Do subsidies boost innovation? Evidence from patent filings of industrial firms in China

Bo Pan*

Management School, University of Sheffield,

Conduit Road, Sheffield S10 1FL, United Kingdom

Junhong Yang

School of Finance and Management, SOAS, University of London,

10 Thornhaugh St, Bloomsbury, London WC1H 0XG, United Kingdom

Abstract

Using a merged dataset of industrial firm-level data and patent filing data in China over the period 1998-2008, we empirically find evidence that government subsidies have a positive effect on firms' innovation activities, suggesting the existence of supplement effect of subsidies on innovation funds in China. In addition, we find that the positive effect is more pronounced for private firms than state-owned enterprises (SOEs). Further results show that the positive effect is stronger for financially constrained firms rather than their financially healthy counterparts. We confirm the causal effect of subsidies on innovation by using an instrumental variables (IV) estimation and a difference-in differences (DID) specification. The estimation results keep consistent with those of various robustness tests. We also find that the positive effect is higher for firms in industries with low external finance dependence (EFD), firms in industries with high-intensiveness, firms in cities with low financial development, and firms in cities in with low foreign direct investment. The paper emphasizes the importance of government subsidies in firms' innovation activities and provides policy implications to maximize the promoting effect of subsidies.

JEL classification: G32; G38; H20; H71; O14; O30; O38

Keywords: Patent filings; Government subsidies; China; Firms' innovation activities; Ownership; Financial constraints; Industry-level; City-level

---

* Corresponding authors.
E-mail address: bpan2@sheffield.ac.uk (B. Pan); junhong.yang@soas.ac.uk (J. Yang)

1. Introduction

Since Schumpeter (1911) identified innovation as the critical dimension of economic development, innovation has been investigated for a long time from many perspectives, including competition (Aghion et al., 2005), institutional ownership (Aghion et al., 2013; Rong et al., 2017), financing constraints (Brown et al., 2009; Brown et al., 2012) etc. As one important policy tool, government subsidies have also become one of the research points related to innovation. Although some scholars have studied the role of subsidies in innovation, there is still a lack of consensus. One view holds that according to the spillover effect of public goods, government subsidies may facilitate corporate innovation since they can solve the problems of knowledge leakage and market failure in the innovation process (Nelson, 1959; Arrow, 1972; Stiglitz, 1989). Another view is that government subsidies may crowd out firms' inputs into research and development (R&D) and thus impede their innovation investment to some extent (Busom, 2000; Wallsten, 2000). China's large heterogeneities in historical, social, cultural and economic aspects make it difficult to draw a generalized conclusion in the largest emerging market. To further understand the relationship between subsidies and innovation, in this paper we explore what is the dominating effect of subsidies on innovation in China. Furthermore, we test whether the impact of subsidies on innovation would change by taking into various kinds of firms, industries, and cities.

After the 1978 reform and open-up to a market economy, China has experienced its phenomenal economic growth with an average rate of around 10% per year, and thus China becomes from one isolated lagging economy to a highly globalized and the world's second-largest economy. Alongside China's rapid economic development, China's innovation has made a tremendous improvement in both quantity and quality during the past four decades especially after China's WTO accession in 2001. For the quantity-level of innovation, according to the statistic of the World Intellectual Property Organization (WIPO), China has become the country receiving the largest number of patent applications worldwide since 2011.[1] For the quality-level of innovation, China's latest ranking is 17th in the report of 'Global Innovation Index 2018' published by the WIPO,[2] which is the first time that China rides to the top 20 countries of the global innovation index. The ranking of China is the highest among all developing economies, and even higher than that of some developed economies such as Canada

[1] *The Economist*, 'How innovation is China? Valuing patents', Jan. 5th, 2013.
[2] The report of 'Global Innovation Index 2018' could be browsed through the website address: https://www.globalinnovationindex.org/Home.

(18th), Australia (20th) and Spain (28th). The impressive progress of China's innovation should be attributed to the Chinese government's emphasis on innovation. One typical example is that in 2006 the State Council of China employs a strategy called 'National Program for Medium- and Long-Term Scientific and Technological Development' (hereafter NPMLT) which aims at promoting China's innovation.[3] Along with the government's attention to innovation, China's innovation input has also increased significantly. According to the OECD statistics, China's total gross spending on R&D is 442,721 million US dollars in 2017, which is higher than that of other OECD members only except the US (483,676 million US dollars).[4] China is one of the few low or low-middle income countries whose R&D intensity (measured by the ratio of R&D expenditure to GDP) has risen by over 1%. The rising R&D intensity may contribute to the surge of China's patent applications. Although China's innovation has greatly improved in the decades, it still faces some considerable challenges such as weak intellectual property protection (IRP), overwhelming dependence on foreign technology, low input-output efficiency, low share of total R&D expenditure allocated to basic research. As China is facing a number of bottlenecks in its economic growth in recent years,[5] the Chinese government has realized innovation especially indigenous innovation would become the main driving force for reversing China's current economic slowdown and thus simplemented many tools to promote innovation. For example, in 2015 the Chinese central government puts forward a strategic plan of 'Made in China 2025' to drive innovation.[6] Therefore, now during China's strategic transition period from investment-driven growth type to innovation-driven growth type (in other words, from 'made in China' to 'invented/designed in China'), to understand the mechanism of how to further facilitate China's innovation is important.

As one important economic intervention tool used by governments to achieve economic targets, subsidies have been explored in academic areas for a long time: production efficiency

[3] The NPMLT strategy has three objectives that could be summarized as follows: first, china committed to increasing its ratio of R&D expenditure to GDP to 2.50% in 2020; second, China committed to stimulate its indigenous innovation and reduce foreign technology dependence; third, corporations would become the main driving forces of innovation. The state council also issued a list of follow-up policies implemented by government ministries and agencies at all levels for supporting the strategy.

[4] The data source of gross spending on R&D is the web site of OECD (2019), available at: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm.

[5] China's economy is now facing some difficulties, such as increased labour costs, high staff turnover, and low manufacturing efficiency compared to global standards. From 1978 to 2014, China's Gross Domestic Product (GDP) maintained a high growth rate of around 10% per annum, while after 2014 its growth has slowed below 7% per annum.

[6] In May 2015, Chinese Premier Li Keqiang and his cabinet issued the plan 'Made in China 2025', which focus to help China move from being the world's 'factory' (producing cheap and low-quality goods) and move to produce higher-value products and services.

(Bagwell & Staige, 1989; Bagwell & Staige, 2006), R&D (Bronzini & Piselli, 2016), firm value or firm performance (Lee et al., 2014; Lim et al., 2018). As regards China, although the 1978 reform makes a gradual shift to China's economy from a centrally planned system to a market-oriented system (Ezzamel et al., 2007), governments (including central and local) still maintain enormous influence over enterprises through policy instruments such as subsidies. Due to this unique government-influenced economic model in China, governments can use subsidies to allocate financial resources to favored enterprises or industries. Government subsidies are also one of the four important financial sources for Chineses firms (Allen et al., 2005).[7] Thus, to understand the role of government subsidies in China's rapid economic rise during recent decades is increasingly important, since there is a global debate about whether government subsidies could give an unfair advantage to Chinese firms to compete with their foreign counterparts (Godement et al., 2011; Hormats, 2011; Fang & Walsh, 2018). Meanwhile, China's innovation has also been dramatically changing from a conventional lagger to a virtual leader, which provides a motivation for us to investigate what is the role of government subsidies in corporate innovation (whether it is positive or not) in the largest emerging market. Although several studies have explored the effect of subsidies on innovation, most of them mainly focus on developed economies (Nelson, 1959; Arrow, 1972; Stiglitz, 1989; Busom, 2000; Wallsten, 2000). In other words, there has been little systematic research on how subsidies affect innovation in emerging economies. Additionally, given the importance of innovation explained above in China's economic transformation period, it deserves more in-depth studies to understand the mechanism of innovation through subsidies in China's unique political and economic system. Thus, our paper can enrich the understanding of the role of subsidies in R&D by examining the link between government subsidies and firms' innovation activities in China,

In this paper, we use a combination of two micro-level data collected by China's official statistics institutions. Specifically, first, we calculate the number of patent applications per firm from the State Intellectual Property Office (SIPO) patent data to measure firms' innovation output, as patents have long been used as an indicator of innovation activities and technological growth (Griliches, 1990; Kortum, 1997). Second, we combine the measure of firms' innovation output with the firm-level data conducted by the National Bureau Statistics (NBS) of China. Finally, we get a huge unbalanced panel of observations covering large and medium-sized

[7] Allen et al. (2005) suggest that the four important financial sources for Chinese firms are bank loans, firms' self-fundraising, foreign direct investment, and government subsidies.

enterprises distributed in 31 provincial regions and 40 (39) GB/T two-digit industries over the period 1998-2008. Through empirical estimations on the combined data, we find a significantly positive effect of government subsidies on firms' innovation activities. Furthermore, we make some additional tests. Since SOEs and private firms face different ownership mechanisms, we find that government subsidies have a stronger positive effect on innovation activities of private firms than those of SOEs. We also find that the positive effect of subsidies on innovation is more pronounced for firms with more financial constraints compared to their financially healthier counterparts.

We employ some methods to mitigate the potential problem of endogeneity. First, to alleviate the reverse causality of the subsidies and innovation, we choose the instrumental variable (IV) method by using city-level fiscal revenue and the median value of government subsidies in each year-city-industry-ownership level as the instrumental variables for subsidies received by firms from governments. We also choose lagged values of government subsidies as the instrumental variable to make an additional test. For further verifying the causal effect of subsidies on innovation, we use a subsample of firms in Suzhou (one prefecture-level city in Jiangsu Province) to make a difference-in-differences (DID) specification, since Zhangjiagang (one county-level city of Suzhou) revised its patent subsidy policies in 2006 while other county-level cities of Suzhou did not make any revisions at the same time. Second, to control for estimation bias of potential omitted variables simultaneously affecting firms' innovation activities, we add the contemporaneous terms of independent variables into our regression models to re-estimate. Third, to overcome concerns about measurement error of firms' innovation activities, we use firms' new product output value as an alternative measure of firms' innovation output and R&D expenditure as a proxy of firms' innovation input to estimate again. These tests alleviate the endogeneity issues existed in the paper and all results confirm a causal and positive effect of subsidies on innovation.

We also use more tests to enhance robustness. First, considering that patents have different levels of quality, we only choose the number of firms' invention patent applications to proxy firms' innovation output in our regressions since invention patents represent good-quality patents. Second, because the number of patent applications per firm is a counting variable that has lots of zero outcomes, we employ the Zero-inflated Poisson method to estimate. Third, we choose the natural logarithm of firm-level financial variables to standardize independent variables in our regressions to estimate. Fourth, due to the data limitation in the year 2008, we choose an alternative sample excluding the data in the year 2008 to estimate. All estimation results of the robustness tests keep qualitatively unchanged.

Additionally, we extend the study to industry-level and city-level. For industry-level, we find that the positive effect of subsidies on innovation is weaker for firms in industries with higher external finance dependence (EFD) but stronger for firms in industries with high-tech intensiveness. For city-level, the positive effect of subsidies on innovation is receded for firms in cities with higher financial development and firms in cities with higher foreign direct investment (FDI). Through the further extension, our paper sheds new lights on the effect of subsidies on innovation based on different industries and cities in China.

Our paper contributes to the literature in the following ways. First, it contributes to the literature on the effects of subsidies on innovation. To the best of our knowledge, our paper is the first to investigate the direct effects of government subsidies on firms' innovation activities in China based on a large number of unlisted firms. Prior studies have investigated the effects of subsidies on innovation while the majority of them focus on developed economies (Nelson, 1959; Arrow, 1972; Stiglitz, 1989; Busom, 2000; Wallsten, 2000; Almus & Czarnitzki, 2003; Kleer, 2010; Bronzini & Piselli, 2016). However, as the largest emerging economy with a unique social system, China should not be ignored. In addition, previous papers focus on the data of listed firms in China (Boeing, 2016), while listed firms cannot fully reflect China's economy.[8] Our paper is distinct from but also complementary to the literature by exploring a large panel based on NBS firm-level data that records all above-scale enterprises (including unlisted and listed).[9] Second, our paper contributes to the literature on the effect of subsidies on innovation by linking the NBS firm-level data with the SIPO patent data that is the unique dataset covering the information of all patent applications in China. Because the NBS firm-level data does not record innovation proxies completely, we can fill the data gap by linking it with the measure of corporate innovation calculated based on the SIPO data. Third, our paper contributes to the literature on the effects of subsidies on firms' performance. Several papers have studied the factors that could be impacted by subsidies in China such as firm value (Lee et al., 2014), corporate social responsibility (Lee et al., 2017), firm performance and the cost of debt (Lim et al., 2018). Using a large sample of unlisted firms, our paper explores the role

[8] Generally, firms that can go public are firms with relatively good qualifications, standard management, and strong profitability. Thus, listed firms are less representative of all china's enterprises.

