Can venture capital trigger innovation? New evidence from China

Ni, H. , Luan, T. , Cao, Y. and Finlay, D.

Author post-print (accepted) deposited in CURVE December 2014

CURVE is the Institutional Repository for Coventry University

http://curve.coventry.ac.uk/open

Can Venture Capital Trigger Innovation: New Evidence From China

Abstract: With the continuing globalization of the world economy, countries seek to develop and support their venture capital market. Whether venture capital really can trigger innovation or vice versa or not at all is of interest not only to academia, but also to commercial firms, venture capital institutions, and government agencies. Based on statistical data collected from the Chinese market, this paper aims to provide material insight on, firstly, whether venture capital can influence innovation and, if so, by how much; and secondly, whether venture capital leads innovation or whether it is innovation which leads developments in venture capital. The innovation of the sample firms is quantified by the consideration of patent counts and associated productivity growth. The sample firms collected from a group of innovation active industries, are selected by a number of discriminative covariates widely cited in the extant literature. The empirical findings demonstrate that venture capital has a positive but limited impact on innovations in the current market. Innovation and productivity growth in particular, may also be triggered by the growth potential of firms. We therefore propose a few possible unique factors to explain the underlying mechanism of venture capital in promoting innovation within the context of the Chinese market.

Keywords: Venture Capital; Innovation; Patents; Total Factor Productivity

1 Introduction

Nowadays, most countries in the world are keen to support research and development in new technology given the growing realisation of the importance of innovation to a booming economy. China's commitment to innovation was inscribed in 2011 in "A Roadmap for Five Years" [1]. Accordingly the Chinese government is putting more effort into supporting research into diverse fields including automotive, pharmaceuticals and other scientific areas. The number of patent applications has grown rapidly since 2002. The China Intellectual Property Statistical Yearbook [2] documented 205,544 applications in 2002 whilst 1,109,428 in 2011. The Derwent World Patents Index [3] estimated that by 2015, Chinese owned companies would be generating 500,000 patents, a number 25% more than the number of patents the US is expected to have.

China's Venture Capital (VC) industry began to develop in the 1980s and its rapid growth commenced in 1998 when the Chinese government implemented a series of policies to stimulate and encourage the development of high-tech companies and VC investment. Global studies have demonstrated a positive

relationship between VC and innovation [34, 10, 52] and VC-backed firms have created almost one third of total market value of all listed companies in the US market given that VCs provide finance to support start-up firms and also offer them expertise in innovation and marketing. However, other studies show that such positive relationships are due to VCs' diligent screening for firms with an already high performance potential [29, 9, 17].

Even though VC does theoretically spur innovation, when it comes to the immature market like China, such an effect might be reduced. Though China has experienced fast economic growth over the past decade, comparing to those mature and well-developed markets, the Chinese market is still young and under-reported in the literature. China's VC market, in particular, has its own unique patterns attributable to special market condition such as a strong interventionist government, inexperienced venture capitalists, inefficient legislative systems for VC investment, Private Equity (PE)-like VC investments [35], low equity ratio in the firms' ownership structure and immature Limited Partner (LP). VC in China mainly invests at firm's pre-IPO stages rather than seed stage thereby a more limited impact upon firm level innovation. Thus, it still remains unknown whether the efforts of the Chinese government and entrepreneurs in deepening the VC market could trigger innovation and/or stimulate economy as expected. Hence, the aim of this study is to test the role of VC in promoting innovation under China's special financial market condition. Also, by analyzing the correlation between VC financing and firms' innovation in China, we hope to provide new evidence and add to the prevailing literature.

However, the challenges for the paper lies in two main fields, namely to appropriately define innovation and in uncovering the direct casual economic impact of VC financing upon firms' innovation activities in particular and their performance in general.

- The definition of innovation has yet to be unambiguously agreed by either market participants or academia. Popular measurements include number of patents acquired, R&D input and Total Factor Productivity (TFP) growth. It seems, however, that any of those three cannot be an unbiased measurement to innovation. For example, patents have multiple categories and firms may not always patent their innovations. Besides, unlike well-developed countries that can offer well-documented data and large samples of firms supported by VC finance, the Chinese VC market, although emerging from the 1980's onwards, does not offer robust or relevant accounting data until 2006 onwards. Relevant firms to incorporate into the data set are thus limited. Indeed, according to official statistics, by the end of 2011, there are 443 out of 2443 listed firms that were reported to be VC financed. In this study, we only focus on the firms being listed on Shanghai stock market, Shenzhen Stock market (A-share market which includes both Chinese mainboard and Small and Medium Enterprises board) and ChiNext (the Chinese version of Nasdaq for growth enterprises) as the accounting information of unlisted firms cannot be accessible from the public official data base.

- The examination on relationship between VC and innovation should depend on two identical firms whose only difference is their financial patterns, that

is we should compare the innovation of a VC-backed firm ideally with its counterpart that had not received VC. However, such counterfactual samples and their dependent conditions are unobservable and difficult to find.

Therefore we then propose to use two methods to overcome those identified difficulties.

- A new measure of innovation. Instead of forming a financing function [22] that assumes a linear relationship among different indicators, we consider R&D-backed patent counts and TFP growth, or a Malmquist index, separately as two independent measures of innovation. The patent counts can be considered as a direct indicator of innovation, while TFP growth is the measure of efficiency and its inference links to the variables applied in calculating TFP. The variable selection is therefore critical.

- Finding counterfactual samples. In order to accurately estimate the direct impact of VC on innovation, we have to match each VC-backed firm with a firm which is as similar as possible in terms of all observable characters. We thus use a propensity score to quantify the similarity and form a control group by matching one VC-backed firm with a non-VC-backed firm and on condition of each having a similar propensity score. Since the VC investment should be made independent (or random) if conditional on certain characters, the selection of these characteristics is critical. We consider variables that are commonly cited in the literature, namely, firm age, firm size as measured by asset, sales, employment, capital intensity and Malmquist index; and also three dummies: industry dummy which specifying the industry bias, the state dummy signaling the existing of government intervention and the patent dummy showing whether the firm had ever registered at least one patent. To find the significance of the difference in performance between VC-backed firms with their selected counterpart across the prescribed time period, we applied Wilcoxon-Mann-Whitney test and Kruskal-Wallist test.

This paper is arranged as follows - following the introduction, section two provides literature review; section three outlines the methodology adopted; section four clarifies the source of the data as well as selecting the variables to measure both innovation and representing the VC related attributes of the firms; section five presents a series of empirical results and brief explanations; section six, discusses the possible underlying reasons behind VCs ineffectiveness and section seven summarizes.

2 Literature review

Studies on the relationship between VC and innovation began in the 1990s. However, There is no agreement amongst researchers as to whether VC conducts an indispensable role in improving innovation amongst firms or industries. Those disagreements are contained mostly within two fields: is VC and innovation linked and, if so, what kind of relationship do they exhibit. Such research is encapsulated by four main theories: 1) VC acts as a spur for innovation, 2) innovation leads to VC investment, 3) VC is neutral to innovation and 4) VC inhibits innovation.

4

2.1 VC spurs innovation

Most of studies observed a positive relationship between innovation and VC investment at both sector and firm level. Kortum and Lerner [34] found that at the industrial level, VC's impact on innovation is three to four times greater than the impact of R&D. Later, Gompers and Lerner [22] noticed that VC-backed firms created nearly one third of total market value of all the public companies in the US. Using German data, Tykvova [52] examined the positive correlation between VC investment and patent application and again concluded that VC can stimulate innovation at firm level. Inderst and Mueller [30] argued that, compared with inactive investors, VC can speed up the growth of new ventures as measured by market share, profits, etc, especially at their early stage. Other studies focused on less developed capital market but also confirmed that VC-backed firms registered more patents than non-VC-backed firms [4, 3, 19, 59].

Generally, VC's effectiveness spur innovation in three ways: the capital effect, the contracting effect, and the innovation-ability-boosting effect. Firstly, venture capitalists offer equity finance thereby bringing more new knowledge and technology than traditional debt finance [45]. The equity finance gives the investors opportunities with which to manage the firms and that in itself reduces the risk of credit rationing and the avoidance of a "lemon market" and information asymmetric [46]. Thus, VC ease the financing constraints faced by most high-tech new start-ups. Venture capitalists not only support new start-ups with financial support but also technological knowledge, product expertise and their network [39, 49, 44]. Consequently, the costs of acquiring information and implementing new firms' inventions are largely reduced [18]. Keuschnigg [33] proved theoretically that if the industry has more active and experienced venture capitalists, new start-ups' chance to success would be largely improved and the innovation rates would then grow more rapidly. Secondly, Pehr-Johan and Persson [38] examined the underlying reason that new start-ups would have more invention from VC exiting mechanism. If venture capitalists choose to exit via trade sales or an IPO, there would be an incentive to ensure the funded firm is attractive through encouraging innovation and registering more patents as patent applications indicate the company's potential in improving its cash flow and may even encourage incumbent firms to make attractive bids to buy such innovative companies to avoid future competition.

