starting two years before the IPO.

Lastly, we examine how innovation affects the IPO review. The CSRC committee rejections are case by case and without a specific criterion. We hypothesize that innovation does not impact the chances of IPO success once it reaches the IPO review process. During the review, the committee looks at factors such profitability sustainability, authenticity of financial data, accurate information disclosure, and company independence. We propose that the CSRC committee does not innately favor highly innovative firms and offer preferential treatment to them. In Table 11, we use a subsample of our data that includes firms that submitted an IPO application to the CSRC. IPO application and IPO review data are collected from the Wind Database. In Panel A, we have a total of 360 firms that submitted an IPO application. Of these firms, 34 of them are initially rejected and 326 firms are initially accepted. We implement t-tests to compare the cumulative patents applied and granted between the two groups and find that they are statistically insignificant. The variables PatApp_Sum and PatGrnd_Sum measure the cumulative patents applied and patents granted from the initial investment year to the year of IPO review. We use the cumulative patents applied and granted to account for the varying IPO year of each firm; similar results hold when we use our baseline innovation measures. Surprisingly, the mean for patent applications and patent granted in the initial rejection group is higher than the initial passed group. In Panel B, we implement t-test to compare the cumulative patents applied and patents granted between firms that are ultimately rejected and firms that are ultimately accepted. Once a firm is initially rejected, it can resolve the rejection issues and reapply, which usually takes several years. Looking at Panel B, the results are still statistically insignificant.

Since our subsample of firms that submitted an IPO application to the CSRC contains limited observations of 360 firms, we also apply Mann-Whitney U test as nonparametric approach for robustness check, which requires fewer assumptions about population. In Panel C, we first pool 34 initially rejected firms and 326 initially accepted firms in ascending order in terms of the cumulative patents applied and granted and mark each firm with its rank. Then we calculate the rank sum for 34 initially rejected firms, and the rank sum for 326 initially accepted firms, and compare if they come from populations with no significant differences. Since the rank sum statistic tends towards a normal distribution, z and p-value are shown in Panel C. Consistent with the results in Panel A, results are all insignificant. The cumulative patents applied and granted for the initial rejection group and initial passed group have no statistically significant differences. Panel D shows consistent results with Panel B that the cumulative patents applied and granted for ultimately rejected group and ultimately accepted group have no significant differences. Our findings show that once a firm reaches the IPO review process, innovation does not affect its chances of being accepted. Thus, the way innovation increases a mainland IPO success is by facilitating firm growth to fulfill the stringent listing requirements of the CSRC.

6. Conclusion

In this paper, we examine the value of innovation for entrepreneurial firms in China in terms of mainland listing likelihood and firm growth. In order to list in mainland China, firms must meet the stringent financial listing criteria and gain regulatory approval from the CSRC. Due to its inherent high-risk nature, whether innovation improves a mainland listing likelihood is an empirical one. Our study shows post initial investment innovation does indeed increase the likelihood of an IPO in mainland China. We utilize two instrumental variables, and the results remain robust. In our robustness tests, we show that (1) innovation improves IPO success in all board listings in mainland China, (2) different time measures of innovation all increase mainland IPO success, (3) baseline is still robust when using VC fixed effects, (4) innovation reduces the likelihood of no exit, increases the likelihood of a mainland IPO, and does not affect being acquired, and (5) patent quality also improves a firm's likelihood in a mainland listing. We demonstrate that the increased mainland IPO likelihood is due to innovation's impact on firm growth. We provide two pieces of evidence to support the theory by showing that innovation positively impacts future financing and human capital growth. Lastly, we show that once the firm reaches the IPO review process, innovation has no impact on the approval rate.

Overall, the paper provides empirical evidence that shows the benefits of promoting innovation for private firms in China. While previous literature focuses on how VCs can influence firm innovation, this study builds upon these ideas and provides fresh insight on how these VC induced innovations can ultimately help the entrepreneurial firms in the form of a higher IPO success rate. It illustrates that by providing financing and assisting with firm innovation, VCs can increase the likelihood of a successful exit for their portfolio firms. We also contribute to the literature on firm exits by showing innovation increases the likelihood of a mainland IPO and does not affect being acquired. More importantly, we explore the effect of innovation on the multiple stages of a mainland listing and provide a distinct angle on innovation's effect on listing likelihood. We propose two mechanisms through which innovation assists with mainland IPO likelihood and provide insight into the opaque IPO review process in China.

The paper not only adds to the literature on innovation and firm exits, but also has certain policy implications. Innovation from private firms is increasingly viewed as a critical component of high-quality development in China. The paper proposes an internal mechanism for Chinese entrepreneurs to actively engage in research and development by demonstrating that firms with high innovation are more likely to have a successful exit through a mainland listing. Additionally, we provide evidence that innovation promotes firm growth through financing and human capital. As entrepreneurs realize the benefits of firm innovation, companies will innovate more and facilitate innovative collaboration. To expand this internal incentive and to promote further private firm innovation, the Chinese government can announce preferential listing treatments towards high-tech and innovative firms using initiatives such as the STAR Board. Additionally, the government can loosen regulatory controls and create a Chinese NASDAQ board that is purely registration and disclosure based.