[9] Above-scale enterprises occupy more than 90% of China's gross industrial product. Thus, compared to listed firms, above-scale enterprises are better to reflect China's whole economy.

of subsidies on innovation in China. Fourth, our paper contributes to the literature on innovation. Some studies have examined various factors affecting innovation in China, including financial constraints (Guariglia & Liu, 2014), institutional ownership (Rong et al., 2017), input tariff liberalization (Liu & Qiu, 2016) and total factor productivity (Boeing et al., 2016). Since subsidies are one of the four main financing sources for China's firms (Allen et al., 2005), it is important to explore innovation from the perspective of subsidies. Fifth, due to the 'lending discrimination' and the regional economic development imbalance in China, for the first time we extend the existing research by linking with the heterogeneity of firms, industries, and cities to observe what is the change to the effect of subsidies on innovation.

The rest of the paper is organized as follows. In section 2, we introduce the background of China's patent applications and government subsidies. In Section 3, we illustrate our theoretical motivation. In Section 4, we explain our estimation specifications and variable measures. In Section 5, we show our data description and summary statistics. In Section 6, we analyze and discuss our empirical results. In Section 7, we make some tests for alleviating endogeneity issues and additional tests. In Section 8, we dram some conclusions.

2. Background of China's patent applications and government subsidies

2.1. China's patent applications

With the China economy on a firmer footing in recent decades, China's patent filings also have experienced a dramatic growth rate. For example, the report of 'World Intellectual Property Indicators 2018' shows that the number of China's patent filings increased from 18,700 in 1995 to 1,381,594 in 2017 with an average annual rate of 23%.[10] The report also admits 'China remained the main driver of global growth in filings', which could be reflected by that China's patent filings account for 43.6% of patent applications worldwide in 2017 and experience a growth rate of more than 10% each year since 2010. Although patent applications in China started late and from a small base, China has become the world leader receiving patent applications, outpacing Europe and South Korea in 2005, Japan in 2010 and the U.S. in 2011. The jump in China's patent applications has therefore drawn a lot of attention from both

[10] The report of 'World Intellectual Property Indicators 2018' could be browsed via: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2018.pdf. Since China revised its statistics method of patent applications in 2017 (China counts all patent applications received before 2017 while starting from 2017 it only counts applications for which the office received with necessary application fees)

economists and innovation scholars. For example, Hu & Jefferson (2009) explore factors that account for China's recent patent explosion including foreign direct investment (FDI), amendments to the patent law and ownership reforms by using a firm-level data set that spans the population of China's large and medium-sized industrial enterprises. Li (2012) suggests that patent subsidy programs implemented by each provincial region have played an important role in the explosive growth of Chinese patenting based on publicly available data. Some papers also find negative factors of China's innovation such as Liu & Qiu (2016) that show a negative relationship between a drastic input tariff liberalization caused by China's WTO accession in 2001 and corporate innovation measured by patent filings.

China issued its reform and opening policy in 1978 and since then began to conceive its first modern patent law. The patent law was passed in 1984 and came into effect in 1985, and has been amended several times in 1992, 2000 and 2008. The first two amendments were made during the negotiation period of China's accession into the WTO in order to keep in accordance with the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). The patent law was amended again in 2008 for pushing China's indigenous innovation. Now China's patent law is pretty much in line with international norms and supports legal law enforcement to the explosive growth of China's patent applications.

Fig. 1 shows clearly the growing trend of the number of total patent applications to the State Intellectual Property Office (SIPO) of China since 1985 when the patent system was first implemented in China. According to the statistics, the number of total patent applications increased from only 18,509 in 1986 to 3,697,845 in 2017 with an average annual growth rate of 19.1%.[11] Specifically, we find that patent applications grew rather modestly until the end of the 1990s, while after 2000 especially 2002 have surged dramatically (except 2014), which may be explained by the benefits of technology embedded in imported inputs caused by China's entry into the WTO in December 2001. Amendments to patent law in 2000 also make a huge contribution to the upsurge in the new century. In addition, we also find that the SIPO receives the bulk of its patent applications from domestic innovators rather than foreign innovators. Although domestic and foreign applications both show growth trends, the growth rates of them are different. Specifically, domestic applications experienced excessive growth from 13,680 in 1986 to 3,536,333 in 2017, while foreign applications had a relatively sluggish

[11] The data in 1985 is recorded from 1st April 1985. Thus, we observe the development trend of China's patent applications from the year 1986 rather than the year 1985. This also applies to the next description of Fig.2.

growth from 4,829 in 1986 to 161,512 in 2017. Thus, the difference in the number of applications between domestic and foreign increased from 8,851 in 1986 to 3,374,821 in 2017. The explosive surge of domestic applications may be interpreted by consistent policies issued by China's government for stimulating indigenous innovation, such as the patent law amendments in 2008 which can encourage indigenous innovation. Geographically, innovators are normally distributed in coastal regions, which indirectly reflects a positive relationship between innovation and economic development level.[12]

[*Insert Figure 1 here*]

There are three types of patents granted by the SIPO: invention, utility model and design. The three types of patents are different in applicable targets, protection period and approval procedures.[13] Among these three kinds of patents, invention patents are regarded as major innovation patents with high quality as they have the most difficult examination requirements. Fig. 2 shows the proportion of the three types of patent applications in China during the period from 1985 to 2017. We can find that the proportion of invention patent applications first had a downward trend from 43.27% in 1986, while after the patent law amendment in 1992 it presented a growth trend to 37.36% in 2017 although the growth trend fluctuated slightly. During the period, the proportion of utility model patent applications first decreased before 2007 and then increased, while the proportion of design patent applications did the opposite (increased before 2007 and then decreased). We also can find that during the period the proportion of invention patent applications almost never outpace 40% (except the year 1985 and the year 1986), which is against the sum of the proportion of utility model patent applications and the proportion of design patent applications always being higher than 60%. The findings suggest although invention patent applications play an increasingly important role in the application system of China's patents, the overall quality of China's patent applications is still not very high.

[*Insert Figure 2 here*]

2.2. China's government subsidies

[12] According to the region classification of China's NBS, China is divided into three parts: coastal (eastern) regions, central regions, and western regions. Coastal regions have the highest economic development level in China. The detailed region classification can be viewed in Appendix D.

[13] The detailed differences of the three types of patents are described in Appendix A.

Subsidies are a form of financial aid or support granted by the government or a public body and extended to a microeconomic sector (or institution, business, or individual) with the aim of promoting economic and social policy (Myers, 2001). Government subsidies can be divided into various types based on targets, such as production subsidies, import/export subsidies, employment subsidies, R&D subsidies, etc. As a form of economic intervention, subsidies are inherently contrary to the free market’s demands. However, according to Schwartz & Clements (1999), there are at least three reasons why governments still use subsidies as a policy instrument in the process of economy-control. First, governments could use subsidies to offset various market imperfections because the free market’s ‘invisible hand’ cannot always allocate resources in the most efficient way. Second, governments could use subsidies to gain economies of scale in production when important sectors are too small in scale to compete with their larger and more mature counterparts in the market. Third, governments could use subsidies to achieve social policy objectives, such as a fairer distribution of consumption or income.

As regards China, the achievement of the three objectives is also inseparable from government massive subsidies to favoured industries or enterprises. As one type of the four most main financing sources (Allen et al., 2005), subsidies play an important role in the surge of China’s economy during the past decades. Since 1953 when China’s central government issued its first ‘Five-year’ plans to manage its industrial development, government subsidies in China are prevalent and persistent. The ‘Five-year’ plans of different periods issued by China’s central government show targeted products, enterprises, and industries that governments need to support in different periods. For example, the 13th Five-year plan covering 2016 to 2020 aims at developing some strategic emerging industries such as information and communication technology, aerospace hardware, new energy fuelled vehicles and marine engineering equipment. Governments employ subsidies to support the development of these sectors.

Besides the central government, local governments also have the incentives to subsidize firms caused by two reasons. First, since the reform and open-up policy in 1978, China’s central government has been delegating the power on subsidy allocation to local governments. The decentralization makes that local governments have considerable discretion in determining the number of subsidies allocated to corporations. Second, since the most important indicator for evaluating local government officials’ performance is the economic performance of their respective areas, local governments should be more concerned about the speed of regional economic development mainly represented by GDP compared to the central government. The decentralization and the evaluation performance mode simultaneously contribute to severe competition among local officials to promote economic development. Thus, local officials are more motivated to assist firms in their respective areas by granting subsidies.

For China's innovation (i.e. patent) subsidy policies, since 1999 Shanghai (the city with the largest economy in China, administratively equal to a province) implemented the first China's patent subsidy policy to promote local enterprises' patenting activities,[14] until 2007 most of the provinces have launched similar programs and many prefecture-level cities have their own subsidies for patent applications (Li, 2012). Government subsidies come in various distribution forms and all seven categories of them given by Schwartz & Clements (1999) have been implemented to facilitate innovation in China.[15] Some policies offer a fixed amount of reimbursement to firms for patent applications, regardless of the actual costs or whether the application is granted. Some policies provide subsides with a cap based on applicants' actual out-of-pocket expenses. Some policies pay a portion of application fees to applicants and award a prize (usually a much larger amount) for applications granted. For example, the State Council of China in 1999 approved the 'innofund program', which is a special government R&D program to support innovation activities of small and medium technology-based enterprises (SMTEs) by appropriation, interest-free bank loans, and equity investment.

Due to the various distribution forms of subsidies, the total amount of government subsidies is potentially unobservable because a fraction of subsidies granted is in a form of non-monetary supports (in other words, indirect grants). A bias is likely to appear since subsidies are underreported in firms' financial statements. In China's context of the study, we

[14] According to China's constitution, cities are divided into three administration levels: 4 municipalities (Beijing, Tianjin, Shanghai, and Chongqing) are first-level (province-level) administrative divisions and directly governed by the central government. The four cities are administratively to other 30 province-level administrative divisions (including Hong Kong, Macao, and Taiwan); prefecture-level cities including 15 sub-provincial cities are secondary-level (prefecture-level) administrative divisions and directly governed by the provincial government. These prefecture-level cities are ranked below province-level while above county-level in the administrative structure of China; county-level cities are third-level (county-level) administrative divisions and governed by the prefecture-level city government. The provincial governments directly govern a few county-level cities. The county-level cities are the lowest-ranking cities in China. According to the 2018 China Statistical Yearbook (http://www.stats.gov.cn/tjsj/ndsj/2018/indexch.htm), by the end of 2017, there are totally 4 municipalities, 294 prefecture-level cities and 363 county-level cities in China.

[15] Schwartz & Clements (1999) define the seven categories of government subsidies as: 'direct government payments to producers or consumers (cash subsidies or cash grants); government guarantees, interest subsidies to enterprises, or soft loans (credit subsidies); reductions of specific tax liabilities (tax subsidies), government equity participations (equity subsidies); government provision of goods and services at below-market prices (in-kind subsidies); government purchases of goods and services at above-market prices (procurement subsidies); implicit payments through government regulatory actions that alter market prices or access (regulatory subsidies)'.

focus on the observable forms of government subsidies that are clearly recorded in firms' income statements (prior to 2007, subsidies are a separate item in the income statement but changed to one part of 'other income' since 2007).

3. Theoretical motivation

The impact of government subsidies on corporate innovation has been discussed for a long time. However, until now the related empirical findings are still inconclusive. A considerable number of scholars (Nelson, 1959; Arrow, 1972; Stiglitz, 1989; Görg & Strobl, 2007; Aerts & Schmidt, 2008) suggest that government subsidies have a positive effect on corporate innovation. On the contrary, some scholars (Busom, 2000; David et al., 2000; Wallsten, 2000; Acemoglu et al., 2018) argue that government subsidies affect corporate innovation negatively.

One view is that government subsidies have a promoting impact on corporate innovation. First, government subsidies could generate incentive effects on firms' innovation activities. Specifically, due to the spillover effect or knowledge leakage caused by R&D projects, innovators could not reap the full benefits of innovation and then weakens firms' R&D incentives (Clarysse et al., 2009), which subsequently leads to a market failure problem that R&D input cannot reach the optimal level (Arrow, 1972; Stiglitz, 1989). In addition, compared to other investments, R&D projects have their unique characteristics such as a demand of high inputs, a high uncertainty risk and a long-term investment cycle, which could hinder firms' motivation for innovation and then cause only firms with sufficient available funds to have the ability to invest in R&D projects. Therefore, due to the knowledge leakage and R&D projects' unique characteristics, firms generally lack motivation for innovation. Government subsidies could stimulate firms' innovation motivation since subsidies can reduce the marginal cost and diversify the uncertainty risk of their R&D projects (Almus & Czarnitzki, 2003; González & Pazó, 2008) by serving as a supplement to the innovation funds needed by firms (Tether, 2002). Second, as a financial intermediation, government subsidies can reduce the problem of information asymmetry between firms and external investors caused by R&D projects' high uncertainty risk (Leland & Pyle, 1977). Specifically, firms generally tend to understate the potential risk and overstate the expected return of the projects that firms hope to invest in, including R&D projects. Market investors thus cannot fully know the real information of these projects. Obtaining government subsidies for a firm may signal to market investors that the firm has gained government recognition and have a greater probability of owing projects with a high quality and a low risk (Lerner, 1999; Feldman & Kelley, 2006; Kleer, 2010). Consequently, firms receiving government subsidies are more likely to raise more funds for innovation from market investors compared to firms without subsidies. Hence, many scholars suggest that government subsidies are a supplement to innovation funds and have a positive effect on firm's innovation activities. The more subsidies from governments, the more firms' innovation activities.