2.2 Innovation leads VC investment

However, some researchers argued that the VC spurring innovation phenomena might actually be the reverse. Hirukawa and Ueda [29] established the innovation first hypothesis, which states that the arrivals of technology innovation can stimulate new business opportunities and bring out new start-ups to exploit such opportunities. Since those new firms do not have enough tangible assets or collaterals, they are constrained by not being able to acquire debt from banking systems. Thus, they seek VC to meet their financial budgets [9, 21, 41]. In addition, the selection process in VC investment filters out less innovative firms by reference to their performance in patenting. Thus, comparatively innovative firms could more easily attract VC investment.

2.3 VC is neutral to innovation

Some researchers also asserted that VC did not exert any impact on innovation. The observed positive correlation is caused firstly by other unobserved factors such as investment opportunities, technology transformation, etc. Therefore, innovation growth is not necessarily created by VC but by increasing business opportunities [55, 11]. And secondly, the positive correlation might be caused by the problematic methodologies adopted by some researchers, since the selection effect and the VC impact on innovation can hardly be separated by regression analysis. Later, the idea of constructing a counterfactual twin firm was adopted and researchers [28, 16, 8, 26] began to use the propensity score matching (PSM) method to find the matched non-VC-backed twin firms. However, Engel and Keilbach [16] concluded that the causality between VC and innovation is weak based on German data. Once the firms are VC funded, they display higher growth rates but do not differ in their innovative output from comparable firms. The study [40] of Austrian VC market also comes to the same conclusion: VC-backed firms do not exhibit high growth in patenting.

Besides, people argued that such weak causality may be due to the measurement of innovation, but not the innovation itself [26]. Bottazzi and Peri [8] stated that patent is not the final step of the innovation path and using patent applications alone to indicate innovation could be biased; indeed the innovation brought in by venture capitalists is not only limited to product innovation, but could also lead to process innovation which can influence the firms' managerial skills, market capacity and profitability. Researchers turn to use multi-indices to capture the true effect upon innovation. Some studies use TFP and Labor Productivity to depict innovation [54, 55]. They found that in manufacturing industry, VC does not exhibit great influence on the industry's TFP growth although it largely improved labor productivities. Jain and Kini [31], Peneder [40] Hellman and Puri [28], Bottazzi and Da Rin [7] also found that VC-backed companies do not have greater registered patents in comparison to non-VC-backed companies but they do reveal greater growth rates in terms of cash flow and sales. Thus, such researchers conclude that VC might improve a firm's process innovation, something which remains unobservable through concentrating upon their patenting activities.

2.4 VC inhibits innovation

Other researchers believe that VC inhibits innovation [5, 48, 14], as most venture capitalists would rather invest in understood innovations rather than radical innovation or remain focused on commercializing the current technology and exit through an IPO or trade sale. Stuck and Weingarten [47] examined 1,303 electronic high-tech firms which listed on the US stock market and they concluded that the VC-backed firms has a lower innovation growth rate than others. Caselli et. al. [10] studied a sample of 37 Italian VC-backed firms that went public on the Italian Stock Exchange between 1995 and 2004, and they found that after receiving VC, the firms experienced high sales growth but fewer patent activities. By using TFP as the innovation indicator, Hirukawa and Ueda [54] found that VC's impact on innovation varies differently among industries, for example, in

drugs and the scientific instrument industry, VC could lower future TFP. In their later study [29],they also found that 1-year lagged VC investment is negatively connected with both TFP growth and patent counts.

The underlying reasons of such negative relations may be due to the short-sightedness and the potential conflict between entrepreneurs and venture capitalists. First, VC has its life cycles, most investors want to get their money back within its life span, and thus, they only focus on business plan and product that can be easily commercialized. Secondly, some venture capitalists put much of the fund not into research but into building relationships and social networking [47]. Thirdly, some venture capitalists would replicate one firm's new idea into other firms which are also in their firm portfolio [53]. In order to protect their technology from replicating, entrepreneurs prefer to do less research and innovation [48]. Other reasons inhibiting innovation are due to inefficient strategic decisions [32, 13]. When the financial resources are abundant, entrepreneurs might make reckless decisions without considering negative outcomes [43]. George [20] analyzed privately-owned firms in the US and finds that profitability declines when firms' assets grows. Also, such negative correlation can be consistent with the boom and bust, that is growth in VC investment under economic boom conditions would lead to a slowdown in TFP growth [1].

By analyzing the current literature, it is clear that there is no clear agreement on whether observed innovation is triggered by VC financing. Such diverse conclusions might possibly be due to the limited scope and methodologies of those studies: i.e. researchers focused on either firm level samples or industrial level samples. For instance, at the firm level, Hellmann and Puri [28] and Engel [16] studied the correlation between VC and firms' performance and patenting activities. At industry level, Kortum and Lerner [34], Tykova [52]and Hirukawa and Ueda [29] examined the relationship between VC and industrial innovation via regression.

On the one hand, if the study focuses simply on industry aspect, the study will fail to capture the effectiveness of VC investment below industry level. On the other hand, if the studies only focus on firm level statistics, it cannot capture the overall influence of VC or the impacts its externalities. Thus based on such observation, we propose to use both firm level and industry level datasets to test both the direct and indirect effects caused by VC and whether such effects are significant.

3 Methodology

The aim of this study is to find out whether and how the VC can affect firms innovation. The degree of innovation therefore needs to be properly measured and quantified by a series of well recognized indicators such as patent counts, TFP growth, etc. Since the innovation can be triggered by multiple factors other than VC, we want to distinguish the contribution made solely by VC financing. In order to ensure an efficient measure of the VC contribution, we apply a matching process which is able to make other factors conditionally independent to the VC. The VC impact is evaluated based on the comparison between the matched pair firms during a given time window. Finally, we further explore the causal links between

VC and innovation by examining whether VC leads innovation or innovation leads VC based on regression analysis.

3.1 Innovation indicator

It is known that a firm's innovation can not be captured by a single measurement. Innovation is sub-divided into two categories, namely product innovation and process innovation [56]. The former aims at increasing price-cost margins by developing new products. In other words, it gives the firm monopoly rent to enlarge its market shares and profits. Engel and Keilbach [17], Caselli *et. al.* [10] and Peneder [40] used the number of patents and R&D inputs to measure the product innovation. Process innovation on the other hand describes innovation that changes firm's management strategies and results in higher operational efficiency and lower unit production costs. Ueda and Hirukawa [29] and Chemmanur *et. al.* [11] used Total Factor Productivity (TFP) as well as TFP growth, or a Malmquist index, to describe the process innovation of their samples. Instead of focusing on one of innovation measurements, we propose to use both types of the measurements to present a more complete picture of the relationship between Chinese VC and innovation at both firm and industry level.

a. Patent

Number of patents is by far one of the most popular measures of product innovation [17, 10, 23]. However, as a patent may vary in its nature, for instance, utility patent, design patent, plant patent, etc and a patent may not be commercialized or venture capitalists might simply encourage a firm to patent their innovation rather than to innovate [54], patent numbers consequently may not represent fully a firm's ability to innovate.