Appendix Table: Variable definition

Name	Description	Definition
IPO	IPO	Equals 1 if the company goes public via IPO in mainland China and 0 otherwise.
PatApp	Patent applications	Natural logarithm of one plus the average annual number of patent applications over the three years after the first round of investment.
PatGrnd	Patent granted	Natural logarithm of one plus the average annual number of patents applied over the three years after the first round of investment that are eventually granted.
Stage	Company stage	Equals 0 if the company is at its seed or early stage at the first round of investment, and 1 otherwise.
Syndicate	Investment syndicate	Equals 1 if the first round of investment has a syndicate and 0 otherwise.
SyndNum	Number of VC	Number of participants for the first round of investment in a syndicate and takes the value of 0 if no syndicate.
FutInvest	Future investment	Equals 1 if there is a follow-up investment after the first round of investment and 0 otherwise.
FutLeadInvest	Future investment of lead VC	Equals 1 if the lead VC of the first round investment participates in a follow-up investment and 0 otherwise.
RMB	RMB investment	Equals 1 if the first round of investment is in RMB and 0 otherwise.
LeadAmt	Investment amount of lead VC	Amount invested by the lead VC for the first round of investment in million RMB.
SameProvince	Same province	Equals 1 if the company and the lead VC are in the same province and 0 otherwise.
LeadExp	Lead VC experience	Number of investments made by the lead VC prior to the year when the company received the first round of investment.
LeadExitSuc	Lead VC successful exit	Number of successful exits characterized by IPO, equity transfer or buyout by lead VC prior to the year when the company received the first round of investment.
StateVC	State VC	Equals 1 if the lead VC ownership structure has government funding and 0 otherwise.
DomVC	Domestic VC	Equals 1 if the lead VC ownership structure is purely domestic and 0 otherwise.
CorpVC	Corporate VC	Equals 1 if the lead VC is a corporate VC and 0 otherwise.
VCAge	VC age	VC age in the year when the company received the first round of investment.
CompanyAge	Company age	Company age in the year when the company received the first round of investment.
Citation	Number of citations	Natural logarithm of one plus the average of total citations for the patents applied over the three years after the first round of investment at the end of 2020.

AvgCitation	Citations per patent	Natural logarithm of one plus the average of citations per patent for each patent applied over the three years after the first round of investment at the end of 2020.
CorrCitation1	Corrected citations per patent	Average number of the natural logarithm of one plus citations-per-patent corrected using HJT (2001)'s fixed effect method over the three years after the first round of investment at the end of 2020.
CorrCitation2	Corrected citations per patent with winsorization	Average number of the natural logarithm of one plus citations-per-patent corrected using HJT (2001)'s fixed effect method. Each winsorized at 1% and 99% levels, over the three years after the first round of investment at the end of 2020.
Job	Number of job postings	Natural logarithm of one plus number of job postings from 2016 to 2020.
GradJob	Number of job postings for post-graduates	Natural logarithm of one plus number of job postings that require a master's degree or above from 2016 to 2020.

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Table 1. Summary statistics

This table reports the descriptive statistics of the 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. The top 100 VCs are identified by their cumulative investment as of 2020. We keep the portfolio companies if, (1) the companies receive the VC's investment as their first-round of financing; (2) the VC's investment is at least one million RMB; and (3) the VC is the lead investor if there is a syndicate. We remove financial firms. IPO equals to 1 if the invested firm become listed in mainland China by 2020, and 0 otherwise. PatApp is the natural logarithm of one plus the average annual number of patent applications over the three years after the first round of investment. PatGrnd is the natural logarithm of one plus the number of patent applications that are eventually granted. Syndicate, SyndNum, FutInvest, FutLeadInvest, RMB, LeadAmt, and SameProvince are the deal characteristics. LeadExp, LeadExitSuc, StateVC, DomVC, CorpVC, and VCAge are the lead VC characteristics. Stage, CompanyAge, Citation, AvgCitation, CorrCitation1, CorrCitation2, Job, and GradJob are the company characteristics. A detailed description of each variable is in the Appendix Table. Columns (1) to (6) show the number of observations, the average, standard deviation, median, 25th percentile, and 75th percentile, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs	Mean	Std.Dev	Median	25%	75%
IPO	2199	0.121	0.327	0.000	0.000	0.000
PatApp	2199	0.583	0.918	0.000	0.000	0.924
PatGrnd	2199	0.510	0.850	0.000	0.000	0.768
Syndicate	2199	0.266	0.442	0.000	0.000	1.000
SyndNum	2199	0.670	1.200	0.000	0.000	2.000
InvestCont	2199	0.513	0.500	1.000	0.000	1.000
InvestLead	2199	0.256	0.437	0.000	0.000	1.000
RMB	2199	0.758	0.429	1.000	1.000	1.000
LeadAmt	2199	50.664	131.021	22.000	10.000	49.765
SameProvince	2199	0.343	0.475	0.000	0.000	1.000
LeadExp	2199	109.271	123.806	64.000	27.000	140.000
LeadExitSuc	2199	15.718	22.238	8.000	1.000	19.000
StateVC	2199	0.439	0.496	0.000	0.000	1.000
DomVC	2199	0.692	0.462	1.000	0.000	1.000
CorpVC	2199	0.017	0.130	0.000	0.000	0.000
VCAge	2199	9.644	11.349	9.000	4.000	12.000
Stage	2199	0.555	0.497	1.000	0.000	1.000
CompanyAge	2199	5.265	5.067	4.000	1.000	8.000
Citation	2199	0.124	0.408	0.000	0.000	0.000
AvgCitation	2199	0.040	0.150	0.000	0.000	0.000
CorrCitation1	2199	0.088	0.268	0.000	0.000	0.000
CorrCitation2	2199	0.074	0.219	0.000	0.000	0.000
Job	2199	3.502	2.568	3.970	0.693	5.631
GradJob	2199	0.683	1.226	0.000	0.000	1.099