Another view holds that government subsidies have a crowd-out effect on firms' input into R&D projects and thus play a discouraging role in corporate innovation. Some scholars suggest that after obtaining government subsidies, in order to pursue more short-term profits firms invest these funds into other projects with a short-term investment cycle rather than long-term projects such as R&D. When the funds for these short-term projects cannot be fully covered, the allocated government subsidies even can substitute for funds that are aimed at R&D projects. Thus, firms receiving government subsidies create a crowding-out effect on their innovation inputs (Yu et al., 2016). At this condition, government subsidies fail to play their expected role as a supplement to innovation funding. In addition, when the amount of government subsidies received by firms is higher, the crowding-out effect on their own R&D inputs will become more obvious because the level of firms' capital risk would be reduced as R&D inputs decrease (Boeing, 2016). Therefore, some scholars argue that government subsidies would crowd out innovation inputs and then have a negative effect on firms' innovation activities.

As the largest emerging market, China benefits tremendously from the 'reform and open up' policy over the past 40 years. China has been deepening the level of its reform and opening-up during these decades. For example, after more than a decade of difficult negotiations, China finally entered the WTO in 2001 by accepting rules such as lowering tariffs and strengthening IRP, etc. However, China's government still insists that China's social system is called the 'socialist political system with Chinese characteristics' rather than capitalism. The interpretation is that different levels of governments in China can use their administrative power to intervene in China's economy such as issuing guiding policies, allocating subsidies to some enterprises, forbidding foreign investment into some specified sectors. Many thanks to the decades of reform and opening up and the unique model of government intervention on building national champions, Chinese companies are increasingly competitive. Now some of these firms are emerging as serious global competitors because they are innovative and entrepreneurial. With the unique social system, China is always debated whether its administrative power could give an unfair advantage to China's firms to compete with their foreign counterparts, especially in investments with a large need of funds such as R&D projects. In addition, China has its own unique economic system. Due to the 'lending discrimination' in China's financial market, compared to the SOEs dominated by state capital, other types of firms such as private firms (main components of China's economy) may be more affected by subsidies from the government as they generally have a bigger funding gap (Bin, 2006). Thus, since until now there is no consensus on the effect of government subsidies on firms' innovation activities especially in emerging markets such as China, we explore it based on a large panel of Chinese unlisted firms to find out which effect can apply in China.

4. Data

This paper relies on a combined database that covers the patent data of the State Intellectual Property Office (SIPO) and the firm-level data of the National Bureau of Statistics (NBS) of China.

4.1. SIPO patent data

The first data source for firms' patent applications is the SIPO patent data (http://www.sipo.gove.cn), which is available since 1985 when the patent system was established in China. The SIPO dataset provides detailed information on all published patent applications, including patent application number, patent application data, applicant's names and addresses, patent IPC classification, i.e., whether the patent is applied as an invention patent, a utility model patent, or a design patent. The data is the most comprehensive coverage of patent information, and thus could be used in exploring China's innovation. However, due to the difficulties in integrating such data with other firm-level data since the SIPO patent data nearly has no same common identifier with other datasets, academic papers using Chinese patent data are still sparse. Some papers (Dang & Motohashi, 2015; Liu & Qiu, 2016) use the official Chinese names of patent applications recorded in the SIPO patent data to merge such data with the NBS firm-level data that we need to use in this study. However, this matching method still has some drawbacks since the names of firms listed in the datasets may not be fully consistent. Specifically, first, in the NBS firm-level data, the recorded variable of firms' official names has many obvious errors.[16] Second, one firm's name could change in the NBS firm-level data but the corresponding applicant firm probably does not timely update in the SIPO patent data or vice versa. Thus, if we directly link the SIPO patent data with the NBS firm-level data by using firms' names, there are potential estimation bias arising from the matching step. Fortunately, He et al. (2018) have created a matching algorithm that fits with the SIPO patent data and the NBS firm-level data from 1998 to 2009.[17] They processed the SIPO patent data and found the corresponding legal person codes of each patent applicant. Thus, we can merge the SIPO patent data processed by He et al. (2018) with the NBS firm-level data by using firms' legal person codes. The merging process is described in Section 4.3.

4.2. NBS firm-level data

The second data source for firm-level financial information is the Annual Survey of Industrial Enterprises over the period 1998-2008, which is drawn from the annual accounting reports conducted by the National Bureau of Statistics (NBS) of China.[18] Thus, the census data is called as NBS firm-level data and the most comprehensive firm-level dataset that spans the population of large and medium-sized firms in China. These firms are either state-owned enterprises (SOE) or non-SOE with annual main business income (i.e., sales) above 5 million Chinese yuan (approximately 680,000 US dollars, according to the official 2008 exchange rate).[19] The data covers roughly 165,000 businesses in 1998 to around 450,000 in 2008 as more enterprises are added during the period. All firms in the dataset are distributed in 39 mining, manufacturing, and public utilities and across all 31 provinces or provincial administrative units (except Hong Kong, Macao, and Taiwan), representing the broad Chinese economy. The dataset features detailed firm characteristics such as official names, locations, industry codes as well as most items of each firms' financial performance every year, including total assets,

[16] For example, we see many problematic names such as '鄂鄂州市隆昌合金钢有限责任公司' (the second 鄂 is redundant and must be a data entry error) and 'S 试第星旆嵋_铣' (the firm name is a total error messed up).

[17] The processed database could be found in He, Z.-L., Tong, T., Zhang, Y. & He, W. Harvard Dataverse http://dx.doi.org/10.7910/DVN/QUH8KT (2017).

[18] Actually, now the dataset has been updated to 2013. However, we have to stop the data until 2008 due to some reasons as follows. First, some key variables are lost after 2007 such as the current-year depreciation that is lost during the period 2008 to 2010, while current-year depreciation is used for calculating cash flow which is one control variable in our regression models. Since in our baseline model all independent variables are lagged by one year, we can choose the latest data until 2008. Second, the patent data for matching with NBS firm-level data is processed by He et al. (2018) until 2010. Third, in 2011 the China NBS adjusts the threshold of 'above-scale' enterprises for this dataset by increasing annual sales from 5 million Chinese yuan to 20 million Chinese yuan. Fourth, the financial crisis in 2008 potentially could make an estimation bias. Based on the above reasons, we have to choose the latest data until 2008.

[19] The firms with annual sales of more than 5 million Chinese yuan are referred to 'above-scale' firms, and thus the dataset is also called 'above-scale' industrial enterprise database.

total liabilities, main business sales, net income, accumulated depreciation, etc. The original sample for the period 1998-2008 contains 2,640,143 observations.[20] Additionally, the data has an advantage in constructing a panel with its unique legal identifier known as the legal person code (*fa ren dai ma*) to each firm (Chang & Wu, 2014).[21] The data has been used in studies of economy and finance on serval topics: competition (Cai & Liu, 2009; Aghion et al., 2015), financial constraints (Ding et al., 2013; Guariglia & Liu, 2014), foreign direct investment (Wang & Wang, 2015; Lin & Ye, 2017) and innovation (Hu & Jefferson, 2009; Liu & Qiu, 2016)

Before the construction of the combined data with the SIPO patent data, we process the NBS firm-level data to secure data quality. First, we supplement 408 observations' legal person codes which are less than nine digits to nine digits by and capitalize all English letters in the legal person code of 5,834 observations in the dataset in order to eliminate the influence of data collection error.[22] Second, we remove 5,838 observations without legal person codes and 641 observations with duplicated legal person codes, as these observations could not be used to construct the panel data.[23] Third, since China's government revised the 'National Industries Classification' in 2002 to keep consistent with the WTO regulation in 2001, we adjust the sector codes for firms prior to 2002 in order to keep the sector codes consistent during the

[20] In order to enhance the data reliability, we compare the NBS firm-level data with the records of China Statistical Yearbook. The detailed description could be viewed in Appendix A.

[21] We do not choose firms' names to construct the panel data since firms could change their names frequently. According to China's Company Registration Rules, the legal person code of one firm is unique nationwide and would not change after the registration of its legal entity even if it has adjusted its name and business nature. Occasionally, firms change their legal person code as firms' ownership has changed, which may be caused by restructuring, joint ventures, mergers and acquisitions, etc. For this situation, these firms generally change their legal entity. Thus, we treat only firms with different legal person codes are different firms and use firms' legal person codes to construct the panel data.

[22] First, in the dataset, 408 observations in 2008 have a legal person code of fewer than nine digits. We manually check them and find that this is a data collection error. If we use figure 0 to complement these observations' legal person codes to nine digits, we can observe that some of these 408 observations in 2008 are the same firms as observations with the corresponding complemented legal person codes in previous years. For example, the observation with the legal person code of '9316247' in 2008 actually is the same firm as the observation with the legal person code of '009316247' in 2007. Second, we also find that this is a data collection error for 5,834 observations with lowercase English letters in legal person codes. After capitalizing all English letters in the legal person code of these observations, we find that observations with the adjusted legal person codes in other years are the same firms as those 5,834 observations. For example, the observations with the legal person codes of 'x20723214' in 2005, 2006 and 2007 are the same firm as the observations with the legal person codes of 'X20723214' in 2004 and 2008.

[23] Some different firms share the same legal person code (probably due to statistical errors) and we cannot distinguish exactly which one of the various observations with the same duplicated legal person code is reliable. The fraction of these observations is quite low, roughly 0.024%, and thus we delete all observations with duplicated legal person codes in order to construct the panel and ensure data reliability.

sample period.[24] We delete 7,646 observations in the industries transferred from manufacturing sectors and in the industries disappeared in the scope of manufacturing sectors after the classification revision in 2002, as firms in these industries could not keep consistent during the sample period. After the industry-matching procedure, we could use the updated industry codes to construct industry dummy variables in regression models. Fourth, we drop 253,108 observations with annual sales of less than 5 million Chinese yuan to avoid the interference of no ‘above-scale’ enterprises.[25] Fifth, we drop 218 observations from the dataset by following the basic rules of the Generally Accepted Accounting Principles (GAAP). Specifically, observations whose total fixed assets are greater than total assets; liquid assets are greater than total assets; current depreciation is greater than accumulated depreciation are taken out of our sample.

4.3. Merging SIPO patent data with NBS firm-level data

We construct our unique dataset by linking the SIPO patent data processed by He et al. (2018) with the NBS firm-level data. Specifically, for the SIPO patent data, we calculate the number of each firm’s all patent applications (including invention, utility model and design) every year as the measure of firms’ innovation output, and then we merge the calculated innovation proxy with the NBS firm-level data through firms’ legal person codes. After merging, we find that only approximately 3.42% of observations in the NBS firm-level data have patent applications, suggesting that the participation rate of applying patents for Chinese firms is low.

To obtain a clear panel, we trim observations in the one percent tails of each of the firm-level continuous regression variables to control for the potential influence outliers.[26] All financial variables are deflated by using the provincial-level Producer Price Index (PPI) of each year during the sample period (1998 - 2008) conducted by the NBS.[27] After all adjustments,

[24] The Chinese description of the ‘National Industries Classification’ revision in 2002 could be viewed via: http://www.stats.gov.cn/tjgz/tjdt/200207/t20020711_16330.html. The detailed information on China’s industry codes and the adjustment in 2002 are shown in Appendix B.
[25] We have discussed that the dataset also records SOEs with annual sales of less than 5 million Chinese yuan. Additionally, in 2004 and 2008, all industrial firms are required to participate in the China NBS survey.
[26] The number of patent applications is a firm-level discrete variable and only less than 4% of the observations have patent applications. Additionally, because we use the natural logarithm of the number of patent applications, the influence of discrete characteristics could be avoided to some extent. Thus, we do not winsorize the variable of innovation output of $log\ (Pat_{i,t} + 1)$ in our regressions.
[27] The information on the provincial-level PPI could be searched on the NBS website (http://data.stats.gov.cn/).

we finally get a huge unbalanced panel data of 2,373,488 observations covering 663,699 mainly unlisted firms for the period 1998-2008.[28]

Based on our adjusted huge unbalanced panel data, we observe patent applications of China's firms from different perspectives (years, regions and industries). Figure 3 and Figure 4 respectively show the development trends of the participation rate of patent applications for firms and the number of patent applications per 1,000 firms in China during the period 1998 – 2008. On the one hand, we can find that from 1998 to 2008, China's firms show an increase in the enthusiasm of applying for patents. Specifically, for the full sample, the participation rate of patent applications increases from 2.10% in 1998 to 4.34% in 2008. There is also an increasing trend for the number of patent applications per 1,000 firms from 73.67 in 1998 to 373.33 in 2008. On the other hand, although firms' patent applications in China have shown obvious growth trends in the decade, we find that the level of China's patent applications is still not high, which can be reflected by the low participation rates of patent applications (never exceed 5%). The increase in firms' enthusiasm for applying patents is possibly interpreted by the policies of promoting innovation issued by Chinese governments, and the low participation rates of Chinese firms' patent applications may be caused by that Chinese firms' face R&D capital constraints.