b. Malmquist Total Factor Productivity index

The Malmquist Total Factor Productivity index or Malmquist index is a measure of productivity growth. The aim of using a Malmquist index is to find out whether the productivity growth can be attributed to VC. The potential mechanism between VC and productivity growth has been addressed in literature [29, 11, 54]. Since the definition of productivity function is less rigid, different formats with various economic implications have been adopted. In order to make the measure of productivity more adaptive, Majumdar proposed data envelopment methodology (DEA) to find out an efficient frontier where the most productive firms are located [36]. The location is defined by either the quantity of inputs per unit of output (input orientated), or the quantity of outputs per unit of input (output orientated). DEA is a non-parametric mathematical programming approach which defines a linear transformation vector λ for each decision making unit(firm) i,

$$
\begin{aligned}
&\min_{\lambda,\theta} \theta, \\
&\text{Subject to} \quad -y_i + Y\lambda \geq 0, \\
&\qquad\qquad\quad \theta x_i - X\lambda \geq 0, \\
&\qquad\qquad\quad \lambda \geq 0, \\
&\qquad\qquad\quad \sum_N \lambda = 1.
\end{aligned}
\tag{1}
$$

where $\{X,Y\} = \{\{x_1,y_1\},\{x_2,y_2\},\ldots\}$ represents the collection of all available firms, $\{x,y\}$ represents a pair of technical input and output, $\theta \leq 0$ is a scalar

proportional to the degree of efficiency, with a value of 1 indicating a point on the efficient frontier. N is the total number of inputs and outputs while the convexity constraint $\sum_N \lambda = 1$ aims to accommodate variable returns to scale. Thus the value of θ we found here can show the productivity for a given firm at a particular time. In order to measure the productivity growth of the firms, we use the Malmquist index which is a "combination" of a few "distances" found by DEA. It is calculated by using cross-period distance function, $D_i^{t_1}(x^{t_0}, y^{t_0})$, shows the efficiency measure of firm i using observations at time t_0 relative to the efficiency frontier found at time t_1. The input orientated Malmquist productivity index consists of four distance functions,

$$M_i^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{2}$$

By using Malmquist productivity index, we can decomposed it into changes in efficiency and changes in technology,

$$M_i^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) =$$

$$\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{3}$$

where first term shows the changes in efficiency from t to $t + 1$, the second term indicates the geometric mean of changes in technology from t to $t + 1$. The changes are quantified by the distance away from frontier.

3.2 Evaluation of VC impact by matching process

VCs tend to select higher quality firms [22] in order to value their investments. As a matter of fact, many innovations that have been made by VC-backed firms should be attributed to some internal factors other than the external VC investments. Since the aim of this paper is to find out the effects of VC on innovation, matched non-VC-backed firms must be found to compare with VC-backed firms according to a set of a *priori* defined characteristics. Such a matching process aims to avoid possible selection bias. The possibility of such bias arises because the apparent difference between different firms may depend on characteristics that affect whether or not a firm received VC rather than the effect of VC *per se*. We use the propensity score method to reduce the bias as much as possible. The idea of the propensity score matching is to find each VC-backed firm a comparable non-VC-backed firm that in the same year has the most similar probability (i.e. propensity score) of receiving VC investment. The probability is calculated by a logit (or probit) regression based on a number of characteristics, also known as covariates, which are used to distinguish VC-backed from non-VC backed firms. The dependent variable of the logit (probit) regression is the VC dummy, whether the firm has received VC financing. By pairing VC-backed firms(treated group) with non-VC-backed firms (control group) provided they have same or very similar propensity score, thus "randomizes" the VC financing. In other words, the VC is made to be independent to the firm characterized by the

selected covariates. The comparison between the treated group and the control group can thus be fair and efficient.

The control group is then formed by picking non-VC-backed firms that have appropriate propensity scores via an appropriate matching method. Such methods are believed to play a key role in robust estimations of treatment effects. We considered a number of matching methods. The nearest-neighbour matching pairs each VC backed firm with exactly a non-VC-backed firm with the closest propensity score. It does not consider the distribution of propensity scores of either VC backed or non-VC-backed firms. Stratification matching requires a relatively even distribution of propensity scores in both groups. These two matching methods are however inappropriate in our study due to the significant differences in covariates that of both VC-backed and non-VC-backed firms.

We therefor conducted Difference-in-Differences(DID) approach to evaluate VC's effectiveness in promoting innovation. The DID estimation we used in this paper is a nonparametric regression based on a kernel-based matching. It can both smooth the unknown function of the mechanism VC exerts on innovation and allows comparison between two-period data [24, 27, 6]. By calculating the weighted mean of the controlled group, DID indicates the average difference between differences amongst the treated group and those on average amongst the matched group, which shows the average treatment effect. Hence, the DID approach allows us to further analyze the VC's effect on innovation by comparing VC-backed firms and its counterfactuals under pre and post VC investment circumstances.

In addition, we propose to use the Wilcoxon-Mann-Whitney test and Kruskal-Wallis analysis of variance to test the significance of the innovation effect exerted by VC investment. The Wilcoxon-Mann-Whitney test is a nonparametric statistical test aimed at assessing whether one group of observations tends to be stochastically larger than the other group of observations, similar to a t-test. However the test is not based on the assumption on the normality of the observations, which makes it more desirable than the t-test in estimating the innovation effect. The independence requirement for the observations can be met by involving prior propensity score analysis, under which VC-backed firms and non-VC-back firms share the same features conditional on firm's covariates. Similarly, Kruskal-Wallis test doesn't assume a normal distribution and is capable of examining groups with unequal size (the kernel matching method may collect a control group which has different number of Non-VC-backed firms than the number of VC-backed firms in treated group). The Kruskal-Wallis test is a nonparametric version of ANOVA with its null hypothesis being two groups of observations originate from the same distribution.

3.3 Regression analysis

Regression analysis is a statistical technique for estimating the relationships among variables. Investigator seeks to find out the causal effect of one variable on another, for example, the increase of patent counts on VC financing. In this paper, we seek to estimate the quantitative effect of VC on the development of innovation at different time periods with assessable statistical significance.

In reality, any effort to quantify the effects of VC on innovation development without considering other factors may also influence innovation and could cause

omitted variable bias. In this paper, we assume that innovation can only be triggered by VC and thus a simple linear regressive result can signal whether there is a causal relationship. Since many innovation-active firms with reputable historical performance, though young in the market, can access many alternative financing sources. The empirical results can be a sufficient whilst not a necessary evidence to the causal relationship between VC and innovation.

4 Data collection and description

4.1 Data source

The data for the empirical tests are taken from several different sources: ZDB (Zero2IPO Database), Wind database, NBSC, annual reports of "Venture Capital Development in China", "China Statistical Yearbook on Science and Technology", "China Statistical Yearbook on Intellectual Property" and CNIPR (China Intellectual Property Right Net) website. China Statistical Yearbook on Science and Technology and China Statistical Yearbook on Intellectual Property remain the most authentic source. Additionally, industrial data of aggregated R&D input and patent applications was gathered from these two Yearbooks. Data on firms' patenting activities are collected firm by firm via CNIPR.

ZDB is the timeliest professional database to provide information on VC and PE investments in China and it contains information on 4700 cases of VC/PE investments, mergers and acquisitions commencing from 1992. Furthermore, it also contains the data from 2007 to 2011 relating to the VC investments according to the industry classification system. Data is drawn from its monthly questionnaire surveys and authoritative media disclosure including the National Bureau of Statistics of China. Cases and financial values of VC investment were collected from ZDB at both firm and industry level.

WIND database is the most authentic database for collecting financial data of listed companies in SSE (Shanghai Stock Exchange) and SZSE (Shenzhen Stock Exchange). Those companies are divided into 13 branches according to the 2002's National Industrial Classification of all Economic Activities. We collected the financial data and issuance information of all listed but non-service-sector companies from WIND. Because the balance sheets of companies in service sector are quite different from the others, and also, those companies seldom have patents applications.

[Table 1 about here.]

Table 1 summarizes the sample firm statistics. Most of VC-backed firms as well as non-VC-backed firms are collected from two major industry sectors: Manufactory and Information Technology. The majority of VC-backed firms have experienced some form of intervention or support by the government (state) while for the non-VC-backed firms, government intervention is minimal. Finally, VC is becoming more active and extensive over the past period.

4.2 Variable selection

a. Innovation sensitive variables

The variables used to compute TFP growth at firm level and industry level are quite different. At firm level, the variables chosen follow the criteria proposed by Dyson [15]: 1) the input factors should cover all used resources and be common to all firms and 2) the output factors should reflect firms activities and performance [25]. Accordingly we use the liquidity ratio, working capital, average number of employees, intangible assets and tangible fixed assets as the input and sales and profit margin as the output. All the nominal values were deflated by consumer prices each year and each company. The visible correlation among selected variables is displayed in Fig. 1.

[Figure 1 about here.]

b. Firm descriptive covariates

The propensity score is calculated by logit (or probit) regression where the dependent variable is a dummy with value 1 indicating receiving VC and otherwise 0; independent variables include firm age, firm size measured by total assets and employment of the firm, industry dummy [40, 12], state dummy [12] and capital intensity [58]. The state dummy is particularly introduced in this study to include the government support/intervention which has always been a determinative factor in the Chinese market. We measure the degree of 'state involvement' by examining the types of largest shareholders. If the largest shareholder are government entities or state-owned enterprise, then we define this company has state involvement, and denoted as 1; otherwise, we define it without any state involvement and denoted as 0. The state dummy data is taken from Sinofin-CCER database [4]. The industry dummy is proposed to identify which industry the firm belongs to. As VC is most prevalent in manufacturing and information technology, firms are excluded who do not belong to these two industries. The industry dummy is 1 means the firm belongs to manufactory industry while 0 means the firm belongs to information technology industry. The capital intensity is defined as the total capital per employee. Malmquist measure is defined as the calculated Malmquist index which measure the productivity growth in the past. Patent dummy indicates whether the firm has received patent before. The value of patent dummy of a firm on a certain year would be 1 as long as one (or more) patent has been registered before, and otherwise 0.