Table 2. Correlation

This table shows the correlation coefficients. The sample includes 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. [need a description of how to choose 100 VCs]. We keep the portfolio companies if, (1) the companies receive the VC's investment as their first-round of financing; (2) the VC's investment is at least one million RMB; and (3) the VC is the lead investor if there is a syndicate. We remove financial firms. IPO equals to 1 if the invested firm become listed in mainland China by 2020, and 0 otherwise. PatApp is the natural logarithm of one plus the average annual number of patent applications over the three years after the first round of investment. PatGrnd is the natural logarithm of one plus the number of patent applications that are eventually granted. Stage, Syndicate, SyndNum, FutInvest, FutLeadInvest, RMB, LeadAmt, and SameProvince are the deal characteristics. LeadExp, LeadExitSuc, StateVC, DomVC, CorpVC, and VCAge are the lead VC characteristics. CompanyAge is the company characteristics. A detailed description of each variable is in the Appendix Table. Pearson's correlation coefficients are shown in the lower triangle, while Spearman's rank correlations are shown in the upper triangle.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 PatApp	1.00	0.97	0.29	0.12	0.13	0.04	-0.02	0.23	0.15	-0.04	0.11	0.13	0.19	0.18	-0.07	0.12	0.31
2 PatGrnd	0.98	1.00	0.29	0.12	0.13	0.04	-0.03	0.24	0.16	-0.05	0.12	0.13	0.20	0.19	-0.07	0.13	0.31
3 Stage	0.26	0.26	1.00	0.08	0.09	-0.10	-0.13	0.29	0.37	-0.13	0.13	0.22	0.24	0.23	-0.02	0.23	0.84
4 Syndicate	0.11	0.11	0.08	1.00	0.99	0.08	0.04	-0.06	0.13	-0.03	0.00	0.02	0.01	-0.03	0.00	-0.03	0.10
5 SyndNum	0.13	0.13	0.11	0.93	1.00	0.08	0.03	-0.05	0.13	-0.03	-0.01	0.02	0.01	-0.03	0.01	-0.02	0.11
6 InvestCont	0.03	0.03	-0.10	0.08	0.07	1.00	0.57	-0.05	-0.09	0.06	-0.06	-0.07	-0.09	-0.05	0.00	-0.11	-0.12
7 InvestLead	-0.03	-0.03	-0.13	0.04	0.02	0.57	1.00	-0.14	-0.06	0.03	-0.03	-0.02	-0.11	-0.15	0.01	-0.06	-0.12
8 RMB	0.19	0.19	0.29	-0.06	-0.04	-0.05	-0.14	1.00	-0.12	0.02	0.13	0.15	0.34	0.62	-0.02	0.16	0.30
9 LeadAmt	0.03	0.04	0.12	0.03	0.04	-0.06	-0.03	-0.09	1.00	-0.26	0.19	0.26	0.11	-0.12	-0.02	0.26	0.41
10 SameProvince	-0.04	-0.05	-0.13	-0.03	-0.04	0.06	0.03	0.02	-0.13	1.00	-0.07	-0.09	0.01	0.12	-0.05	-0.12	-0.15
11 LeadExp	0.07	0.07	0.08	-0.01	-0.02	-0.04	-0.01	0.12	0.02	-0.05	1.00	0.89	0.26	-0.01	-0.11	0.60	0.17
12 LeadExitSuc	0.08	0.07	0.12	0.02	0.01	-0.04	-0.02	0.15	0.03	-0.06	0.92	1.00	0.31	0.04	-0.13	0.67	0.25
13 StateVC	0.14	0.15	0.24	0.01	0.02	-0.09	-0.11	0.34	0.03	0.01	0.29	0.33	1.00	0.59	-0.12	0.32	0.27
14 DomVC	0.16	0.15	0.23	-0.03	-0.02	-0.05	-0.15	0.62	-0.07	0.12	0.04	0.12	0.59	1.00	0.01	0.02	0.24
15 CorpVC	-0.06	-0.06	-0.02	0.00	0.02	0.00	0.01	-0.02	0.00	-0.05	-0.08	-0.08	-0.12	0.01	1.00	0.02	-0.03
16 VCAge	0.03	0.04	0.14	0.01	0.02	-0.08	-0.03	-0.01	0.18	-0.12	0.19	0.20	0.06	-0.14	0.00	1.00	0.26
17 CompanyAge	0.25	0.25	0.74	0.09	0.11	-0.11	-0.11	0.27	0.11	-0.13	0.10	0.12	0.25	0.22	-0.04	0.12	1.00

Table 3. Within-VC IPO frequency

This table shows the within-VC IPO frequency. We examine the IPO counts and frequencies of the firms within VCs according to their innovation ranking. We sort firms into high and low groups within each lead VC according to the within-VC median patent numbers. In Panel A, we pool the high groups and low groups together respectively, and calculate the average patent applied in column (1), average patent granted in column (2), and IPO frequency in column (3). In Panel B, we sort firms into high and low groups within each lead VC according to the within-VC median patent numbers. For each high and low group, we calculate the total number of patents and IPO counts. We report the mean, 25 percentile, 50 percentile, and 75 percentile for the differences in Column (1), Column (3), Column (4) and Column (5), respectively. Column (2) reports the T-statistics. In Panel C, we calculate the mean number of patents and IPO frequency. For each lead VC, we calculate the difference of mean number of patents and mean IPO frequency between the high group and low groups. We report the mean, 25 percentile, 50 percentile, and 75 percentile for the differences in Column (1), Column (3), Column (4) and Column (5). Column (2) reports the T-statistics.