[*Insert Fig. 3 here*]

[*Insert Fig. 4 here*]

Figure 3 and Figure 4 also compare SOEs and private firms in China. It is clear that compared to private firms, SOEs have a higher level of patent applications over the whole sample period, no matter in the participation rate of patent applications or the number of patent applications per 1,000 firms. Specifically, the participation rate of patent applications for SOEs and private firms respectively is 2.96% and 1.69% in 1998. Although the rate for SOEs and the rate for private firms grow separately to 7.32% and 3.46% in 2008, we can find that the difference in participation rates between SOEs and private firms rises from around 1.27% in 1998 to 3.86% in 2008. It also can apply to the number of patent applications per 1,000 firms and the gap of the numbers between SOEs and private firms increases from almost 22.97 to

[28] Appendix A shows details of the structure of the unbalanced panel. Additionally, because the data in 1998 and 1999 are used to construct lagged values in regression models. To enhance compatibility with the data in our regression estimations, in Table 2 of summary statistics we only summarize the data in our regression models during the period from 2000 to 2008.

561.51. A reasonable explanation for the enlarged gap is that SOEs can expand their advantages in applying for patents by enjoying the privilege of cheap loans from banks dominated by state capital or easily get support from governments such as subsidies. In addition, the relatively weak China's IRP possibly limits private firms' patent applications since they have to protect business interests, while SOEs can use their good connections with governments to fully ensure their benefits.

Figure 5 and Figure 6 respectively show the snapshots of the average participation rate of patent applications for firms and the average number of patent applications per 1,000 firms across prefecture-level administrative divisions in China during the period 1998 - 2008.[29] We can find that cities in coastal regions have a higher level of patent applications than cities in central and western regions, no matter in the participation rate of firms' patent applications or the number of patent applications per 1,000 firms. It keeps consistent with the conventional view that patenting activities are positively related to economic development.[30] Specifically, we find that more than two-thirds of the cities in coastal regions ((38+31)/101=68.32% and (39+29)/101=67.33%) have higher values than the median values of the average participation rates (1.87%) and the average number (62.71) across cities. However, the proportions of cities in central regions and western regions owning values greater than the median values of the average participation rates (1.87%) and the average number (62.71) across cities are all below half. The findings can suggest that the development level of patenting activities in coastal regions is better than that in central and western regions. The detailed data of the distribution of the number of prefecture-level administrative divisions for Figure 5 and Figure 6 are shown in Appendix E.

[29] There are totally three main administration levels in China. We have introduced in Note 14 that four municipalities (Beijing, Tianjin, Shanghai, and Chongqing) are administratively equivalent to other 30 province-level administrative divisions (including Hong Kong, Macao, and Taiwan). The second level is prefecture-level administrative divisions (prefecture-level cities, areas, autonomous prefectures or leagues). The third level is county-level administrative divisions (districts, county-level cities, counties, autonomous counties, banner or autonomous banner). According to the 2018 China Statistical Yearbook (http://www.stats.gov.cn/tjsj/ndsj/2018/indexch.htm), by the end of 2017, there are totally 34 province-level administrative divisions (excluding Hong Kong, Macao, and Taiwan), 334 prefecture-level administrative divisions and 2,851 county-level administrative divisions in China. Our maps of Figure 5 and Figure 6 are based on 4 municipalities and 334 prefecture-level administrative divisions. Hong Kong, Macao and 21 cities in Taiwan are included in the maps, but they miss the data records.

[30] The economic development among regions in China is not balanced. Coastal regions are the most important areas in China's economy. For example, according to the 2018 China Statistical Yearbook, China's gross domestic product (GDP) is 82,712.77 billion yuan and the sum of GDP for 11 provinces in coastal regions (excluding Hong Kong, Macao and Taiwan) is 47,124.47 billion yuan that is 56.97% of the country's GDP. In contrast, the sum of GDP for 8 provinces in central regions and sum of GDP for 12 provinces in western regions are only 20,733.38 billion yuan and 16,856.16 billion yuan that are respectively 25.07% and 20.38% of the country's GDP.

[*Insert Fig. 5 here*]

[*Insert Fig. 6 here*]

5. Estimation specifications and variable measures

5.1. Baseline specification

We choose a modified Euler equation that is first used to test the presence of financial constraints on investment (Whited, 1992; Bond et al., 2003). As a dynamic structural model, the Euler equation model has the advantage of controlling expected future profitability. Thus, financial variables in the regression do not pick investment opportunities (Bond et al., 2003). The baseline model is shown as following Eq. (1)

$$Log\ (Pat_{i,t}+1) = \beta_1 Log\ (Pat_{i,t-1}+1) + \beta_2 Log\ (Pat_{i,t-1}+1)^2 + \beta_3 S_{i,t-1} + \beta_4 Cf_{i,t-1} + \beta_5 Dbt_{i,t-1} + \beta_6 Sub_{i,t-1} + V_i + V_t + V_o + V_j + V_p + e_{i,j,o,p,t} \quad (1)$$

$Pat_{i,t}$ is the measure of firms' innovation output calculated by the number of patent applications for a firm *i* in a given year *t*. However, we encounter a problem that in our dataset the majority of observations have zero patent filings (that is $Pat_{i,t}$ equals 0) because the majority of firms do not submit patent applications to the SIPO during the sample period. Thus, we construct a measure of $Pat_{i,t}$ by using the natural logarithm of it - $Log\ (Pat_{i,t}+1)$ to avoid the problem of too many zeros. We then use the transformation $Log\ (Pat_{i,t}+1)$ as the dependent variable in our regression models. In addition, we also choose the published year of each patent applicant to re-calculate firms' innovation output for robustness check and the estimation results keep qualitatively same.

Using patents to measure innovation output has pros compared to other proxies (Bronzini & Piselli, 2016). Specifically, first, patents are less exposed to personal or subjective considerations. Second, patents are better to reflect innovation quality, because experts who can judge novelty and utility must examine one innovation product and then decide whether it can be patented. Third, Griliches (1990) suggests that patent activity can be interpreted as an indicator of the growth of economically valuable knowledge, and therefore a good measure of invention activity. Thus, given these advantages of patents, we believe that the number of patent applications is a suitable measure of innovation output in our empirical research.

In addition to patent filing data, there are other measures of innovation activities such as new product output value and R&D expenditure. Since in the NBS firm-level dataset the record of new product output value is incomplete,[31] we have to use the variable of new product output value as an alternative measure of firms' innovation output to alleviate the potential measurement error of innovation output. We also choose the variable of R&D expenditure as a measure of firms' innovation input for a robustness test to check whether the effect of subsidies on innovation keeps consistent.[32]

Our main explanatory variable is $Sub_{i,t}$ which represents total subsidies a firm i receives from government in year t. We standardize the variable by using the variable itself divided by total assets. For other control variables, we denote a firm i's ratio of sales to total assets in year t as $S_{i,t}$, its ratio of cash flows to total assets in year t as $Cf_{i,t}$ and its ratio of new long-term debts to total assets in year t as $Dbt_{i,t}$.[33] All independent firm-level continuous variables are lagged by one year $(t-1)$ to meet the modified Euler equation to eliminate simultaneity issues. We also add some dummy variables into the regression model. V_i is firm fixed effects. V_t is year fixed effects to control the impact of economic cycle changes. V_o is ownership dummy variables to control the effects of different ownerships which are grouped based on the fraction of firms' registered paid-in capitals.[34] V_j is industry dummy variables because government subsidies are generally distributed to firms in emerging strategic industries or industries that governments need to support.[35] V_p is geographical dummy variables because the regional gap of economic development makes that firms in China's various places differ in their ability and

[31] The data of new product output value is available from the years 1998-2008 but missing in 2004 and 2008. Thus, during the sample period 1998-2008 in the paper, the new product output value is less satisfactory than patent filing.
[32] The data of R&D expenditure is only available for the years 2001-2003 and 2005-2007.
[33] New long-term debts are the difference between the contemporaneous long-term debts and the lagged long-term debts. Thus, in the dataset observations with new long-term debts are recorded from 1999.
[34] Following Guariglia & Liu (2014), we use the fraction of firms' registered paid-in capitals to construct firms' ownership categories. Based on the majority (at least 50%) of registered paid-in capital (see Ayyagari et al., 2010, for a similar approach), all firms are divided into six categories: state-owned enterprises (SOEs); foreign firms; private firms; collective firms; Hong Kong, Macao or Taiwan (HMT) firms; and mixed ownership firms. The detailed description of ownership classification is in Appendix D.
[35] Due to the limitation of statistical software packages, GB/T two-digit sector codes rather than three-digit codes and four-digit sector codes are used as industry dummies in Eq. (1) to control industry fixed effects.

probability to obtain subsidies from governments. $e_{i,j,o,p,t}$ is an idiosyncratic error term. Table 1 shows the definitions of all regression variables in Eq. (1).

[*Insert Table 1 here*]

Table 2 shows the pairwise correlation analysis of the main regression variables. We can find that except the lagged innovation variable of $Log\ (Pat_{i,t-1}+1)$ and the lagged squared innovation variable of $Log\ (Pat_{i,t-1}+1)^2$, there is no collinearity between other variables. The correlation index between our dependent variable (innovation output variable of $Log\ (Pat_{i,t}+1)$) and main explanatory variable (subsidy variable of $Sub_{i,t-1}$) is 0.0188 and the significance level is 1%, which can indirectly suggest a positive relationship between firms' patenting activities and government subsidies. The finding possibly shows that government subsidies have a promoting effect on firms' innovation output.

[*Insert Table 2 here*]

5.4. Summary statistics

Table 3 summarizes means (and medians in parentheses) of the main variables for the full sample, firms with/without patent applications, SOEs and private firms. The observations with patent applications (52,147) are approximately one out of twenty observations without patent applications (1,058,235), reflecting a low participation rate of patenting activities in China. Additionally, there are 90,124 SOE firm-year observations compared to 446,572 private firm-year observations (around 40% of the full sample), suggesting that private firms are still the main components of Chinese corporations.

[*Insert Table 3 here*]

We can clearly find that firms with patent applications have a greater number of patent applications (mean value of 1.454), a higher ratio of new product output value to total assets (mean value of 7.530%) and a higher ratio of R&D expenditure to total assets (mean value of 0.501%) than firms without patent applications. The corresponding figures for the latter are 0.000, 1.785% and 0.080% respectively. Meanwhile, innovate firms have a higher ratio of lagged government subsidies to total assets (mean value of 0.260%) compared to that of non-innovate firms (mean value of 0.182%). The finding may indirectly reflect a positive relationship between firms' innovation activities and government subsidies. More subsidies revived by firms from government possibly can increase firms' innovation activities. It is no doubt that the value of the lagged patent variable is higher for innovate firms (mean value of 0.760) than non-innovate firms (mean value of 0.024). Moreover, innovate firms have a lower ratio of sales to total assets (mean value of 125.652%) compared to non-innovate firms (mean value of 192.177%). We also find that the ratio of cash flow to total assets and the ratio of new long-term debt issue to total assets is lower and higher for firms with patent applications (mean values of 8.645% and 0.319% respectively) than firms without patent applications (mean values of 9.752% and 0.064% respectively). The finding may be caused by the large demand for funds of R&D characteristics which is that firms' limited internal finance generally cannot solo support their innovation activities so firms have to depend on external finance. For other firm-level variables, patenting firms are larger and more mature in terms of real total assets (average value is 776.732 million yuan) and age (average value is 14.647 years old) compared to their non-patenting counterparts (whose corresponding values are 82.779 million yuan and 11.501 years old). Firms with patent applications are more politically affiliated (mean value is 66.575) and have more percentage of state shares (mean value is 10.231%) than firms without patent applications (whose mean value of political affiliation is 74.352 and 8.105%).[36] We also find innovate firms are more likely to establish in coastal regions (mean value of 1.320) rather than non-innovate firms (mean value of 1.357).[37]

Table 3 also compares SOEs and private firms. We find that SOEs own more innovation activities versus private firms, which can be shown by that the average values of all the three innovation indexes are higher for SOEs (average values of 0.083, 2.527% and 0.113% respectively) than private firms (average values of 0.054, 2.105% and 0.095% respectively). It is no doubt that the ratio of government subsidies to total assets for SOEs (mean value of 0.277%) is higher than private firms (mean value of 0.168%) since SOEs can easily obtain more subsidies from governments by using their close connection with governments. SOEs have a lower ratio of sales to total assets (mean value of 86.131%) compared to their private counterparts (mean value of 222.384%), which may be explained by that private firms are more likely to own a better operational performance. Meanwhile, SOEs have a lower ratio of cash flow to total assets (mean value of 4.377%) than private firms (whose corresponding figure is

[36] We define all variables in Appendix D to show that political affiliation is a categorical variable. In the Chinese dataset, its Chinese appellation is 'zhengzhilishu'. If the variable value of one firm is higher, the firm tends to own less political affiliation. On the contrary, firms displaying lower variable values are more likely to be highly political affiliated or controlled by the government.

[37] We define coastal regions as 1, central regions as 2 and western regions as 3.