The observable heterogeneity among VC-backed and non-VC-backed firms are represented only by the selected covariates which are, therefore, critical to the quality of the matching process. The discriminative efficiency of those covariates can be not only proved by reference to the literature but also by the statistics shown in the "Unmatched" rows of Table 2.

5 Empirical research on Chinese data

Data was collected from firms operating in two industries, manufactory and information technology, both with and without VC financing from 1994-2011. In order to get a full picture of the causal relationship between VC and innovation, we implement difference-in-differences matching approach based on propensity score matching and regression analysis respectively. Both patent counts and TFP growth

have been used, but due to data absence prior to 2006, a Malmquist index was calculated and a firm matching by propensity score from the years 2006-2011.

Firm level regression analysis was conducted with a focus on individual firm's innovation behaviour with the aim of the analysis to identify the "direction" of the causal relationship: whether it is the VC that leads innovation, or innovation leads VC.

5.1 Matching analysis

[Table 2 about here.]

Table 2 summaries the descriptive statistics of nine quoted covariates, Age, Asset, Sales, Employment, Capital intensity, State, Industry, Patent, Malmquist(calculated by Sales and Profit margin). Due to the data absence for earlier years, the value of covariates has been weighted averaged over 6 years (2006-2011). For example, the age of unmatched VC-backed firms can be calculated by

$$age = \frac{\sum_{t=1}^{n} x(t)w(t)}{\sum_{t=1}^{n} w(t)} \tag{4}$$

where $x(t)$ is the averaged age at year t, $w(t)$ is the number of observations at year t, n is the total number of years. While for the matched non-VC-backed firms, the number of observations is determined by the matching scheme. As this paper adopts the kernel matching scheme, a weighted mean matching method, the number of selected non-VC-backed firms may vary according to the parameter setting. The actual number of observations is shown in Table 3. The statistics shows that apart from sales and industry, other seven covariates all have quite strong discriminative ability in distinguishing VC-backed from non-VC-backed firms. As shown, VC tends to finance young, asset-light, small size (by the number of employees and capital per employee), government supported and previously innovative (higher Malmquist index value and more patents) firms. The bias measures the degree of difference between VC-backed and non-VC-backed firms in terms of the changes in the covariates. The aim of propensity score matching is to make the value of covariates of VC-backed firms close to those of non-VC-backed firms. Therefore a perfect matching would evidence no bias. The reduction of bias reflects the efficiency of propensity score matching. T test results indicate that apart from sales mean value of covariates of VC-backed firms are significantly different from those of non-VC-backed firms before matching. After matching, though the value of T statistics is still too large to indicate insignificant difference between VC-backed firms and non-VC-backed firms as we intend to achieve, the reduction in the value of T statistics still shows the effectiveness of propensity score matching. However, difference between VC backed firm and non VC backed firms might still be affected to small extent by remaining differences in covariates.

[Table 3 about here.]

Table 3 shows the innovation performance, measured by patent counts and Malmquist indices (TFP growth) calculated by either sales or profit margin, of both VC-backed firms and their selected counterparts and non-VC-backed firms

with similar propensity scores, before and after VC event. In order to account for the time effects, 4 different window sizes (1 - 4 years span) were selected to measure the VC impact at different points in the innovation process over time. In order to make full use of the information available, all VC-backed firms' patent counts and Malmquist indices were collected. Since the number of patents recorded among the sample firms (listed on either Shanghai or Shenzhen Stock Exchange) is small, the number of observations of patent counts is far less than the number of available Malmquist indices. The number of observations, either patent counts or Malmquist indices, is reducing as the time spread increases from 1 year to 4 years because the data is only accessible during 2006 - 2011. The student-t statistics provides a measure of "divergence" between VC-backed firms and non-VC-backed firms. It can be seen that for most of time span as well as innovation measures, VC enlarges the divergence. Therefore as both VC-backed and non-VC-backed firms gain in terms of various innovation measures, we can conclude VC has some positive influence on recipient firms' innovation.

[Table 4 about here.]

Table 4 shows the Difference-in-Differences measure results and associated significance tests. We can firstly conclude that VC exerts a positive impact on innovation though the impact is not significant. Secondly, innovation does not respond to VC financing immediately. Regarding patent counts, 3 or 4 years might be a better cycle period than 1 or 2 years. For TFP growth, VC tends to have a longer effects but the influence is not stable. Since the number of observations is different for the different time windows, we introduce two significant tests to provide the further evidence. Since Difference-in-Differences calculates the distance between the different innovation gains (i.e. increases on patent counts) of VC-backed firms and non-VC-backed firms during a same period, two significance tests were applied to exam whether the two groups of innovation gains (two distributions formed by repeated sampling) have the same mean (Wilcoxon-Mann-Whitney) and variance (Kruskal-Wallis). The statistics shows that for patent counts, apart from 4 year results, the other three DID measures are not reliable. Their P values suggest that the null hypothesis that two groups of innovation gains are significantly different either by mean or variance cannot be rejected. For the 4 year results, as the number of observation is limited (20 VC-backed and 25 non-VC-backed), the results are not conclusive. Whilst for the Malmquist indices, the results are encouraging. Thus one can confirm a positive and sustainable VC impact on TFP growth of recipient firms but the VC impact on patent counts is visible but not reliable. Extra data and experiments in the future are needed to ensure the robustness of the results.

5.2 Regression analysis

In order to verify whether the innovation-first or VC-first hypothesis is applicable to Chinese VC market, we designed 3 experiments. The first experiment aimed at studying whether VC events, particularly the first round, and/or R&D inputs have leading or lagged impacts on firms' patent applying. The second is to find out whether the follow up VC are also effective on motivating firms' innovations. The last one is to exam whether VC inputs can affect the TFP growth.

14

[Figure 2 about here.]

Fig. 2 shows the potential relationship between the amount of first round VC being invested and the number of patents applied before and afterward the event, as the first round VC is known to has superior motivations on firms being invested [51]. The figure shows a "VC first" pattern as the figures in the right column in Fig. 2 display clear trends (relative large K which means slope and R^2 which represents the goodness of fit) than the figures in the left column. Every point in the Fig. 2 represents a VC event occurred for a firm. The lower number of points in the bottom row is a reflection of the limitation of firm data prior to 2006. Though the trend is visible, the causal relationship is still not significant due to a low R^2 and sparse distribution around the regressive line, which implies an untrusted regression. Another visible finding is both the trend and the level of goodness of fit are more evident with the increase in the time span. This result is in line with what was found in the previous section, that innovation will respond to the VC input but not immediately.

[Figure 3 about here.]

Fig. 3 uses R&D as input instead of VC. The linear regression results have similar patterns as Fig. 2, whilst the trends are less clear, as the value of slope K are found smaller and the goodness of fit are also of lower levels. The external VC can thus be proved to have more direct impacts on patent application than internal R&D investments.

[Figure 4 about here.]

The all over VC effects on innovation is shown in Fig. 4. The trend is less clear than the Fig. 2 as the following rounds of VC may not be as effective as the first round VC. The figure thus doubly confirms that the first round VC is always more influential.

[Figure 5 about here.]

Fig. 5 pairs each VC investment with receiving firms' Malmquist indices in different years. Neither the leading Malmquist indices nor the lagged Malmquist indexes has significant correlation with VC inputs as being shown by the almost uniformly distributed patterns.

6 Why does VC in China has limited impact in innovation

The result of our empirical study supports the view that VC and innovation are positively linked in China. But VC financing is more efficient in supporting the growth of TFP of recipient firms than their patent growth. The observed increase in patenting can be attributed to both the VCs selection process and VC financing. Meanwhile, both VC-first hypothesis and innovation first hypothesis were supported in the Chinese market. The above result comes to the conclusion that the degree of VC influence on innovation in China is not as significant as evidenced in many developed countries and those studies documented in literature. The differences between the Chinese and the western VC market might be accounted for by the following four aspects.