Panel A.	Average PatApp	Average PatGrnd	IPO freq
	(1)	(2)	(3)
High	9.475	7.495	0.203
Low	0.103	0.077	0.073
Diff	9.372	7.419	0.129

Panel B.	Mean	T-stat	25%	50%	75%
	(1)	(2)	(3)	(4)	(5)
Difference in total PatApp	110.722	5.173	9.167	52.833	124.833
Difference in total PatGrnd	87.583	5.149	6.000	40.667	93.333
Difference in IPO count	2.319	4.745	0.000	1.000	3.000

Panel C.	Mean	T-stat	25%	50%	75%
	(1)	(2)	(3)	(4)	(5)
Difference in mean PatApp	9.201	6.503	3.000	5.276	9.766
Difference in mean PatGrnd	7.469	5.710	2.167	4.319	8.375
Difference in IPO freq	0.069	2.030	0.000	0.000	0.230

Table 4. Innovation and future IPOs

This table reports the results of the baseline analysis. The sample is 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. The dependent variable is IPO that equals 1 if the invested company becomes listed in mainland China by 2020, and 0 otherwise. Columns (1)-(4) present the estimates based the OLS regressions, and Columns (5)-(8) present the estimates based on the logistic regressions. PatApp is the natural logarithm of one plus the average annual number of patent applications over the three years after the first round of investment. PatGrnd is the natural logarithm of one plus the number of patent applications that are eventually granted. Stage, Syndicate, SyndNum, FutInvest, FutLeadInvest, RMB, LeadAmt, and SameProvince are the deal characteristics. LeadExp, LeadExitSuc, StateVC, DomVC, CorpVC, and VCAge are the lead VC characteristics. CompanyAge is the company characteristics. A detailed description of the control variables is in the Appendix Table. Investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PatApp	0.070***	0.057***			0.539***	0.471***		
	(6.56)	(5.67)			(6.81)	(5.63)		
PatGrnd			0.076***	0.063***			0.571***	0.502***
			(6.63)	(5.76)			(6.94)	(5.73)
Stage		0.010		0.010		0.358		0.353
		(0.58)		(0.58)		(1.62)		(1.58)
Syndicate		0.005		0.008		0.581*		0.582*
		(0.12)		(0.17)		(1.82)		(1.80)
SyndNum		0.037**		0.037**		0.150		0.153
		(2.07)		(2.02)		(1.29)		(1.29)
FutInvest		0.029*		0.029*		0.356*		0.356*
		(1.84)		(1.84)		(1.88)		(1.87)
FutLeadInvest		0.031*		0.032*		0.434**		0.435**
		(1.71)		(1.75)		(2.21)		(2.23)
RMB		0.065***		0.064***		0.978***		0.990***
		(4.17)		(4.13)		(3.09)		(3.14)
LeadAmt		0.000		0.000		0.000		0.001
		(0.50)		(0.49)		(1.11)		(1.14)
SameProvince		-0.013		-0.012		-0.188		-0.182
		(-1.09)		(-1.03)		(-1.10)		(-1.08)
LeadExp		0.000		0.000		0.002		0.002
		(0.37)		(0.35)		(1.27)		(1.26)
LeadExitSuc		0.000		0.000		-0.101		-0.010
		(-0.49)		(-0.45)		(-1.17)		(-1.12)
StateVC		0.025		0.024		0.269		0.252
		(1.12)		(1.08)		(1.08)		(1.01)
DomVC		0.005		0.006		0.092		0.097
		(0.25)		(0.28)		(0.33)		(0.35)
CorpVC		0.032*		0.033*		0.693**		0.696**
		(1.71)		(1.79)		(2.20)		(2.23)
VCAge		0.000		0.000		0.006		0.005
		(0.72)		(0.70)		(0.88)		(0.84)
CompanyAge		0.004*		0.004*		0.032*		0.032*

		(1.69)		(1.68)		(1.72)		(1.73)
Invest Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,199	2,199	2,199	2,199	1,859	1,859	1,859	1,859
Adj. R^2	0.188	0.224	0.189	0.225				
Pseudo R^2					0.203	0.263	0.203	0.263