10.596%). The difference in the ratio of the new long-term debt issue to total assets between SOEs and private firms is statistically insignificant (p-value is 0.105). As regards other variables, SOEs are larger (the average value of real total assets is 397.523 million yuan) than private firms (whose corresponding value is 43.140 million yuan) since SOEs are the dominating power in China's financial market. SOEs are also mature (average age is 26.197 years old) than private firms (average age is 9.643 years old) because SOEs are possibly established early with support from the state while private firms are not allowed until after the 1980s. It is no doubt that SOEs are more political affiliated (39.784) and have more percentage of state shares (93.134%) than private firms (whose mean values of political affiliation and percentage of state shares are 82.002 and 0.272%). Additionally, SOEs tend to locate in central and western regions (mean value of 1.780) while the vast majority of private firms prefer coastal regions (mean value of 1.330).

6. Empirical results and analyses

6.1. Estimation method

One significant feature of our data is that the majority of firms do not own patent applications in some of the year, so our dependent variable $Log\ (Pat_{i,t} + 1)$ is left-censored at zero. Additionally, our data is a huge unbalanced panel. Considering firms' heterogeneity, we therefore employ the Random-effects Tobit estimator in this paper (Tobin, 1958). In order to ensure robustness, we also estimate the Pooled Tobit based on the full sample. Since the Tobit is a non-linear estimation method and its coefficients are biased for the average marginal effect on actual dependent variable, we have to estimate average marginal effects. According to Cong (2001), in the study we report all three types of marginal effects of the Tobit estimation.[38] First describes the average marginal effect of the explanatory variables on the probability that firms will have patent applications. We call it as marginal effect in probability. Second measures the marginal effect of the independent variables on the expected value of firms' patent applications given that the data are truncated, which estimates the subsample of

[38] Cong (2001) describes the three types of marginal effects of the Tobit estimation as follows: first is the marginal effects of probability that measures how the probability of being uncensored changes with respect to the regressors; second is the marginal effects of the truncated expected value of dependent variable, which describes the changes in dependent variable with respect to changes in the regressors among the subpopulation for which dependent variable is not at a boundary; third is the marginal effects of the censored expected value of dependent variable that measures how the observed dependent variable changes with respect to the regressors.

observations with patent applications. We call it as marginal effect in quantity of truncated data. Third measures the marginal effect of the independent variables on firms' patent applications given that the data are censored, which estimates all observations regardless of whether they have patent applications or not. We call it as marginal effect in quantity of censored data.

6.1. Basic results

Table 4 shows the estimation results based on the full sample. The left-censored observations are the firms without patenting activities (or without innovation activities), while the uncensored observations are firms with patent activities (or with innovation activities). We observe that more firms' subsidies received from governments increase both the likelihood and the intensity of firms' innovation activities. We report the estimation results of baseline Eq. (1) using Random-effects estimation in Table 4. In columns (1) to (3) we find that the signs of the marginal effects of the subsidy variable ($Sub_{i,t-1}$) are all significantly negative at 1%. To be specific, the magnitude of the marginal effect in probability of $Sub_{i,t-1}$ in column (1) is 0.193 (19.3%) and significant at the 1% level, which means that a 10% increase in the ratio of firms' subsidies received to total assets produces an average increase of 0.0193 (1.93%) in the probability that firms own patent applications for. The magnitude of the marginal effect in quantity of truncated data of $Sub_{i,t-1}$ in column (2) is 0.721 (72.1 %) and significant at the 1% level, suggesting as the ratio of firms' subsidies received to total assets increases by 10%, the number of patent applications would rise by 0.0721 (7.21 %) but only for firms with patent applications. The marginal effect in quantity of censored data of $Sub_{i,t-1}$ in column (3) is 0.238 (23.8%) and significant at the 1% level, showing that a 10% increase in the ratio of firms' subsidies received to total assets leads to an average increase of 0.0238 (2.38%) in the number of patent applications for firms with patent applications and firms without. The estimation results clearly show that there is a significantly positive relationship between firms' subsidies obtained from governments and firms' innovation activities. The results suggest that more government subsidies could promote more firms' innovation activities, verifying the supplement effect of subsidies to innovation funds since government subsidies could meet firms' motivation for R&D and reduce information asymmetry between firms and market investors.

[*Insert Table 4 here*]

For other control variables, we find that that the marginal effects of $Log\ (Pat_{i,t-1} + 1)$ on $Log\ (Pat_{i,t} + 1)$ are all significantly positive at the 1% level and the marginal effects associated with $Log\ (Pat_{i,t-1} + 1)^2$ are all significantly negative at the 1% level, keeping consistent with the theoretical assumption. The signs of the marginal effects of $S_{i,t-1}$ are all significantly negative at 1% level, which may reflect that Chinese firms would not innovate as their market shares expand. The finding could be explained by the short-sighted behaviours of Chinese firms. Although the marginal effects of $Cf_{i,t-1}$ and $Dbt_{i,t-1}$ are all significantly positive at 1% level, we find that the magnitudes of the marginal effects of $Cf_{i,t-1}$ are all larger than those of $Dbt_{i,t-1}$, showing that firms prefer internal finance (cash flow) to external finance (bank loans) to support patent activities. We also estimate the Pooled Tobit in columns (4) to (6) and find the empirical results keep qualitatively unchanged.

6.2. Firms' ownership

There are obvious differences between firms of various ownerships in resource acquisition and signal transmission through the mechanism of using subsidies for innovation (Liang et al., 2012). Since SOEs and private firms are the two main forces of China's economic development, we compare the estimation results of SOEs and private firms to test what is the difference in the effect of subsidies on innovation between the two groups. We have used the lagged terms of explanatory variables in our regression models, so we also choose the lagged firms' ownership for the comparison in the section.

Table 5 shows the estimation results of baseline Eq. (1) using Random-effects for SOEs and private firms. We find that the marginal effects of $Sub_{i,t-1}$on $Log\ (Pat_{i,t} + 1)$ for SOEs are all significantly greater than those of private firms. Specifically, for private firms in columns (2), (4) and (6) the marginal effect in probability of $Sub_{i,t-1}$ is 0.294, the marginal effect in quantity of $Sub_{i,t-1}$ of truncated data is 1.237, and the marginal effect in quantity of $Sub_{i,t-1}$ of censored data is 0.375. The marginal effects are all significant at the 1% level. By contrast, in columns (1), (3) and (5) the marginal effects of $Sub_{i,t-1}$ for SOEs are statistically insignificant. We also make more t-tests to observe the significance levels of the differences. The results suggest that government subsidies have a more promoting effect on patenting activities of private firms rather than those of SOEs.

[*Insert Table 5 here*]

The difference in the effect of subsidies on innovation between SOEs and private firms could be explained as follows. First, from the perspective of resource acquisition, compared to private firms, SOEs could easily get financial support from governments such as subsidies because SOEs are controlled or operated by governments (Li et al., 2008; Guariglia & Mateut, 2016). The financial advantage could cause a problem of soft budget constraints to SOEs (Lin & Tan, 1999; Chow et al., 2010; Liang et al., 2012), which makes that using subsidies to promote innovation performance is not important for SOEs. Additionally, the financial advantage of SOEs could result in a problem of resource slack that deepens the agency problem (Greve, 2003). Thus, the incentives of using subsidies to innovate are not strong for managers of SOEs who are likely to invest in less risky activities rather than R&D. Second, administratively appointed managers of SOEs often lack professional management ability, which also weakens the efficiency of SOEs in transforming innovative resources such as subsidies into innovative output (Cuervo & Villalonga, 2000; Carman & Dominguez, 2001). By contrast, although private firms have a high enthusiasm for innovation, they are normally constrained by available funds due to the 'lending bias' in China (Chen et al., 2012).[39] Thus, using subsidies to promote innovation performance is important for private firms. Third, private firms have more autonomy and flexibility in the implementation of innovation strategy compared to SOEs, since private firms do not face the problems that SOEs have such as managers' administration promotion pressure, redundant employees, policy burdens (Lin & Tan, 1999). These organizational advantages enable private firms to transform innovative resources into innovative output more effectively (Liang et al., 2012).

6.3. Heterogeneity of firms' financing constraints

Since the 'lending bias' existed in China's financial market, firms in China generally face different levels of financial constraints. Thus, we take the heterogeneity of firms' financial constraints into account. Specifically, we first use firms' size and age to measure firms' financial constraints due to two reasons. First, small and young firms generally face high-cost external financing since they are typically characterized by high idiosyncratic risk and high bankruptcy costs (Carpenter et al., 1994; Chirinko & Schaller, 1995; Czarnitzki & Hottenrott, 2011; Guariglia & Yang, 2016). Second, small and young firms cannot enjoy the benefits of

[39] Due to the unique state-dominated financial system in China, compared to SOEs, private firms face institutional discrimination from state-controlled 'Big-five' commercial banks that have always been dominant players in China's financial markets. The 'Big-Five' commercial banks in China are Bank of China Limited, Agricultural Bank of China Limited, Industrial and Commercial Bank of China Limited, China Construction Bank Corporation, and Bank of Communications.

economies of scale that large and mature firms own, thus they do not have enough physical assets as collateral or long records of accomplishment to obtain external finance such as bank loans. Thus, compared to large and mature firms, small and young firms have a large probability of facing more financial constraints. Second, we choose firms' political affiliation and state shares as proxies of firms' financial constraints. Since firms with political affiliation and firms with state shares tend to own more connections with governments, they are more likely to get loans from the bank system dominated by state capitals (Johnson & Mitton, 2003; Khwaja & Mian, 2005) and thus face less financial constraints compared to firms without political affiliation and firms without state shares. Last, Following Hadlock & Pierce (2010), we choose the SA index to measure firms' financial constraints. Firms with higher SA index are more financially constrained firms while firms with lower SA index are less financially constrained firms.

Table 6 shows the estimation results based on firms' heterogeneity of financial constraints. Due to space limitation, we only report marginal effects in quantity of censored data while the estimation results of other two types of marginal effects keep qualitatively consistent. We make t-tests to observe whether the differences in marginal effects between two groups are significant. In columns (1) and (2) showing the estimation results of small firms and large firms, we find that the marginal effect of $Sub_{i,t-1}$ on $log\ (Pat_{i,t}+1)$ is significantly stronger for small firms (0.212) rather than large firms (0.152). In columns (3) and (4), we observe that the marginal effect of $Sub_{i,t-1}$ for young firms (0.305) is significantly greater than that for mature firms (0.203). The results suggest that the positive effect of government subsidies on patenting output is more pronounced for small firms and young firms rather than their large counterparts and mature competitors.

[*Insert Table 6 here*]

Table 6 also compares firms without political affiliation and firms with political affiliation in columns (5) and (6), firms without state shares and firms with state shares in columns (7) and (8). We find that the marginal effect of $Sub_{i,t-1}$ on $log\ (Pat_{i,t}+1)$ for firms without political affiliation (0.460) is statistically significant at the 1% level, while insignificant 0.044 for firms with political affiliation. In addition, the positive marginal effect of $Sub_{i,t-1}$ for firms without state shares is larger (0.256) and more significant (at the 1% level) than that for firms with state shares (its magnitude is 0.145 at the 10% significant level). The results show that patenting activities of firms without political affiliation and firms without state shares are more positively affected by government subsidies than those of firms with political affiliation and firms with state shares.

Based on firms' size and age, we also calculate the index of firms' financial constraints – the SA index and divide the full sample into two parts: firms with low SA index and firms with high SA index. The former are less financially constrained firms while the latter are more financially constrained firms. Table 6 displays the estimation results of firms with low SA index and firms with high SA index. Specifically, in columns (9) and (10). we find that the marginal effect of $Sub_{i,t-1}$ is significantly 0.204 for firms with a high SA index while only significantly 0.173 for firms with a low SA index. The findings show that government subsidies have a stronger effect on innovation activities of firms with a high SA index than those of firms with a low SA index.

Totally, the positive effect of subsidies on innovation is more pronounced for more financially constrained firms, which means the supplement effect of subsidies on innovation is stronger for firms with more financial constraints. Specifically, the supplement effect is stronger for small firms, young firms, firms without political affiliation, firms without state shares and firms with high SA index rather than large firms, mature firms, firms with political affiliation, firms with state shares and firms with low SA index.

7. Endogeneity issues and robustness tests

In the regressions where government subsidies affect firms' innovation decisions, there may be a potential tendency that firms with more innovation activities are more likely to obtain subsidies from governments (more innovation, more subsidies), that is, a reverse causality of endogeneity problem between corporation innovation and government subsidies would occur. Thus, for alleviating the reverse causality, in Section 7.1, we choose the instrumental variables (IV) approach and the quasi-natural experiment to estimate respectively. Besides that, some potential omitted variables in regression models and variable measurement errors of explanatory variables might yield inconsistent and biased estimates. We, therefore, apply more robustness tests for eliminating the endogeneity problem. In Section 7.2, we add the contemporaneous terms of the firm-level financial variables at the right-hand side to control for potential omitted variables. In Section 7.3, we use alternative measures of firms' innovation activities to alleviate potential measurement errors in our regression model. At last, we make other more robustness tests.