6.1 Government intervene

In contrast to other developed countries, Chinese government, especially the local governments play a pivotal role in conducting VC investments. Aiming at boosting the economy growth and solving the financing problems for small and median enterprises, many local governments establish Government Guided Funds to connect those enterprise with qualified financial intermediates. Sponsored by local governments, such government funds collaborate with VCs by the ways of step-by-step equity participation, government-following-up investment and investment reimbursements/subsidies. With the help of the Government Guided Funds and prevailing VCs, the shortage in capital faced by those new-born, mature and reconstructed businesses would be largely improved.

The drawbacks of such Government Guided Funds in the real market operation are: 1) Lack in continuity of the sources of the funds; 2) Conflicts in interest between Government Guided Funds and VC: VC investors would be more likely to invest recklessly whilst Government Guided Funds have to consider government policy requirements and the interest of general public. Besides, as the Government Guided Funds need to ensure that their investment projects are compatible with the reginal development strategy, the effectiveness of the Government Guided Funds on supporting innovative firms has been therefore limited. 3) Low risk tolerance of the Government Guided Funds. Since the Government Guided Funds are linked to the fiscal account of local government, the safety requirements on their capital are thus incompatible with the VC's requirement on high return. Consequently the Government Guided Funds may not be able to promote VC in depth.

6.2 Environmental condition

Appropriate environment conditions are indispensable for VC to promote innovation in supported firms.

a. Market conditions. Due to the inefficient low ratio of converting innovation to marketable products, as well as the limitation on commercialization and industrialization of the new tech products, the market is always short of investable projects. Such shortage hinders the foundation of the development of the VC market, intensifies the competitiveness and over prices the investment costs.

Besides, the stage of capital market maturity is critical to a healthy development of VC investment. The exit mechanism for VC is the most important part in VC markets. Generally, such exits mechanism range from the most successful (profitable) IPO, equity transfer, management buyout, to the most unsuccessful bankruptcy or liquidation. The success of exit depends heavily on the development of the capital market. In the US, large numbers of successful VC exits can be partly attributed to M&A as well as the establishment of the NASDAQ. However, though China established its Growth Enterprise Market, the exit mechanism for VC is still relatively undeveloped. Challenges such as lacking of value-discovering ability and global financial crisis limit the development of the newborn Chinese Growth Enterprise Market and its crucial incorporation of facilitating VC exit.

b. Basic conditions. Firstly, we are short of professional VCs with extensive knowledge of techniques, finance, management, marketing and law. Secondly, other financial intermediates need to be developed to support the VC market. The development of other financial services like credit ranking and consulting is the most important driving force for further improvement of VC companies and businesses. Those intermediates can bring together the investable projects and appropriate VCs. Currently these intermediates are still at a very early stage in their development.

6.3 Unqualified Venture Capitalists

In North America, VCs mainly invest in high-tech firms at their early stages. They are active investors, usually appointing executives and monitoring closely during the investment period. On the other hand, Private Equity (PE) is usually invested in a firm's later stage. In the west, VC and PE have two very different implications [42]. However, in China the two terms are often used interchangeably [2]. Besides, the huge return from IPO makes Chinese VC investors prefer to invest in a company at its pre-IPO stage rather than at its seed stage. Consequently, VC investment can hardly be an alternative to solve problems of financial constraints that exist for most small but growing enterprises [50].

In China, VC funds are supported by governments, local or foreign institutions/individuals. VCs in government funded VC are often former government officials who have less experience in capital operation. Besides, the performance incentives for those investment executives are usually inadequate [2]. The lack of sufficient incentives and experience in government backed VC may reduce the likelihood of strong support and value-adding services [37].

Corporate-backed VC began its development after 1990s with managers typically coming from securities firms, banks or industry [37]. Thus in contrast to the mature foreign VC industry, China's VC industry has less qualified and experienced VC managers. For example, White *et. al.* [57] found that managers in domestic VC have only 2.1 average years of relevant experience while the average length of tenure in foreign VC operating in China is 11.9 years. Besides, the foreign VCs are usually able to provide contacts to potential customers and partners in foreign markets [37].

Comparatively, the foreign VCs have greater expertise in VC management. Whereas, the shortages of those experienced VCs are their politically vulnerability and lack the intimate connections to Chinese government and local markets. Because in China, governments hold most projects and resources, networking is very important for VCs to find an investment target. Thus, for domestic VCs, they do not have the excellent manage skills and expertise to improve innovation and growth rate of their funded firms. For the foreign VCs, they can hardly find satisfying investment projects. Those aspects limited VCs' role in promoting the operation efficiency and growth rate of the funded firms.

In China, VC supported firms are characterised by low equity ratios a feature attributable firstly by firms' unwillingness to dilute their shares and secondly by VCs limited ability in making appropriate investment strategies and controlling the associated risks. On the other hand, the low equity ratio in a single firm reflects the over diversification of investment which makes it impossible for the

VCs to focus on the most valuable R&D with the consequence that VC-backed firms are unable to further develop new technology and improve their innovation ability. Thus, the difference we observed in innovation and performance between VC-backed and non-VC-backed firms is somehow insignificant.

6.4   Immature Limited Partner

The immature of Limited Partner (LP) is another reason lead to VC's ineffectiveness in China. In some developed VC markets, LPs are from wealthy individuals, corporations, foundations, pension funds and endowments [2] and their rights are limited to only those monies provided to the VC fund. However, in China, LPs are an exception to this. The funds are typically corporate funds related to banks or corporations. Such corporate VC allows additional interference in the management of funds operation in one of two ways: firstly, LPs would interfere with the funds operations and secondly, they could also intervene with the funded firms to ensure the commitment in corporations' and the funded firms' strategy [14].

Corporate VC on the one hand can provide the funded firms with novel technology and add to their firm values. However, on the other hand, it might interfere with the development of the funded firms' strategies to prevent them from competing with their parent company. Thus sometimes, although we observe a positive relationship between VC investment and lagged patent activities, we do not discover significant increasing TFP and growth along with the investment. Besides, LPs in China are also comprised by entrepreneurs from private-owned companies. Those people distrust others to manage their money and would rather manage their VC funds by themselves. Lacking the necessary managerial and financial experience, those funds either have poor performance or only focus on high return business such as real estate. Therefore, Chinese VCs have difficulties in inducing innovations.

7   Summary

China's VC market began in the 1990s, however, its development was inhibited due to inadequacies in the regulatory system and risk control mechanisms. It was not until 1998 that China's VC industry started re-developing as Chinese governments implemented a series of policies to stimulate and encourage the development of high-tech firms and the VC market itself. In 2007, the VC industry underwent its fastest development with the establishment of CGEM (China Growth Enterprise Market, the equivalent to NASDAQ) and a new "Law of the People's Republic of China on Partnerships". VC investments in China increased rapidly over the last decade. Supported by the government, VC has brought out lots of innovative firms like the Alibaba Group, Baidu.com and AsiaInfo Linkage, etc. It seems like China's VC market is providing the wherewithal to cultivate innovation. However, our study concludes with a less encouraging view:, namely VC in China is less effective in improving firms' patenting and productivity growth.

The empirical finding does suggest that VC has a limited but positive effect on patenting activities while its direct impact on recipient firms' TFP growth

18

is somewhat stronger. Whilst the response of recipient firms' innovation to VC financing has some time delay. VC tends to lead innovation especially in patenting. The reason behind might be explained by the special features of China's VC industry:(1) VCs are sponsored and protected by government and their policies; (2) the overall market context does not provide a VC-friendly environment; (3)VCs needs more attention and education before becoming professional; (4) LPs tend to interfere venture fund management.

In this paper, the research undertaken is still in the process of being understood more fully. However it is clear that what was expected to be witnessed, namely the impact of VC upon innovation in terms of short term patent growth and TFP growth may not yet be demonstrable under the conditions prevailing within Chinese market. However, instead of the expected impact on innovation, VC may influence the overall performance of a firm or even a group of firms within the same industry, the so-called spillover effects. Future research being undertaken will provide new evidence from Chinese market in the future.

References

[1] D. Abreu and M.K. Brunnermeier. Bubbles and crashes. *Econometrica*, 71(1):173–204, 2003.

[2] D. Ahlstrom, G.D. Bruton, and K.S. Yeh. Venture capital in china: Past, present, and future. *Asia Pacific Journal of Management*, 24(3):247–268, 2007.

[3] C. Antonelli and M. Teubal. Venture capitalism, new markets and innovation-led economic growth. *International Center for Economic Research (Torino, Italy), Working Paper*, (03), 2009.

[4] F. Bertoni, A. Croce, and D. D'Adda. Venture capital investments and patenting activity of high-tech start-ups: A micro-econometric firm-level analysis. *Venture Capital*, 12(4):307–326, 2010.