Table 5. Innovation and future IPOs: Instrumental variable

This table reports the estimates based on the two-stage least squares (2SLS) regressions. The sample is 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. The dependent variable is IPO that equals 1 if the invested company becomes listed in mainland China by 2020, and 0 otherwise. In Panel A, we use Jurisdiction as the instrumental variable for PatApp and PatGrnd, respectively. Jurisdiction measures the difference between the year when local court receives the jurisdiction over patent dispute cases and initial investment year. In Panel B, we use InvFder as the instrumental variable for PatApp and PatGrnd, respectively. InvFder is a dummy that equals 1 if the firm founder had previously applied for an invention patent for the firm, and 0 otherwise. In both panels, Columns (1) and (2) report the first stage and second stage results of the 2SLS for PatApp. Columns (3) and (4) report the first stage and second stage results of the 2SLS for PatGrnd. Control variables as those in Table 3 are included. Investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A.	1st: PatApp (1)	2nd: IPO (2)	1st: PatGrnd (3)	2nd: IPO (4)
Jurisdiction	0.012***		0.010***	
	(3.49)		(3.47)	
PatApp		0.225**		
		(2.18)		
PatGrnd				0.265**
				(2.20)
F-statistic	12.15		12.07	
Kleibergen-Paap rk LM statistic	7.04		7.39	
Cragg-Donald Wald F statistic	18.54		15.77	
Anderson-Rubin Wald test	6.30		6.90	
Controls	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1953	1953	1953	1953

Panel B.	1st: PatApp (1)	2nd: IPO (2)	1st: PatGrnd (3)	2nd: IPO (4)
InvFder	0.476***		0.408***	
	(12.74)		(11.70)	
PatApp		0.071**		
		(2.28)		
PatGrnd				0.083**
				(2.23)
F-statistic	162.34		137.00	
Kleibergen-Paap rk LM statistic	25.58		22.89	
Cragg-Donald Wald F statistic	146.41		124.93	
Anderson-Rubin Wald test	5.48		5.48	
Controls	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2199	2199	2199	2199

Table 6. Innovation and future IPO: Robustness tests

This table provides the results of the robustness tests from a series of regressions. The sample is 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. The dependent variable is IPO that equals 1 if the invested company becomes listed in mainland China by 2020, and 0 otherwise. In Panel A, we exclude the firms that go public via STAR & ChiNext markets in Columns (1) and (2) and exclude the firms that go public via main boards in Columns (3) and (4). Panel B shows the result of different patent measures using different time periods after the initial investment year. In Columns (1) and (2), PatApp and PatGrnd are based on the two-year average patent application and patent granted data while we drop firms that go public within two years of initial VC investment. In Columns (3) and (4), PatApp and PatGrnd are based on the four-year average patent application and patent granted data while we drop firms that go public within four years of initial VC investment. In Column (5) and (6), PatApp and PatGrnd are based on the five-year average patent application and patent granted data while we drop firms that go public within five years of initial VC investment. In Panel C, we include the lead VC fixed effects in the setting of Table 3 and accordingly drop the control variables related to VC characteristics. In all panels, investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A.	Main boards		STAR & ChiNext Market	
	(1)	(2)	(3)	(4)
PatApp	0.046***		0.024***	
	(5.91)		(2.67)	
PatGrnd		0.051***		0.027***
		(5.86)		(2.83)
Controls	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,084	2,084	2,047	2,047
Adj. R^2	0.233	0.234	0.117	0.117

Panel B.	Two-year		Four-year		Five-year	
	(1)	(2)	(3)	(4)	(5)	(6)
PatApp	0.058***		0.049***		0.043***	
	(5.74)		(4.90)		(4.82)	
PatGrnd		0.065***		0.054***		0.045***
		(6.19)		(5.12)		(4.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,246	2,246	2,132	2,132	2,074	2,074
Adj. R^2	0.238	0.240	0.190	0.190	0.180	0.179

Panel C.	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PatApp	0.060***	0.049***			0.483***	0.417***		
	(5.92)	(5.11)			(5.54)	(4.48)		
PatGrnd			0.065***	0.054***			0.510***	0.443***
			(5.99)	(5.21)			(5.66)	(4.56)
Stage		0.020		0.020		0.493*		0.491*
		(1.09)		(1.10)		(1.98)		(1.94)
Syndicate		0.0004		0.003		0.668*		0.666*
		(0.01)		(0.05)		(1.88)		(1.86)
SyndNum		0.036*		0.036*		0.117		0.120
		(1.94)		(1.90)		(0.92)		(0.94)
FutInvest		0.029*		0.029*		0.409*		0.410*
		(1.74)		(1.74)		(1.98)		(1.98)
FutLeadInvest		0.030		0.031		0.453**		0.451**
		(1.59)		(1.63)		(2.04)		(2.05)
RMB		0.081***		0.080***		1.203***		1.212***
		(4.03)		(4.01)		(3.06)		(3.08)
LeadAmt		0.000		0.000		0.000		0.000
		(0.11)		(0.11)		(0.57)		(0.60)
SameProvince		-0.010		-0.009		-0.221		-0.217
		(-0.69)		(-0.64)		(-1.02)		(-1.01)
CompanyAge		0.002		0.002		0.024*		0.024*
		(1.12)		(1.12)		(1.33)		(1.33)
Invest Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,199	2,199	2,199	2,199	1,457	1,457	1,457	1,457
Adj. R^2	0.241	0.268	0.242	0.269				
Pseudo R^2					0.212	0.263	0.211	0.263