7.1. Reverse causality solving

7.1.2 IV approach

For eliminating the reverse causality of the endogeneity issue, we choose the instrumental variable (IV) method to re-estimate. A proper IV must be related to potential endogenous variables but unrelated to unobserved variables that possibly affect dependent variables. The first IV used for government subsidies received by firms ($Sub_{i,t}$) is the amount of annual public finance revenue in prefecture-level cities divided by the number of firms in prefecture-level cities each year ($Fin\_Rev_{c,t}$).[40] Since government subsidies come from public finance revenue, if the value of public finance revenue divided by the number of firms in one city were greater, the possibility of obtaining subsidies from governments for firms in the city would be higher. Information on public finance revenue at the city level is collected from China city statistical yearbook.[41] We also use the median value of government subsidies in each year-city level ($Med\_Sub_{c,t}$) as the second IV for subsidy variable ($Sub_{i,t}$). A greater value of the second IV is associated with a higher probability of obtaining subsidies for firms. Because we use the lagged values of subsidy variable ($Sub_{i,t-1}$) into our regression models, we also choose the lagged values of our two IVs ($Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$) in our estimations. We suggest that these two IVs can help us to identify the probability of firms getting subsidies from governments and the amount of subsidies received by firms from governments. However, the two IVs are not directly correlated with the unobserved terms that can affect innovation activities of individual firms.

The selection of the first IV ($Fin\_Rev_{c,t-1}$) is mainly based on the institutional background in China. Since economic performance is the most important factor in officials' politic promotion in China, local government officials generally have strong incentives to grant subsidies to firms in their governance areas to stimulate economic growth. In addition, the Chinese central government has delegated the authority for allocating subsidies to local governments. Thus, the firms in cities with greater public finance revenue are more likely to obtain subsidies from governments as the local government officials of these cities have a strong ability to allocate subsidies. The median value of government subsidies in each year-city level ($Med\_Sub_{c,t-1}$) can reflect city governents' enthusiasm for granting subsidies. Thus,

[40] The monetary unit of the prefecture-level public finance revenue is million Chinese yuan.
[41] The data of public finance revenue at the city level is only recorded from the year 2001. However, since our main results are estimated from the year 2000, the influence of the data missing in the year 2000 is negligible.

the two variables are directly related to the possibility of firms owning subsidies from governments and the amount of subsidies received by firms while they cannot directly affect individual firms' innovation.

Table 7 reports the estimation results of the IV method. Columns (1) to (4) show the results when $Sub_{i,t-1}$ is only instrumented by $Fin\_Rev_{c,t-1}$. Column (1) reports the first-stage regression results based on Newey's two-step estimator (Newey, 1987).[42] The coefficient value of $Fin\_Rev_{c,t-1}$ (0.003%) shows that the ratio of public finance revenue divided by the number of firms at the prefecture-city level ($Fin\_Rev_{c,t-1}$) is significantly and positively correlated with the amount of subsidies received by firms from governments. The findings suggest that firms tend to obtain more governments subsidies when they are located in cities where local governments have more public finance revenues. The statistical first-stage F-values (418.100) is far greater than the rule of thumb of 10, showing that the IV ($Fin\_Rev_{c,t-1}$) is valid and does not suffer from a possible weak instrument bias (Staiger & Stock, 1997; Stock & Yogo, 2005). Columns (2) to (4) demonstrates the second-stage estimation results when $Sub_{i,t-1}$ is only instrumented by $Fin\_Rev_{c,t-1}$. Although the magnitudes of the marginal effects of $Sub_{i,t-1}$ (41.993%, 153.064%, and 58.750% respectively) are larger compared to those of our main empirical results, we find that all marginal effects of the instrumented $Sub_{i,t-1}$ still keep statistically significant and positive.

[*Insert Table 7 here*]

Columns (5) to (8) show the estimation results when $Sub_{i,t-1}$ is instrumented by $Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$. Column (5) shows the first-stage regression results and it is no doubt that the median value of government subsidies in each year-city level ($Med\_Sub_{c,t-1}$) is significantly and positively (198.118%) correlated with government subsidies received by firms. The coefficient of $Fin\_Rev_{c,t-1}$ keeps statistically significant and positive (0.003%). The first-stage estimation results successfully confirm the relevance of these two IVs to subsidy variable ($Sub_{i,t-1}$). The statistical first-stage F-values (418.190) is larger than the rule of thumb of 10, suggesting that the instrumental variables ($Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$) are valid and do not face a potential weak instrument bias. Columns (6) to (8) report the second-stage

[42] For the IV Tobit estimation in STATA process, we have to add the option 'twostep' after the code 'ivtobit' to estimate the first-stage regression results, which is based on Newey's two-step estimator. For the marginal effects of the second-step regression results, we could not use the option 'twostep' and we have to use the default estimator of maximum likelihood.

estimation results when $Sub_{i,t-1}$ is instrumented by $Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$. We find that the marginal effects of $Sub_{i,t-1}$ are all positive (7.591%, 27.674%, and 10.619% respectively) at the 1% significant level, which keeps consistent with our main empirical results. The estimation results of the two IV methods verify that government subsidies have a positive effect on firms' innovation activities in China, even after considering the endogenous nature of subsidies.

To test the condition that the only role that the instruments ($Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$) play in influencing innovation activities is through its effect on $Sub_{i,t-1}$, we also conduct a Wald test of exogeneity and an Anderson-Rubin test. Specifically, the Wald test measures whether the error terms in the structural equation and the reduced-form equation for the endogenous variables are correlated. In Table 7, the significant p-value statistics (0.000) suggest that our regressors are not exogenous and confirms the necessity of introducing instrumental variables. The Anderson-Rubin (AR) test is a joint test of the structural parameter and the exogeneity of the instruments. The null hypothesis of the AR test is that all regressors are exogenous and the minimum canonical correlation is zero. In Table 7, the significant p-value statistics (0.000) lower than 0.05 suggest that our model is identified and/or our instruments are valid. Additionally, we also conduct a Hausman test and a Smith-Blundell test to confirm the existence of endogenous variables (Blundell & Smith, 1986).

7.1.2 Quasi-natural experiment (DID specification)

In the subsection, we provide clear identification of the causal effect of subsidies on innovation by using a difference-in-differences (DID) specification. In 2006, the State Council of China initiated the 'National Program for Medium- and Long-Term Scientific and Technological Development' to promote innovation. As a response to the central strategy, some local authorities changed their subsidy policies for patent applications. For example, in 2006, Zhangjiagang, one county-level city of Suzhou (a prefecture-level city in Jiangsu province) revised its subsidy policies for patent applications by increasing the amount of subsidies per patent application, while subsidy policies in other neighbouring county-level cities of Suzhou remained unchanged (Lei et al., 2012). Specifically, the county-level cities of Suzhou all implemented subsidy policies for patent application in 2003.[43] On June 12th, 2006,

[43] In 2006, Suzhou prefecture-level city is made up of 7 county-level districts (Municipal district, Canglang, Pingjiang, Jinchang, Huqiu, Wuzhong and Xiangcheng) and 5 county-level cities (Changshu, Zhangjiagang,

Zhangjiagang increased the amount of subsidies from 1,500 yuan, 1,000 yuan and 500 yuan to 3,000 yuan, 1,500 yuan and 1,000 yuan for applications of invention patents, utility model patents, and design patents respectively. It even awarded more 10,000 yuan for the grant of each invention patent application. However, at the same time, the subsidy policies in other county-level cities of Suzhou kept unchanged.[44] Thus, the exogenous shock to subsidies for firms' patent applications in Zhangjiagang provides us an ideal opportunity of using a quasi-natural experiment to identify the causal effect of subsidies on patent filings.

For the specification, first, we choose a dummy variable $Treat$ that equals 1 for the treatment group (firms distributed in Zhangjiagang) and 0 for the control group (firms distributed in other neighbouring county-level cities of Suzhou), which can capture the difference in $Log(Pat_{i,t} + 1)$ between the treatment and control groups before the policy revision. Second, to separate the full sample period into the pre-revision and post-revision periods, we use a time dummy variable $Post$ that equals 1 staring from 2006 and 0 otherwise, which can check the difference in $Log(Pat_{i,t} + 1)$ between the pre-revision and post-revision periods for the firms in the control group. The aggregate factors that could change $Log(Pat_{i,t} + 1)$ can be captured by the dummy variable $Post$, even in the absence of the policy revision in 2006. Third, we construct interaction term $(Treat * Post)$ to yield the average treatment effect, which compares the difference between the treatment and control groups in their average differences between the pre-revision and post-revision periods. Last, we replace the subsidy variable $(Sub_{i,t-1})$ with the interaction term $(Treat * Post)$ in baseline Eq. (1) to re-estimate.[45]

Table 8 shows the estimation results of marginal effects in quantity of censored data based on our DID specification due to space limitation, while other two types of marginal effects keep qualitatively unchanged. In column (1), the marginal effect of the interaction term $(Treat * Post)$ is statistically significant and positive (0.029), suggesting that after the revision of subsidy policies in 2006, firms in Zhangjiagang which face a larger amount of patent subsides undertake more patenting activities. We do not include county dummy variables and year dummy variables because doing it would introduce collinearity with the single terms of

Kunshan, Wujiang and Taicang). The county-level districts are the centre areas of one prefecture-level city. Thus, we make a combination of all seven county-level districts and call it as Suzhou urban districts.

[44] The detailed information of the amount of subsidies of patent applications for all county-level cities of Suzhou are shown in Appendix F.

[45] Here we use the county-level cities as the geographical dummy variables since we only estimate the subsample of firms in Suzhou.

$Treat$ and $Post$. The marginal effect of the single term ($Treat$) is insignificant, suggesting that there is no a significant difference in $Log(Pat_{i,t} + 1)$ between Zhangjiagang and other county-level cities in the pre-treatment period.[46] The significant positive marginal effect of the single term ($Post$) shows a positive trend in $Log(Pat_{i,t} + 1)$ for the firms in other county-level cities from the pre-revision to post-revision periods. In column (2) we check when we add the geographical effect and the year effect in estimation but do not cover the single terms of $Treat$ and $Post$, and the estimated marginal effect of the interaction term ($Treat * Post$) keeps statistically significant and positive (0.032). The findings confirm our main empirical results and then successfully test the causal effect of subsidies on innovation. Due to space limitation, we do not show the estimation results of other control variables while they keep qualitatively consistent with our main empirical results.

[*Insert Table 8 here*]

Next, we conduct a series of validity checks for the experiment setting and report the estimation results in Table 8. First, we make a test for the 'parallel trend' assumption which is necessary for a DID approach. Specifically, we construct a time series of interaction terms between $Treat$ and the year dummies for the pre-revision period, that is, $Treat * Year$ with $Year$ indicating 2000 through 2005.[47] We then add these interaction terms in estimation and report the results in column (3) of Table 8. The estimated marginal effects of these interaction terms are all statistically insignificant, showing that before the policy revision in 2006 there is no a significant change for the difference in patenting activities between the treatment and control groups. Thus, the 'parallel trend' assumption of patenting activities for the two groups before the revision could be achieved. Meanwhile, the marginal effect of the interaction term ($Treat * Post$) keeps significantly positive (0.032), which again verifies the impact of the revision that more subsidies significantly lead to more innovation. Besides that, we make a graph to compare the growth trends of average patent applications in the treatment and control groups. In Figure 7, we find that the pre-treatment trends of patent applications in the treatment and control groups seem to be parallel, while the gap between the two trend lines increases substantially from the year 2006. Based on above tests, the 'parallel trend' assumption could

[46] The main effect of the single term ($Treat$) only applies when $Post$ equals 0, which can capture the difference in $Log(Pat_{i,t} + 1)$ in the pre-treatment period. The main effect of the single term ($Post$) also applies when $Treat$ equals 0.

[47] We introduce in the Note 28 that the data in years 1998 and 1999 are used to construct control variables. Thus, the estimation for the full sample covers years from 2000 to 2008.

be achieved. Second, we compare the difference between the treatment and control groups for each year after the revision by including a time series of interaction terms between $Treat$ and the year dummies for the post-revision period which is $Treat * Year$ with $Year$ indicating 2006 through 2008 into the model. In column (4), the marginal effects of the interaction terms ($Treat * Year2006$ and $Treat * Year2007$) are statistically significant and positive while the marginal effect of $Treat * Year2008$ is insignificant. We also find the marginal effect of $Treat * Year2007$ (0.051) is higher than that of $Treat * Year2006$ (0.042). The results indicate that the revision has a promoting effect which becomes larger from 2006 to 2007 while has little effect in 2008. Third, for remedying the drawback that the interaction term ($Treat * Post$) dose not consider year-to-year changes for the full sample period, we use a flexible estimation by constructing a time series of interaction terms between $Treat$ and the year dummies for the full sample period, that is, $Treat * Year$ with $Year$ indicating 2000 through 2008. In column (5), the estimated marginal effects of these interaction terms are all statistically insignificant for years before 2006, but become statistically significant and positive for every year from 2006 outwards. The magnitude of the marginal effect $Treat * Year2007$ (0.067) is higher than that of $Treat * Year2006$ (0.059) and $Treat * Year2008$ (0.022), showing that the revision has the largest promoting effect on innovation in the year 2007.