[5] A. Bhide. *The origin and evolution of new businesses*. Oxford University Press, USA, 2000.

[6] R. Blundell and M. Costa Dias. Evaluation methods for non-experimental data. *Fiscal studies*, 21(4):427–468, 2000.

[7] L. Bottazzi and M. Da Rin. Venture capital in europe and the financing of innovative companies. *Economic Policy*, 17(34):229–270, 2002.

[8] L. Bottazzi and G. Peri. The international dynamics of r&d and innovation in the long run and in the short run. *The Economic Journal*, 117(518):486–511, 2007.

[9] J.S. Cans and S. Stern. Incumbency and r&d incentives: Licensing the gale of creative destruction. *Journal of Economics & Management Strategy*, 9(4):485–511, 2000.

[10] S. Caselli, S. Gatti, and F. Perrini. Are venture capitalists a catalyst for innovation? *European Financial Management*, 15(1):92–111, 2009.

[11] T.J. Chemmanur, K. Krishnan, and D.K. Nandy. How does venture capital financing improve efficiency in private firms? a look beneath the surface. *Review of financial studies*, 24(12):4037–4090, 2011.

[12] A. Croce, J. Martí, and S. Murtinu. The impact of venture capital on the productivity growth of european entrepreneurial firms: Screening or value added effect? *Journal of Business Venturing*, 2012.

[13] D. de Meza and C. Southey. The borrower's curse: optimism, finance and entrepreneurship. *Economic journal*, 106(435):375–386, 1996.

[14] G. Dushnitsky and M.J. Lenox. When does corporate venture capital investment create firm value? *Journal of Business Venturing*, 21(6):753–772, 2006.

[15] R.G. Dyson, R. Allen, A.S. Camanho, V.V. Podinovski, C.S. Sarrico, and E.A. Shale. Pitfalls and protocols in dea. *European Journal of Operational Research*, 132(2):245–259, 2001.

[16] D. Engel. The impact of venture capital on firm growth: an empirical investigation. *ZEW Discussion Paper No. 02-02*, 2002.

[17] D. Engel and M. Keilbach. Firm-level implications of early stage venture capital investmentan empirical investigation. *Journal of Empirical Finance*, 14(2):150–167, 2007.

[18] R.L. Florida and M. Kenney. Venture capital-financed innovation and technological change in the usa. *Research Policy*, 17(3):119–137, 1988.

[19] G. Gebhardt. A soft budget constraint explanation for the venture capital cycle. *German Economic Review*, 10(1):71–90, 2009.

[20] G. George. Slack resources and the performance of privately held firms. *Academy of Management Journal*, 48(4):661–676, 2005.

[21] R.J. Gilbert and D.M.G. Newbery. Preemptive patenting and the persistence of monopoly. *The American Economic Review*, 72(3):514–526, 1982.

[22] P. Gompers and J. Lerner. The venture capital revolution. *The Journal of Economic Perspectives*, 15(2):145–168, 2001.

[23] Z. Griliches. Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4):1661–1707, 1990.

[24] S. Guo and M.W. Fraser. Propensity score analysis. *Statistical methods and applications*, 2010.

[25] G.E. Halkos and N.G. Tzeremes. Productivity efficiency and firm size: An empirical analysis of foreign owned companies. *International Business Review*, 16(6):713–731, 2007.

[26] B.H. Hall and R.H. Ziedonis. The patent paradox revisited: An empirical study of patenting in the us semiconductor industry, 1979-1995. *RAND Journal of Economics*, 32(1):101–128, 2001.

[27] J.J. Heckman, H. Ichimura, and P.E. Todd. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654, 1997.

[28] T. Hellman and M. Puri. The interaction between product market and financing strategy: The role of venture capital. *Review of Financial Studies*, 13(4):959–984, 2000.

[29] M. Hirukawa and M. Ueda. Venture capital and innovation: Which is first? *Pacific Economic Review*, 16(4):421–465, 2011.

[30] R. Inderst and H.M. Mueller. Early-stage financing and firm growth in new industries. *Journal of Financial Economics*, 93(2):276–291, 2009.

[31] B.A. Jain and O. Kini. Venture capitalist participation and the post-issue operating performance of ipo firms. *Managerial and Decision Economics*, 16(6):593–606, 1995.

[32] D. Kahneman and D. Lovallo. Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, 39(1):17–31, 1993.

[33] C. Keuschnigg. Public policy and venture capital backed innovation. In *Presented at 3rd German-Norwegian Seminar on Public Economics*, 2003.

20

[34] S. Kortum and J. Lerner. Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, 31(4):674–692, 2000.

[35] M.M. Liu, J.A. Zhang, and B. Hu. Domestic vcs versus foreign vcs: a close look at the chinese venture capital industry. *International Journal of Technology Management*, 34(1):161–184, 2006.

[36] S.K. Majumdar. X-efficiency in emerging competitive markets: the case of us telecommunications. *Journal of Economic Behavior & Organization*, 26(1):129–144, 1995.

[37] C.A. McNally. *China's emergent political economy: capitalism in the dragon's lair*, volume 75. Psychology Press, 2008.

[38] P.J. Norbäck and L. Persson. The organization of the innovation industry: Entrepreneurs, venture capitalists, and oligopolists. *Journal of the European Economic Association*, 7(6):1261–1290, 2009.

[39] E. Norton and B.H. Tenenbaum. The effects of venture capitalists' characteristics on the structure of the venture capital deal. *Journal of Small Business Management*, 31:32–32, 1993.

[40] M. Peneder. The impact of venture capital on innovation behaviour and firm growth. *Venture Capital*, 12(2):83–107, 2010.

[41] M.R. Reinganum. The anomalous stock market behavior of small firms in january: Empirical tests for tax-loss selling effects. *Journal of Financial Economics*, 12(1):89–104, 1983.

[42] W. Robbie and K. Mike. Venture capital and private equity: A review and synthesis. *Journal of Business Finance & Accounting*, 25(5-6):521–570, 1998.

[43] J. Ross and B.M. Staw. Organizational escalation and exit: Lessons from the shoreham nuclear power plant. *Academy of Management Journal*, 36(4):701–732, 1993.

[44] H.J. Sapienza and M.A. Korsgaard. Procedural justice in entrepreneur-investor relations. *Academy of Management Journal*, 39(3):544–574, 1996.

[45] J.E. Stiglitz. Credit markets and the control of capital. *Journal of Money, Credit and Banking*, 17(2):133–152, 1985.

[46] J.E. Stiglitz and A. Weiss. Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410, 1981.

[47] B. Stuck and M. Weingarten. How venture capital thwarts innovation. *Spectrum, IEEE*, 42(4):50–55, 2005.

[48] K. Subramanian. A theory of financing of ideas. Technical report, Emory University Working Paper 39, 2006.

[49] D.J. Teece. Reflections on profiting from innovation. *Research Policy*, 35(8):1131–1146, 2006.

[50] Luan Tianhong. *Research on PE development in Wenzhou*. Zhejiang Gongshang University, 2010.

[51] Luan Tianhong. *Venture Capital Development in Zhejiang Province*. Zhejiang Gongshang University, 2011.

[52] T. Tykvova. Venture capital in germany and its impact on innovation. *Social Science Research Network Working Paper*, 2000.

[53] M. Ueda. Banks versus venture capital: Project evaluation, screening, and expropriation. *The Journal of Finance*, 59(2):601–621, 2004.

[54] M. Ueda and M. Hirukawa. Venture capital and productivity. Technical report, Working Paper. University of Wisconsin, 2003.

[55] M. Ueda and M. Hirukawa. Venture capital and industrial innovation. 2006.

[56] J.M. Utterback and W.J. Abernathy. A dynamic model of process and product innovation. *Omega*, 3(6):639–656, 1975.

[57] S. White, J. Gao, and W. Zhang. *China's venture capital industry: institutional trajectories and system structure*. Insead, 2002.

[58] C.H. Yang, C.H. Huang, and T.C.T. Hou. Tax incentives and r&d activity: Firm-level evidence from taiwan. *Research Policy*, 2012.

[59] Dakai Yang and Tongyao Shao. Research developing about venture capital and innovation. *Social Sciences in Nanjing*, 7:959–984, 2010.