Table 7. Innovation and future IPO: Multinomial logistic model

This table shows the effect of firm innovation on different types of exits using multinomial logistic model. The sample includes 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. We consider three possible VC exits. Exit equals 1 if the invested company goes public, equals 2 if the company is acquired, and equals 0 otherwise. Panel A shows the result of the multinomial logit regression using PatApp as the independent variable. Panel B shows the result of the multinomial logit regression using PatGrnd as the independent variable. In both panels, Column (1) shows the results for the benchmark group of the no exit, Column (2) shows the results for the group of IPO companies, and Column (3) shows the results for the group of acquired companies. Control variables as those in Table 3 are included. Investment year fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A.	α_0: No exit	α_1: IPO	α_2: Acquired
	(1)	(2)	(3)
		Parameters	
PatApp	0.000	0.518***	0.025
	(0.00)	(7.95)	(0.19)
		Partial Effects	
PatApp	-0.042***	0.045***	-0.003
	(-4.15)	(8.17)	(-0.40)
Controls	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes
N = 2,199	Pseudo R^2 = 0.140, Log pseudolikelihood = -1170.7036		

Panel B.	α_0: No exit	α_1: IPO	α_2: Acquired
	(1)	(2)	(3)
		Parameters	
PatGrnd	0.000	0.553***	-0.010
	(0.00)	(8.10)	(-0.06)
		Partial Effects	
PatGrnd	-0.042***	0.049***	-0.006
	(-3.59)	(8.66)	(-0.60)
Controls	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes
N = 2,199	Pseudo R^2 = 0.141, Log pseudolikelihood = -1169.872		

Table 8. Innovation and future IPO: Patent Quality

This table shows the effect of patent quality on IPO success in mainland China. The sample is 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. The dependent variable is IPO that equals 1 if the invested company goes public in mainland China by 2020, and 0 otherwise. In Panel A, the variable HighQ takes the value of 1 if the proportion of invention patent granted over total patent granted is larger than its 75% quantile, and 0 otherwise. In Panel B, different measures of citations are used as a measure of patent quality. In Column (1), Citations is defined as the natural logarithm of one plus the number of citations for the patents applied over the three years after the first round of investment at the end of 2020. In Column (2), AvgCitation is defined as the natural logarithm of one plus the average number of citations for each patent applied over the three years after the first round of investment at the end of 2020. In Column (3), CorrCitation1 is defined as the average number of the natural logarithm of one plus citations-per-patent corrected using HJT (2001)'s fixed effect method over the three years after the first round of investment at the end of 2020. In Column (4), CorrCitation2 is defined as the average number of the natural logarithm of one plus citations-per-patent corrected using HJT (2001)'s fixed effect method. Each winsorized at 1% and 99% levels, over the three years after the first round of investment at the end of 2020. Investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A.	(1)	(2)
PatApp	0.033**	
	(2.55)	
PatApp x HighQ	0.036**	
	(2.41)	
PatGrnd		0.039***
		(2.62)
PatGrnd x HighQ		0.037**
		(2.16)
Controls	Yes	Yes
Invest Yr FE	Yes	Yes
Industry FE	Yes	Yes
N	2,199	2,199
Adj. R^2	0.227	0.227

Panel B.	(1)	(2)	(3)	(4)
Citations	0.058***			
	(2.80)			
AvgCitation		0.173***		
		(3.36)		
CorrCitation1			0.136***	
			(4.30)	
CorrCitation2				0.142***
				(3.46)
Controls	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,199	2,199	2,199	2,199
Adj. R^2	0.209	0.210	0.216	0.212

Table 9. Innovation and future round of VC investment

This table shows the results of the Cox proportional hazards model of firms receiving the second round of investment. The sample includes 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. We estimate the following model, $\lambda(ti) = \lambda0(ti)\exp(-\beta' Xi)$, where the dependent variable $\lambda(ti)$ is the probability that firm *i* will receive the second round of investment at time *t* with the "survival condition" that it does not receive second round investment at time t. Xi includes the variable of interest and control variables related to firm i. If a firm receives the second round of investment on time *t*, we classify it as an adopting firm and define *t* as the time interval between the year of the initial investment and the time it received the second round of investment. Conversely, if a firm has not received the second round of investment during our sampling period, we classify it as a "censored" observation and set *t* as the time interval between the year of the initial investment and the ending time cut. Panel A shows the estimates using 3.1 years after the initial investment year as the cutoff for receiving second round of investments. Panel B shows the estimates using 4.1 years after the initial investment year as the cutoff for receiving second round of investments. Panel C shows the estimates using 5.1 years after the initial investment year as the cutoff for receiving second round of investments. In all panels, Columns (1) and (2) present the estimates when PatApp is used, and Columns (3) and (4) presents the estimates when PatGrnd is used. Investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Three-year	(1)	(2)	(3)	(4)
PatApp	0.137***	0.171***		
	(3.33)	(4.09)		
PatGrnd			0.136***	0.177***
			(2.95)	(3.79)
Controls	No	Yes	No	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,093	2,093	2,093	2,093

Panel B. Four-year	(1)	(2)	(3)	(4)
PatApp	0.141***	0.173***		
	(3.38)	(3.99)		
PatGrnd			0.141***	0.180***
			(3.04)	(3.75)
Controls	No	Yes	No	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,029	2,029	2,029	2,029

Panel C. Five-year	(1)	(2)	(3)	(4)
PatApp	0.123***	0.153***		
	(2.94)	(3.44)		
PatGrnd			0.120***	0.156***
			(2.60)	(3.19)
Controls	No	Yes	No	Yes
Invest Yr FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,976	1,976	1,976	1,976