[*Insert Figure 7 here*]

We further take more tests for the validity check and report them in Table 7. First, we assume that the policy revision happened in 2005 and construct the dummy variable $Post$ equals 1 starting from 2005 and 0 otherwise. The dummy variable $Treat$ keeps unchanged, 1 for firms in Zhangjigang and 0 for firms in other county-level cities. We then run the data until 2006 and the marginal effect of the interaction term ($Treat * Post$) reported in column (6) is statistically insignificant, suggesting that if the policy revision happened in 2005, the patenting activities for firms in Zhangjiagang could not be affected. Second, we assume that one of the other county-level cities without the policy revision such as Changshu (one of county-level cities of Suzhou) is affected by the policy revision, and thus construct the dummy variable $Treat$ equals 1 for firms in Changshu and 0 otherwise. The dummy variable $Post$ keeps unchanged, 1 starting from 2006 and 0 otherwise. In column (7) we report the marginal effect of the interaction term ($Treat * Post$) that is statistically insignificant, suggesting that the firms in Changshu are not affected by the policy revision. The validity of the DID approach could be checked through the estimation results of the tests.

The reasons that why we only choose the prefecture-city of Suzhou for the experiment are described as follows: first, China has a huge number of prefecture-level administration divisions, thus we cannot track the changes in patent subsidy policies of every city.[48] Following Lei et al. (2012), we can easily obtain the information on patent subsidy policies of all county-level cities of Suzhou and we just need to check the credibility of the information online. Second, Suzhou is closed to Shanghai and in one of the most economically developed regions in China,[49] which has a large number of firms especially private firms and thus can be used as a good example to reflect China. Therefore, we choose the firms in Suzhou as the subsample into the quasi-natural experiment to explore the causal effect of subsidies on innovation.

7.2. Potential omitted variables - Augmented specifications

As mentioned above, the baseline Eq. (1) only considers the impact of lagged terms of independent variables while contemporaneous terms may also affect firms' innovation activities. Thus, an estimation bias of omitted variables would appear. To address the concern, we include the contemporaneous terms of all firm-level financial variables to augment the baseline Eq. (1). Specifically, we not only add the contemporaneous subsidy variable ($Sub_{i,t}$) but also include the contemporaneous cash flow variable ($Cf_{i,t}$) as firms' R&D projects are largely affected by their contemporaneous internal cash flow. In addition, since there is a potential correlation between internal cash flow and sales (Dechow et al., 1998), we also add the contemporaneous sales variable ($S_{i,t}$) in the regression to avoid an estimation bias. We also add the contemporaneous term of the new long-term debt issue ($Dbt_{i,t}$) into the specification.

Table 9 shows the estimation results of the augmented Eq. (1) covering contemporaneous terms of all firm-level financial variables. We find that the estimation results keep qualitatively consistent with those of our main results: the sum of the marginal effects of subsidy variables ($Sub_{i,t-1}$ and $Sub_{i,t}$) is still statistically significant and positive. Specifically, in columns (1) to (3), the magnitudes of the sum of the marginal effects of subsidy variables ($Sub_{i,t-1}$ and $Sub_{i,t}$) are 0.275, 1.015 and 0.331 respectively and significant at the 1% level, verifying that more subsidies increase innovation activities. In addition, we notice that the magnitudes of the contemporaneous subsidy variable are larger (0.191, 0.704 and 0.229 respectively) compared

[48] In Note 14 and Note 29, we have introduced the number of prefecture-level administration divisions in China.
[49] In a survey released in 2005 by the NBS of China on economic competence of Chinese small cities, the county-level cities of Suzhou all ranked among the top 10 in the whole nation.

to those of the lagged subsidy variable (0.084, 0.311 and 0.101 respectively), showing that contemporaneous subsidies have a greater positive effect on innovation activities. The findings confirm the necessity of including the contemporaneous terms in the estimation.

[*Insert Table 9 here*]

7.3. Potential measurement errors - Alternative measures of firms' innovation activities

In our main results, we use the number of patent applications per firm to measure innovation output. However, using the number of patent applications to measure innovation output still has disadvantages in a brief discussion (Griliches, 1990). It is well known that not all innovation outputs would be patented. Specifically, first, the requirements of patent applications are strict. The number of patent applications cannot fully reflect the further improvement for products that have been patented, thus firms' innovation performance may be undervalued. Second, in order to secure business economic returns, to a large probability firms would not patent their innovation outputs to avoid the premature leakage of innovation information. Only innovation outputs whose patents have economic value above a certain minimal threshold are patented (Griliches, 1990). Third, China's relatively weak IRP also can hamper firms' enthusiasm for patent applications. Thus, using the number of patent applications may yield measurement bias for innovation output. Since the lagged innovation variables of $Log(Pat_{i,t-1}+1)$ and $Log(Pat_{i,t-1}+1)^2$ are control variables in our regression models, the measurement errors of innovation may cause an endogeneity problem. For eliminating it, we choose another measure of firms' innovation output by using the ratio of firms' new product output value to total assets ($Np_{i,t}$) in baseline Eq.(1) to re-estimate.[50] Compared to the number of patent applications, new product output value can reflect the industrialization performance of innovation achievements. In other words, new product output value can measure commercialized innovation output while patents can only measure technological innovation outputs (Guo et al., 2016). Besides that, we also choose the ratio of

[50] In the China Statistical Yearbook (2006), new products are defined as "those new to the Chinese market that either adopt completely new significant principles, technologies or designs, or are substantially improved in comparison with existing products in terms of performance and functionality, through significant changes in structure, materials, design or manufacturing process." As a good indicator of innovation output, new product output value has been widely used in recent papers related to innovation (Henard & Szymanski, 2001; Guariglia & Liu, 2014). Because in the NBS firm-level dataset the variable of new product output values is only recorded from 1998 to 2007 and missing in 2004, we have to use it in a robustness test.

firms' R&D expenditure to total assets ($Rd_{i,t}$) to proxy firms' innovation activities based on R&D input level to estimate baseline Eq. (1).

Table 10 shows the corresponding estimation results. In columns (1) to (3) when firms' innovation output is measured by the ratio of firms' new product output value to total assets, we find that the signs of the marginal effects of $Sub_{i,t-1}$ still keep significantly positive (0.083, 0.047 and 0.024). Next, in columns (4) to (6), the marginal effects of $Sub_{i,t-1}$ are also statistically significant and positive (0.406, 0.006 and 0.004) when innovation activities are measured by the ratio of firms' R&D expenditure to total assets. The findings of the robustness tests using alternative measures of firms' innovation activities suggest that no matter which proxy of innovation activities we employ, the positive effect of subsidies on innovation can hold.

[*Insert Table 10 here*]

Besides the aforementioned estimation methods, our results keep consistent when we use various robustness tests. First, following some studies (Lei et al., 2012; Li, 2012), since invention patents represent good-quality patents, we only select the number of invention patent applications to proxy firms' innovation output. Compared to two other types of patents, invention patents are the most technologically innovative and require more R&D efforts. Second, since the number of patent applications per firm is a count variable the majority of whose values are 0, we employ the Zero-inflated Poisson method to estimate again.[51] Third, since we choose the natural logarithm of the number of patent applications as the dependent variable, we also use the natural logarithm to standardize firm-level financial variables to estimate. Fourth, due to the data limitation in the year 2008, we use an alternative sample excluding the data in the year 2008 to estimate. Table 11 shows the results of all robustness estimations that keep qualitatively unchanged with our main empirical results.[52]

[*Insert Table 11 here*]

[51] In our main estimations, we do not winsorize the innovation output variable of $log\ (Pat_{i,t}+1)$ since we use the natural logarithm to eliminate the effect of discrete values. In the part, we winsorize the number of patent applications per firm that is not presented by the natural logarithm ($Pat_{i,t}$) at its 99 percentage to avoid the influence of extreme values. Additionally, according to Vuong (1989), since the statistics value of Vuong in our estimation is relatively large (67.37>1.96), we should choose Zero-inflated Poisson regression rather than standard Poisson regression.

[52] For brevity, we only report the marginal effects in quantity of censored data.

7.4. Additional analysis

Due to the different characteristics of industries and cities, we also test what changes to the positive effect of subsidies on innovation based on different industries and cities. For industries, we first compare firms in industries with different levels of external finance dependence (EFD) and second compare firms in industries with different levels of high-tech intensiveness. For EFD, we follow Rajan & Zingales (1998) and Acharya & Xu (2017) to compute the level of industry EFD. Specifically, we first calculate the fraction of firms' capital expenditure that cannot be financed by their internal cash flow to proxy firms' EFD. Then, we obtain the median value of all firms' EFD in one industry each year to construct a time series of the industry's EFD level. Finally, we choose the median value of the time series of one industry's EFD level as the industry's dependence on external finance ($Dependence_j$) over the period 1998 to 2008. As regards the classification of high-tech intensiveness, we make it based on the 'High-tech industries classification' conducted by the NBS of China.[53] The industries whose codes are listed in the classification are regarded as the industries with high-tech intensiveness and the rest as the industries without high-tech intensiveness. We construct a dummy variable ($High-tech_j$) that equals 1 for the industries with high-tech intensiveness and otherwise as 0. In order to test the changes to the positive effect of subsidies on innovation with respect to industry variables, we construct the interaction terms ($Sub_{i,t-1} * Dependence_j$ and $Sub_{i,t-1} * High-tech_j$) and respectively add them into baseline Eq. (1) to re-estimate.

Table 12 shows the estimation results with industry variables. In columns (1) to (3), we find that the marginal effects of the interaction term ($Sub_{i,t-1} * Dependence_j$) show statistically significant and negative (-0.513, -1.888 and -0.615), indicating that the positive effect of subsidies on innovation would be reduced with higher industry EFD. The explanation is that a higher EFD in China may reflect a greater borrowing capacity for firms, thus the supplement effect of subsidies on innovation funds would be alleviated for these firms with a strong financing ability. The magnitudes of the single term of $Sub_{i,t-1}$ become smaller (0.158, 0.583 and 0.190) compared to those in Table 4, which is not particularly interesting given that the main effect of $Sub_{i,t-1}$ only applies when $Dependence_j$ equals zero. The same also applies to the single term ($Dependence_j$).

[53] The website link of the classification of high-tech industries could be browsed via: http://www.stats.gov.cn/tjsj/tjbz/201812/t20181218_1640081.html

[*Insert Table 12 here*]

Next, in columns (4) to (6), the marginal effects of the interaction term ($Sub_{i,t-1} * High - tech_{j,t-1}$) are statistically significant and positive (0.279, 1.034 and 0.384), which means that the positive effect of subsidies on innovation is stronger for firms in industries with high-tech intensiveness. The finding is possibly interpreted by that firms in industries with high-tech intensiveness generally have a greater demand for funds to support their large number of innovation activities caused by their industry characteristics, thus having a higher incentive of using subsidies to stimulate R&D. As a comparison, firms in industries without high-tech intensiveness do not have a high requirement of innovation funding.

For cities, we first compare firms in cities with different levels of financial development and second compare firms in cities with different levels of foreign direct investment. Following Hsu et al. (2014), we use the ratio of deposits to gross regional product (GRP), the ratio of loans to GRP, and the ratio of household savings to GRP to respectively measure city-level financial development in years ($Fin - dev_{c,t}$). For city-level foreign direct investment in years ($For - inv_{c,t}$), we choose the natural logarithm of the number of foreign new contracts signed, the ratio of agreed foreign investment to GRP, and the ratio of actual foreign investment to GRP to proxy it. Information on all city-level financial variables is collected from China city statistical yearbook.[54] As similar as the industry variables, for exploring the influence of city-level financial variables on the positive effect of subsidies on innovation, we construct the related interaction terms ($Sub_{i,t-1} * Fin - dev_{c,t-1}$ and $Sub_{i,t-1} * For - inv_{c,t-1}$) and put them into baseline Eq. (1) to re-estimate respectively.

Table 13 presents the corresponding estimation results. In panel A, we observe that the marginal effects of the interaction term ($Sub_{i,t-1} * Fin - dev_{c,t-1}$) are statistically significant and negative no matter the city-level financial development is measured by which ratio, showing that higher financial development would reduce the stimulating effect of subsidies on innovation. The finding could be explained by that firms located in cities with a higher level of financial development are more likely to easily obtain funds from the banking system since banks in these cities have a strong lending capacity. If firms can easily get funds from other financing sources, the promoting effect of subsidies on innovation may be reduced.

[54] In China city statistical yearbook, the data related to financial development is recorded from 2003 and the data related to foreign direct investment is recorded from 2000.

[*Insert Table 13 here*]

In Panel B, we find that the marginal effects of the interaction term ($Sub_{i,t-1} * For - inv_{c,t-1}$) are statistically significant and negative, suggesting that higher city-level foreign direct investment would also decrease the positive effect of subsidies on innovation. The interpretation is similar to that of financial development. Since firms could enjoy the benefits of financing sources from as foreign direct investment, the positive effect of subsidies on innovation would be cut down.