Table 1 Sample Composition for VC-backed and non-VC-backed firms

Covariate		VC-backed				Non-VC	
		VC Amount	No. of VC	No. of firms	%	No. of firms	%
Industry	Manufactory	26918	1500	293	75.3	1199	57.6
	IT	5916	298	59	15.2	144	6.9
	Others	1227	247	37	9.5	739	35.5
State	Yes	-	-	332	85.4	970	46.6
	No	-	-	42	10.8	993	47.7
	Unknown	-	-	15	3.8	119	5.7
Year	Before	5640	427	427	22.0	2044	13.3
	2006	1793	142	142	7.3	2329	15.2
	2007	3222	195	195	10.0	2276	14.8
	2008	4306	251	251	12.9	2220	14.5
	2009	6171	300	300	15.5	2171	14.1
	2010	7910	326	326	16.8	2145	14.0
	2011	5019	300	300	15.5	2171	14.1

Note: "State" dummy indicates the exists of government intervene of a firm up to 2011, repeated intervenes to a same firm don't count. "VC Amount" is the total amount of VC received up to 2011 in million yuan. "No. of VC" is the number of VC receipts up to 2011. "No. of firms" is the number of firms which have even received VC up to 2011. For example, if a firm received VC support for 5 years by 2011, the contribution of the firm to the "No. of VC" is 5, while the contribution to "No. of firms" is 1. The percentage is calculated only based on "No. of firms". In the year column, "before" means the aggregate amount of VC investment before year 2006.

Table 2 The Statistic Description of Covariates: Average of data from 2006 to 2011

Covariate		VC-backed	Non-VC-backed	Bias %	T test
Age	Matched	6.992	7.568	8.238	3.254
	Unmatched	6.992	13.58	94.23	31.48
Asset	Matched	1.38 e9	2.15 e9	55.80	6.545
	Unmatched	1.38 e9	4.61 e9	234.1	11.33
Sales	Matched	7.00 e3	7.00 e3	0.000	0.002
	Unmatched	7.00 e3	7.01 e3	0.143	0.168
Employ	Matched	1.40 e3	1.52 e3	8.571	0.654
	Unmatched	1.40 e3	3.92 e3	180.0	22.89
Cap.Int.	Matched	7.65 e3	7.60 e3	-0.654	-1.373
	Unmatched	7.65 e3	6.71 e3	-12.29	-6.351
State	Matched	0.887	0.768	-13.42	-6.235
	Unmatched	0.887	0.555	-37.43	-55.87
Industry	Matched	0.835	0.842	0.838	0.941
	Unmatched	0.835	0.889	6.467	6.642
Patent(d)	Matched	0.407	0.384	-5.651	-1.214
	Unmatched	0.407	0.334	-17.94	-10.25
Malm(s)	Matched	3.845	3.741	-2.705	-0.354
	Unmatched	3.845	3.456	-10.12	-8.211
Malm(p)	Matched	4.715	4.671	-0.932	-0.993
	Unmatched	4.715	4.481	-4.963	-1.119

Note: The table summarizes the statistics of covariates for both VC-backed and non-VC-backed firms during 2006-2011. The value of every covariate has been averaged by the number of its yearly observations. "Employ" indicates the number of employees, and "Cap.Int." indicates the capital intensity. "State","Industry","Patent(d)" are three dummy variable. "Malm(s)" and "Malm(p)" are the Malmquist indices calculated by Sales and Profit margin. "Unmatched" means all original available observations, while "matched" non-VC-backed firms are those selected by the propensity score matching scheme. "Bias %" measures the percentage difference in covariate between VC-backed firms and non-VC-backed firms. "T test" shows the student-t test statistics with the null hypothesis that VC-backed firms and non-VC-backed firms have same mean value of covariates.

Table 3 The Statistic Description of VC Impact

Period			Pre - VC			Post - VC		
			VC-backed	Control	T	VC-backed	Control	T
1 Yr	Patent	Mean	19.65	19.01	6.004	21.14	19.91	6.015
		Obs	89	91	-	89	91	-
	Malm(s)	Mean	3.511	3.472	1.237	3.752	3.653	0.982
		Obs	285	297	-	285	297	-
	Malm(p)	Mean	4.352	4.286	4.412	4.896	4.711	5.086
		Obs	285	297	-	285	297	-
2 Yr	Patent	Mean	15.64	14.61	3.128	17.98	16.00	4.670
		Obs	45	52	-	45	52	-
	Malm(s)	Mean	4.021	3.997	1.982	4.251	4.012	1.315
		Obs	234	247	-	234	247	-
	Malm(p)	Mean	4.220	3.984	3.008	4.885	4.391	5.672
		Obs	234	247	-	234	247	-
3 Yr	Patent	Mean	16.45	16.02	2.765	20.25	19.22	3.130
		Obs	32	38	-	32	38	-
	Malm(s)	Mean	3.598	3.532	1.965	3.952	3.891	2.071
		Obs	201	209	-	201	209	-
	Malm(p)	Mean	4.251	4.037	2.312	4.851	4.513	2.998
		Obs	201	209	-	201	209	-
4 Yr	Patent	Mean	16.54	16.81	-0.231	20.21	19.81	2.871
		Obs	20	23	-	20	23	-
	Malm(s)	Mean	3.625	3.412	0.980	4.001	3.765	1.769
		Obs	165	172	-	165	172	-
	Malm(p)	Mean	4.210	4.241	-0.098	4.852	4.765	1.654
		Obs	165	172	-	165	172	-

Note: The table summarizes the innovation performance of both VC-backed firms and selected non-VC-backed firms in the control group at different time spans. "Patent" shows the average number of patents over given number of "Obs" observations, while "Malm(s)" and "Malm(p)" are the Malmquist indices. "Control" represents the selected non-VC-backed firms that form the control group. "T" is the Student-t statistics which is used to exam the difference between VC-backed firms and non-VC-backed firms in terms of innovation measure. The "Period", i.e. 1 Yr, means the length of time window between "Pre-VC" and "Post-VC".

Table 4 The Difference-in-Differences Measure and Statistics Significant Test

| Period		DID	Mann-Whitney		Kruskal-Wallis	
			Z	Pr	Chi2	Pr
1 Yr	Patent	0.590	1.501	0.128	2.564	0.095
	Malm(s)	0.060	7.299	0.005	72.06	0.008
	Malm(p)	0.119	15.34	0.000	248.1	0.000
2 Yr	Patent	0.950	2.853	0.080	7.546	0.079
	Malm(s)	0.215	4.766	0.017	48.71	0.015
	Malm(p)	0.258	17.76	0.000	279.0	0.000
3 Yr	Patent	0.600	5.765	0.017	9.364	0.010
	Malm(s)	-0.005	-5.921	0.000	34.50	0.000
	Malm(p)	0.124	15.02	0.000	220.0	0.000
4 Yr	Patent	0.670	6.132	0.005	12.20	0.007
	Malm(s)	0.023	4.887	0.010	51.08	0.012
	Malm(p)	0.118	12.98	0.000	145.3	0.000