Table 10. Innovation and job hiring

This table shows the effect of innovation on human capital measured in job hiring. The sample includes 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. We obtain the job posting data of invested companies from RESSET and manually match the sample using the company names. Job is defined as the natural logarithm of one plus number of job postings from 2016 to 2020. GradJob is defined as the natural logarithm of one plus number of job postings that require a master's degree or above from 2016 to 2020. In Panel A (B), we drop firms with zero patents and separates the sample into quintiles according to PatApp (PatGrnd). We report the average number of Job and GradJob in each quintile. Panel C report the estimates from a series of OLS regressions where the dependent variables are Job and GradJob in Columns (1)-(4) and (5)-(8), respectively. In Columns (1), (3), (5), and (7), the independent variable is PatApp. In Columns (2), (4), (6), and (8), the independent variable is PatGrnd. The control variables as in Table 3 are included. Investment year fixed effects and industry fixed effects are included. Standard errors are clustered at lead VC level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. PatApp	1=Low	2	3	4	5=High
Job	242.262	353.761	385.548	322.358	536.640
GradJob	5.467	8.104	11.513	12.585	17.175

Panel B. PatGrnd	1=Low	2	3	4	5=High
Job	361.978	279.252	346.567	333.218	556.809
GradJob	7.887	9.669	9.803	11.067	18.152

Panel C.	Job				GradJob			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PatApp	0.653***		0.549***		0.291***		0.221***	
	(10.24)		(8.73)		(7.47)		(5.88)	
PatGrnd		0.725***		0.611***		0.314***		0.237***
		(10.70)		(9.05)		(7.65)		(5.90)
IPO			1.816***	1.805***			1.222***	1.221***
			(11.12)	(10.92)			(8.78)	(8.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invest Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,199	2,199	2,199	2,199	2,199	2,199	2,199	2,199
Adj. R^2	0.267	0.269	0.309	0.310	0.195	0.195	0.277	0.277

Table 11. Innovation and IPO Review

This table shows the results of innovation's impact on China's IPO review process. The initial sample includes 2,199 unique investments made by the top 100 VCs in China during 2000 to 2013. There are 360 firms that submitted an IPO application. In Panel A and Panel B we implement the t-test. Panel A compares the cumulative patents applied and patents granted from the initial investment year to the year of IPO review for firms that were initially rejected by the CSRC and firms that passed the review. Panel B compares the cumulative patents applied and patents granted from the initial investment year to the year of IPO review for firms that were ultimately rejected by the CSRC at the end of 2020 and firms that passed the review. In both panels, Columns (1) and (3) show the average number of patents applied and granted. Columns (2) and (4) show the number of firms that submitted an IPO application. Columns (5) and (6) show the difference between two groups of firms and t-statistics. In Panels C and D, we repeat the analysis in Panels A and B using the Mann–Whitney U test. In both panels, Columns (1) and (3) show the rank sums of firms in ascending order of patents applied and granted. Columns (2) and (4) show the number of firms that submitted an IPO application. Columns (5) and (6) show the z-statistics and p-values.

Panel A.	Initially rejected firms		Passed firms		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	N	Mean	N	(1)-(2)	T-stat
PatApp_Sum	8.021	34	7.609	326	0.412	0.339
PatGrnd_Sum	7.013	34	6.501	326	0.512	0.468

Panel B.	Ultimately rejected firms		Passed firms		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	N	Mean	N	(1)-(2)	T-stat
PatApp_Sum	5.863	20	7.677	340	-1.814	-1.173
PatGrnd_Sum	5.076	20	6.564	340	-1.488	-1.072

Panel C.	Initially rejected firms		Passed firms		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
	Rank sum	N	Rank sum	N	z	P-value
PatApp_Sum	6653.5	34	58326.5	326	0.897	0.370
PatGrnd_Sum	6785.0	34	58195.0	326	1.126	0.260

Panel D.	Ultimately rejected firms		Passed firms		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
	Rank sum	N	Rank sum	N	z	P-value
PatApp_Sum	3371.500	20	61608.500	340	-0.529	0.597
PatGrnd_Sum	3445.500	20	61534.500	340	-0.365	0.715

Online Appendix Table
Table B1. Within-VC IPO frequency for each VC

This table groups firms into high(1) and low(0) groups within each lead VC according to the within-VC median patent numbers. We also report the frequencies of IPO for each group.

Lead_VC	Group	IPOfreq	N
DCM 中国	0	0.000	7
DCM 中国	1	0.000	1
IDG 资本	0	0.071	85
IDG 资本	1	0.167	18
PreAngel Fund	0	0.000	8
PreAngel Fund	1	0.000	2
东方富海	0	0.034	29
东方富海	1	0.185	27
中信产业基金	0	0.333	3
中信产业基金	1	0.500	2
中国风投	0	0.200	15
中国风投	1	0.000	13
中科招商	0	0.095	42
中科招商	1	0.385	39
中路资本	0	0.000	27
中路资本	1	0.000	12
中金资本	0	0.000	3
中金资本	1	0.500	2
九鼎投资	0	0.114	79
九鼎投资	1	0.230	74
五源资本	0	0.000	14
五源资本	1	0.250	4
信中利资本	0	0.000	9
信中利资本	1	0.250	4
元禾控股	0	0.026	38
元禾控股	1	0.162	37
光大控股	0	0.000	5
光大控股	1	0.750	4
光速中国	0	0.000	5
光速中国	1	0.000	2
凯鹏华盈	0	0.000	9
凯鹏华盈	1	0.000	5
创东方	0	0.067	15
创东方	1	0.167	6
创新工场	0	0.000	19
创新工场	1	0.000	6
北极光	0	0.056	18