Note: The table reports the Difference-in-Differences measures with associated significance test results. "DID" is the Difference-in-Differences measure, "Z" and "Chi2" are the statistics generated by Wilcoxon-Mann-Whitney test and Kruskal-Wallis analysis of variance, "Pr" is the associated probability (P value). The null Hypothesis H0 indicates "there's no difference between two groups". From the regression, Yr 1 and Yr 2 do not exhibit significant difference in patent outcomes, however, Yr 3 and Yr 4 do show the difference..
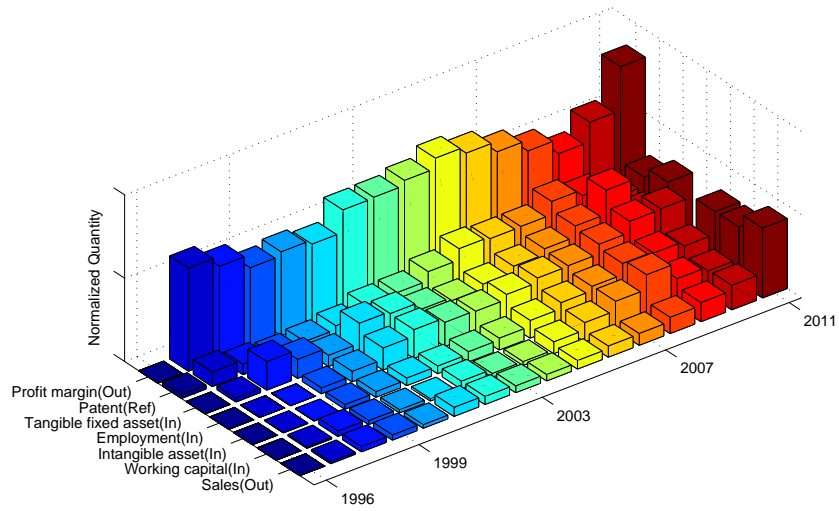
Figure 1 The figure shows the quantitative relations among liquidity ratio, working capital, employees (employment), intangible assets, tangible fixed assets, sales and profit margin. The number of patents is also illustrated for reference. The variables are scaled for better review.
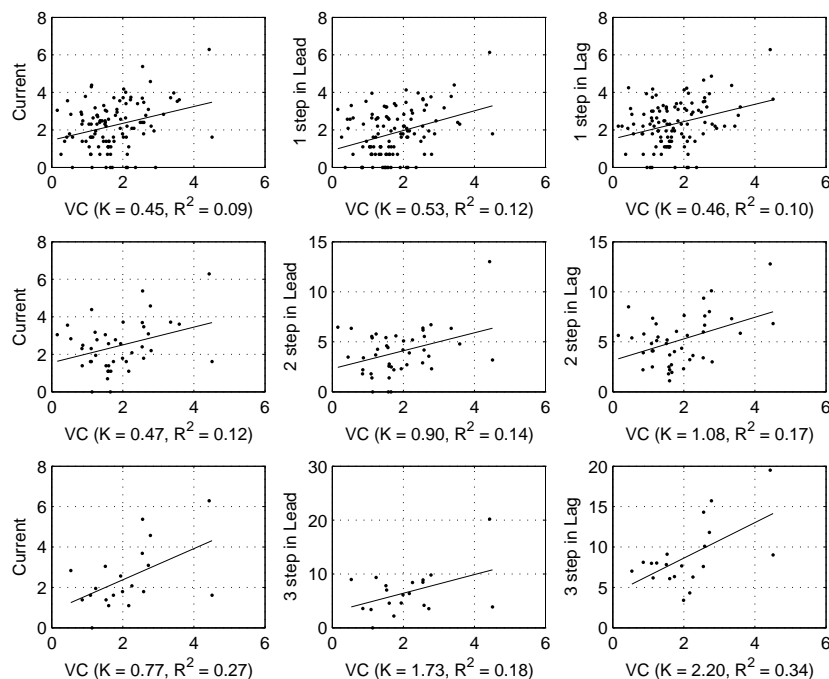
Figure 2 The figures show the potential causality between the first round VC
support and the patent counts during 7 years (1994-2011). Both the number
of patents and the amount of VC are taken the logarithm. K represents the
slope and R^2 indicates the goodness of fit. Each point in the figure represents
a "VC event": the amount of VC input and the consequent innovation output
in terms of patent counts. The figures show weak causal relationship between
VC financing and patent counts at different steps of lag and lead. The "VC
first" pattern is more clear than the "Patent first" pattern.
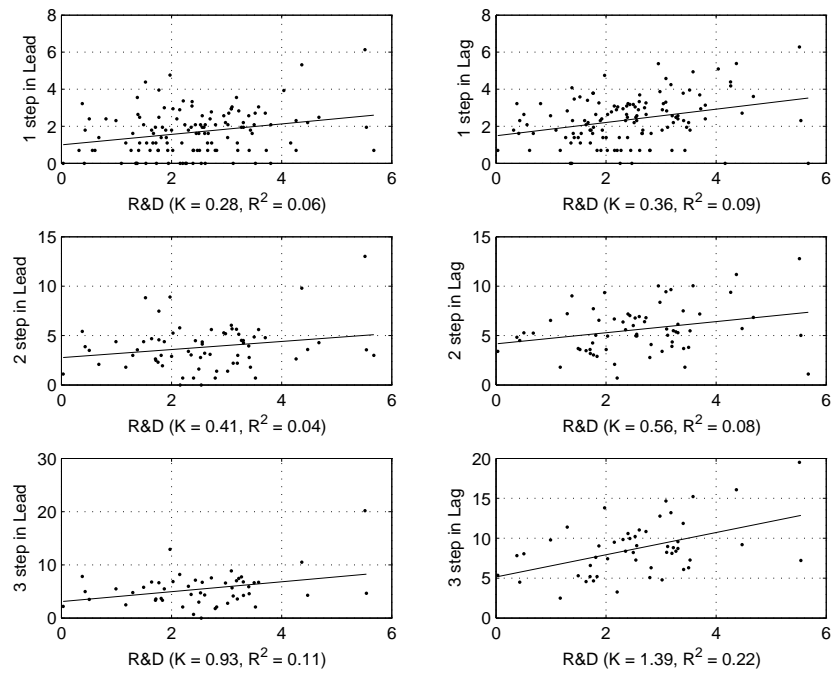
Figure 3 A comparative experiment shows the relationship between R&D input made on the year when first round VC happened and the number of patents acquired in the leading and lagged years during 7 years (1994-2012). The figures show similar patterns as Fig. 2 and "R&D first" trend though not as significant as "VC first" trend in Fig. 2.
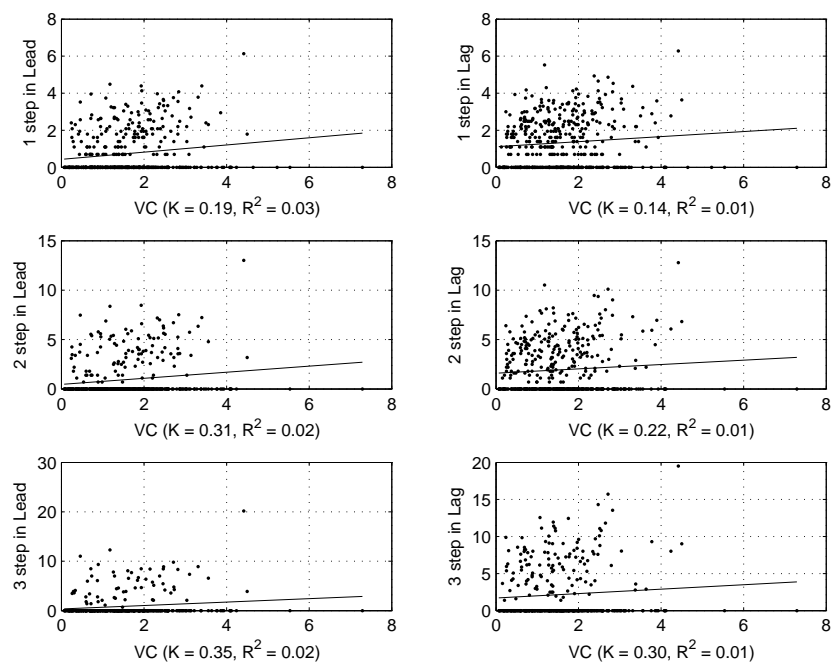
Figure 4 The figures depict the effects of all rounds VC to the number of patents in the leading and lagged years.
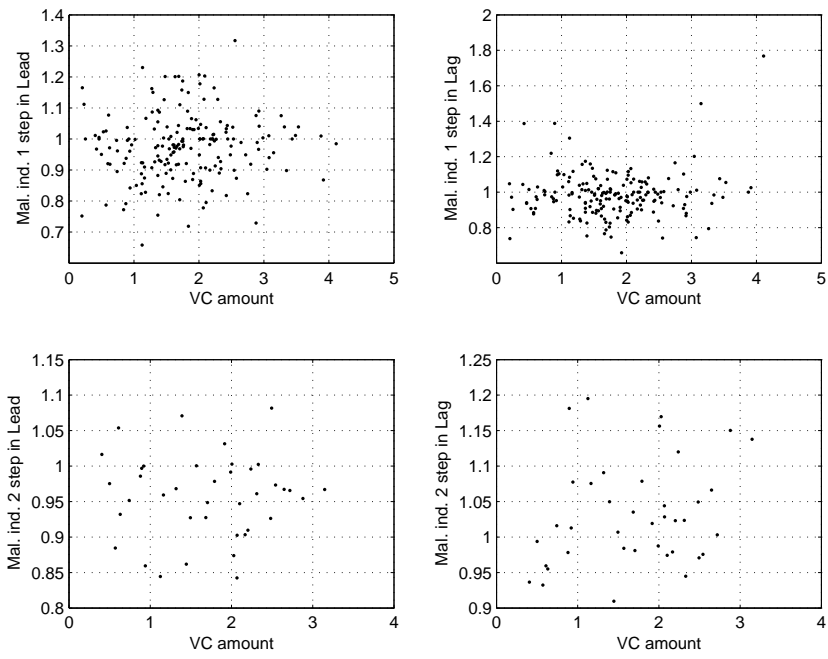
Figure 5 The figures draws the VC inputs against the Malmquist indexes in the leading and lagged periods.