北极光	1	0.222	9
华平	0	0.091	11
华平	1	0.000	1
华映资本	0	0.000	8
华映资本	1	0.000	7
华睿投资	0	0.111	18
华睿投资	1	0.357	14
合力投资	0	0.000	3
合力投资	1	0.000	1
同创伟业	0	0.054	37
同创伟业	1	0.171	35
君联资本	0	0.175	40
君联资本	1	0.438	16
启明创投	0	0.043	23
启明创投	1	0.182	11
启赋资本	0	0.000	3
启赋资本	1	0.333	3
基石资本	0	0.200	10
基石资本	1	0.500	10
广发信德	0	0.200	5
广发信德	1	0.333	3
建银国际	0	0.000	13
建银国际	1	0.308	13
德同资本	0	0.038	26
德同资本	1	0.176	17
德迅投资	0	0.000	17
德迅投资	1	0.000	5
戈壁	0	0.000	19
戈壁	1	0.000	12
时代伯乐	0	0.000	5
时代伯乐	1	0.000	5
普华资本	0	0.000	2
普华资本	1	0.000	1
景林投资	0	0.000	8
景林投资	1	0.286	7
松禾资本	0	0.097	31
松禾资本	1	0.148	27
毅达资本	0	0.000	21
毅达资本	1	0.263	19
浙商创投	0	0.125	8
浙商创投	1	0.000	7
海纳亚洲	0	0.000	7
海纳亚洲	1	0.000	4

海通开元	0	0.571	7
海通开元	1	0.750	4
涌铧投资	0	0.667	6
涌铧投资	1	0.600	5
深创投	0	0.103	117
深创投	1	0.193	109
清源投资	0	0.000	2
清源投资	1	0.000	1
清科创投	0	0.000	7
清科创投	1	0.000	2
湖北高投	0	0.286	7
湖北高投	1	0.000	4
盛世景投资	0	0.000	3
盛世景投资	1	0.000	2
真格基金	0	0.000	22
真格基金	1	0.000	7
硅谷天堂	0	0.077	13
硅谷天堂	1	0.200	10
粤科金融	0	0.176	17
粤科金融	1	0.235	17
红杉中国	0	0.104	48
红杉中国	1	0.050	20
纪源资本	0	0.000	8
纪源资本	1	0.000	4
经纬中国	0	0.000	24
经纬中国	1	0.000	7
老鹰基金	0	0.000	3
老鹰基金	1	0.000	3
联创资本	0	0.031	32
联创资本	1	0.185	27
联想之星	0	0.000	9
联想之星	1	0.000	7
腾讯投资	0	0.000	13
腾讯投资	1	0.333	3
英特尔资本	0	0.286	7
英特尔资本	1	0.000	4
赛伯乐	0	0.000	9
赛伯乐	1	0.000	8
赛富投资基金	0	0.000	39
赛富投资基金	1	0.136	22
软银中国资本	0	0.000	25
软银中国资本	1	0.000	14
达晨创投	0	0.082	49

达晨创投	1	0.348	46
金沙江创投	0	0.000	12
金沙江创投	1	0.000	3
金浦产业投资	0	1.000	1
金浦产业投资	1	1.000	1
金石投资	0	0.222	9
金石投资	1	0.625	8
金雨茂物	0	0.200	5
金雨茂物	1	0.500	4
钟鼎资本	0	0.500	2
钟鼎资本	1	0.000	2
阿里巴巴	0	0.100	10
阿里巴巴	1	0.000	1
青松基金	0	0.000	8
青松基金	1	0.000	1
顺为资本	0	0.000	6
顺为资本	1	0.000	2
高盛	0	0.125	8
高盛	1	0.333	3
鼎晖投资	0	0.056	18
鼎晖投资	1	0.231	13

Table B2. Patent Dispute Jurisdiction

This table shows the number of cities that have courts with local jurisdiction over patent dispute cases in mainland China from 1985 to 2013.

Year	Jurisdiction
1985	35
1987	1
1988	1
1998	1
1999	1
2002	3
2003	2
2004	1
2005	3
2006	9
2007	7
2008	2
2009	1
2010	2
2011	1
2012	2
2013	3

Table B3. Pre-investment innovation and future IPO

This table reports the results of our baseline analysis. The dependent variable is IPO, which takes on the value of 1 if the invested company eventually IPOs in mainland China. Columns (1)-(4) are the OLS results and Columns (5)-(8) are the logistic regression results. The main variables of interests are PatApp and PatGrnd. A detailed description of the control variables can be found in the Appendix Table. The unit of observation is number of unique invested firms. All regressions are clustered at lead VC level. Robust *t*-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PrePatApp	-0.003	-0.010			0 .006	-0.023		
	(-0.16)	(-0.68)			(0.05)	(-0.18)		
PrePatGrnd			0.005	-0.003			0.060	0.030
			(0.26)	(-0.19)			(0.45)	(0.22)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Invest Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,199	2,199	2,199	2,199	1,859	1,859	1,859	1,859
Adj. R^2	0.159	0.205	0.159	0.205				
Pseudo R^2					0.168	0.239	0.168	0.239