8. Conclusion

Using panel data covering mainly unlisted firms in China over the period 1998-2008, we find that firms with more government subsidies are more likely to innovate. The estimation results of the paper also have some policy implications for China from the perspective of the incentive mechanism. First, since subsidies could play an active role in improving firms' innovation performance, governments should implement subsidy schemes that could motivate firms' innovation activities. Second, our study shows that government subsidies have various effects on innovation activities of firms with different types of ownership, and thus governments should further adjust the objective mechanism of subsidies. Specifically, more subsidies should be allocated to private firms that have a strong demand for innovation and R&D funds, rather than strong and large-sized SOEs. Third, considering our estimation results showing that subsidies have a stronger positive effect on innovation activities of more financially constrained firms compared to those of less financially healthier firms, governments should apply more subsidy policies to financially constrained firms, such as small firms, young firms, firms without political affiliation, firms without state shares, firms with a higher SA index. For example, in May 1999, the State Council of China approves a special government R&D program called as 'Innovation Fund for Technology Based Firms' which aims to 'facilitate and encourage the innovation activities of small and medium technology-based enterprises (SMTEs)'. More policies as similar as the program should be issued for financial constrained firms. Fourth, since the positive effect of subsidies on firms' innovation activities could be influenced by some other factors including industry external finance dependence, industry high-tech intensiveness, city financial development level, city foreign direct investment level. Governments need to make allocation types of subsidies become more various to strengthen the efficiency of funds. Specifically, governments would use new measures to replace traditional ways of direct grants. For example, some western countries such as Sweden, Netherlands, and Switzerland have issued some specified bonds related to technological innovation. If firms could achieve the objective of technological innovation over a specified period, governments would issue the bonds to these firms. This method could improve the efficiency of government subsidies and then achieve the maximum effect of subsidies on innovation.

We also use various robustness tests to confirm our empirical findings. First, for reducing the concern of potential reverse causality, We first use the IV method with the city-level fiscal revenue as the instrumental variable for the amount of subsidies and next we set a quasi-natural experiment of exploring firms in all county-level cities of Suzhou among which one revised its subsidy policies for patent applications in 2006. Second, we also choose alternative measures of innovation and add potential omitted variables to re-estimate to eliminate the endogeneity problem. Last, we employ more tests to enhance the robustness of our main results.

The paper still has some limitations. First, we only explore the effect of direct government funds on corporate innovation but do not take into account the different effects of various forms of government subsidies on innovation. We need to do more robustness tests. Second, although we have tested whether the effect of government subsidies would change based on the heterogeneities in firms, industries, and cities, we still can expand it to other more factors that are potentially related to corporate innovation. In total, with the in-depth transformation of China’s economic system, we hope that more researches will focus on the relationship between government subsidies and corporate innovation in the future.

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N. and Kerr, W., 2018. Innovation, reallocation, and growth. *American Economic Review*, *108*(11): 3450-91.

Aerts, K. and Schmidt, T., 2008. Two for the price of one?: Additionality effects of R&D subsidies: A comparison between Flanders and Germany. *Research Policy*, *37*(5): 806-822.

Allen, F., Qian, J. and Qian, M., 2005. Law, finance, and economic growth in China. *Journal of Financial Economics*, 77(1): 57-116.

Almus, M. and Czarnitzki, D., 2003. The effects of public R&D subsidies on firms' innovation activities: the case of Eastern Germany. *Journal of Business & Economic Statistics*, *21*(2): 226-236.

Aghion, P., Cai, J., Dewatripont, M., Du, L., Harrison, A. and Legros, P., 2015. Industrial policy and competition. *American Economic Journal: Macroeconomics*, *7*(4): 1-32.

Arrow, K.J., 1972. Economic welfare and the allocation of resources for invention. In *Readings in industrial economics* (pp. 219-236). Palgrave, London.

Ayyagari, M., Demirgüç-Kunt, A. and Maksimovic, V., 2010. Formal versus informal finance: Evidence from China. *Review of Financial Studies*, 23(8): 3048-3097.

Bagwell, K. and Staiger, R.W., 1989. The role of export subsidies when product quality is unknown. *Journal of International Economics*, *27*(1-2): 69-89.

Bagwell, K. and Staiger, R.W., 2006. Will international rules on subsidies disrupt the world trading system?. *American Economic Review*, 96(3): 877-895.

Bin, J.W.L., 2006. Institutional Environment, State Ownership and Lending Discrimination. *Journal of Financial Research*, 11: 011.

Blundell Richard, W. and Smith Richard, J., 1986. An exogeneity Test for a Simulation Equation Tobit Model with an Application to Labour Supply. *Econometrica*, 54(3).

Boeing, P., 2016. The allocation and effectiveness of China's R&D subsidies – Evidence from listed firms. *Research Policy*, 45(9): 1774-1789.

Boeing, P., Mueller, E. and Sandner, P., 2016. China's R&D explosion – Analyzing productivity effects across ownership types and over time. *Research Policy*, 45(1): 159-176.

Bond, S., Elston, J.A., Mairesse, J. and Mulkay, B., 2003. Financial factors and investment in Belgium, France, Germany, and the United Kingdom: A comparison using company panel data. *Review of Economics and Statistics*, *85*(1): 153-165.

Bronzini, R. and Piselli, P., 2016. The impact of R&D subsidies on firm innovation. *Research Policy*, 45(2): 442-457.

Brown, J.R., Fazzari, S.M. and Petersen, B.C., 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance*, 64(1): 151-185.

Brown, J.R., Martinsson, G. and Petersen, B.C., 2012. Do financing constraints matter for R&D?. *European Economic Review*, 56(8): 1512-1529.

Busom, I., 2000. An Empirical Evaluation of the Effects of R\&D Subsidies. *Economics of Innovation and New Technology*, *9*(2): 111-148.

Cai, H. and Liu, Q., 2009. Competition and corporate tax avoidance: Evidence from Chinese industrial firms. *Economic Journal*, 119(537): 764-795.

Carman, J.M. and Dominguez, L.V., 2001. Organizational transformations in transition economies: Hypotheses. *Journal of Macromarketing*, 21(2): 164-180.

Carpenter, R.E., Fazzari, S.M., Petersen, B.C., Kashyap, A.K. and Friedman, B.M., 1994. Inventory investment, internal-finance fluctuations, and the business cycle. *Brookings Papers on Economic Activity*, 1994(2): 75-138.

Chang, S.J. and Wu, B., 2014. Institutional barriers and industry dynamics. *Strategic Management Journal*, 35(8): 1103-1123.

Chen, V.Z., Li, J., Shapiro, D.M. and Zhang, X., 2014. Ownership structure and innovation: An emerging market perspective. *Asia Pacific Journal of Management*, 31(1): 1-24.

Chirinko, R.S. and Schaller, H., 1995. Why does liquidity matter in investment equations?. *Journal of Money, Credit and Banking*, 27(2): 527-548.

Chow, C.K., Song, F.M. and Wong, K.P., 2010. Investment and the soft budget constraint in China. *International Review of Economics and Finance*, 19(2): 219-227.

Clarysse, B., Wright, M. and Mustar, P., 2009. Behavioural additionality of R&D subsidies: A learning perspective. *Research Policy*, *38*(10): 1517-1533.

Cuervo, A. and Villalonga, B., 2000. Explaining the variance in the performance effects of privatization. *Academy of Management Review*, 25(3): 581-590.

Czarnitzki, D. and Hottenrott, H., 2011. R&D investment and financing constraints of small and medium-sized firms. *Small Business Economics*, 36(1): 65-83.

Dang, J. and Motohashi, K., 2015. Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review, 35*: 137-155.

David, P.A., Hall, B.H. and Toole, A.A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy*, 29(4-5): 497-529.

Dechow, P.M., Kothari, S.P. and Watts, R.L., 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics*, 25(2): 133-168.

Ding, S., Guariglia, A. and Knight, J., 2013. Investment and financing constraints in China: does working capital management make a difference?. *Journal of Banking and Finance*, 37(5): 1490-1507.

Ezzamel, M., Xiao, J.Z. and Pan, A., 2007. Political ideology and accounting regulation in China. *Accounting, Organizations and Society*, 32(7-8): 669-700.

Fang, J. and Walsh, M., 2018. Made in China 2025: Beijing's manufacturing blueprint and why the world is concerned. Available at: https://www.abc.net.au/news/2018-04-29/why-is-made-in-china-2025-making-people-angry/9702374.

Feldman, M.P. and Kelley, M.R., 2006. The ex ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research Policy*, *35*(10): 1509-1521.

Godement, F., Parello-Plesner, J. and Richard, A., 2011. The Scramble for Europe. European Council on Foreign Relations. Available at: https://www.ecfr.eu/page/-/ECFR37_Scramble_For_Europe_AW_v4.pdf.

Cong, R., 2001. Marginal effects of the tobit model. *Stata Technical Bulletin*, 10(56).

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4): 1661.

González, X. and Pazó, C., 2008. Do public subsidies stimulate private R&D spending?. *Research Policy*, *37*(3): 371-389.

Görg, H. and Strobl, E., 2007. The effect of R&D subsidies on private R&D. *Economica*, *74*(294): 215-234.

Greve, H.R., 2003. A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, 46(6): 685-702.

Guariglia, A. and Liu, P., 2014. To what extent do financing constraints affect Chinese firms' innovation activities? *International Review of Financial Analysis*, 36: 223-240.

Guariglia, A. and Mateut, S., 2016. External finance and trade credit extension in China: does political affiliation make a difference?. *European Journal of Finance*, 22(4-6): 319-344.

Guariglia, A., Liu, X. and Song, L., 2011. Internal finance and growth: microeconometric evidence on Chinese firms. *Journal of Development Economics*, 96(1): 79-94.

Guariglia, A. and Yang, J., 2016. A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance*, 36: 111-130.

Guo, D., Guo, Y. and Jiang, K., 2016. Government-subsidized R&D and firm innovation: Evidence from China. *Research Policy*, *45*(6): 1129-1144.

He, Z.L., Tong, T.W., Zhang, Y. and He, W., 2018. A database linking chinese patents to china's census firms. *Scientific Data*, *5*: 180042.

Henard, D.H. and Szymanski, D.M., 2001. Why some new products are more successful than others. *Journal of Marketing Research*, 38(3): 362-375.

Hormats, R.D., 2011. Addressing the Challenges of the China Model. https://china.usc.edu/robert-hormats-addressing-challenges-china-model-may-11-2011.

Hsu, P.H., Tian, X. and Xu, Y., 2014. Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112(1): 116-135.

Johnson, S. and Mitton, T., 2003. Cronyism and capital controls: evidence from Malaysia. *Journal of Financial Economics*, 67(2): 351-382.

Khwaja, A.I. and Mian, A., 2005. Do lenders favor politically connected firms? Rent provision in an emerging financial market. *Quarterly Journal of Economics*, 120(4): 1371-1411.

Kortum, S.S., 1997. Research, patenting, and technological change. *Econometrica: Journal of the Econometric Society*, 1389-1419.

Lee, E., Walker, M. and Zeng, C., 2014. Do Chinese government subsidies affect firm value?. *Accounting, Organizations and Society*, 39(3): 149-169.

Lei, Z., Sun, Z. and Wright, B., 2012. Patent subsidy and patent filing in China. *University of California, Berkeley, mimeo*.

Leland, H.E. and Pyle, D.H., 1977. Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance*, *32*(2): 371-387.

Lerner, J., 1999. The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program. *The Journal of Business*, *72*(3): 285-318.

Li, H., Meng, L., Wang, Q. and Zhou, L.A., 2008. Political connections, financing and firm performance: Evidence from Chinese private firms. *Journal of Development Economics*, 87(2): 283-299.

Li, X., 2012. Behind the recent surge of Chinese patenting: An institutional view. *Research Policy*, *41*(1): 236-249.

Lim, C.Y., Wang, J. and Zeng, C.C., 2018. China's "mercantilist" government subsidies, the cost of debt and firm performance. *Journal of Banking and Finance, 86*: 37-52.

Lin, S. and Ye, H., 2017. Foreign direct investment, trade credit, and transmission of global liquidity shocks: Evidence from Chinese manufacturing firms. *Review of Financial Studies*, *31*(1): 206-238.

Liang, X., Lu, X. and Wang, L., 2012. Outward internationalization of private enterprises in China: The effect of competitive advantages and disadvantages compared to home market rivals. *Journal of World Business*, 47(1): 134-144.

Lin, J.Y. and Tan, G., 1999. Policy burdens, accountability, and the soft budget constraint. *American Economic Review*, *89*(2): 426-431.

Liu, Q. and Qiu, L.D., 2016. Intermediate input imports and innovations: Evidence from Chinese firms' patent filings. *Journal of International Economics*, 103: 166-183.

Kleer, R., 2010. Government R&D subsidies as a signal for private investors. *Research Policy*, 39(10): 1361-1374.

Myers, N., 2001. *Perverse subsidies: how tax dollars can undercut the environment and the economy*. Island Press.

Nelson, R.R., 1959. The simple economics of basic scientific research. *Journal of Political Economy*, 67(3): 297-306.

Newey, W.K., 1987. Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, *36*(3): 231-250.

OECD, 2019. Gross domestic spending on R&D (indicator). Available at: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm.

Rong, Z., Wu, X. and Boeing, P., 2017. The effect of institutional ownership on firm innovation: Evidence from Chinese listed firms. *Research Policy*, 46(9): 1533-1551.

Schumpeter, J.A., 1911. *The Theory of Economics Development*. Harvard University Press, Cambridge, MA.

Schwartz, G. and Clements, B., 1999. Government subsidies. *Journal of Economic Surveys*, *13*(2): 119-148.

Staiger, D. and Stock, J.H., 1997. Instrumental Variables Regression with Weak Instruments. *Econometrica*, 65(3): 557-586.

Stiglitz, J.E., 1989. Markets, market failures, and development. *American Economic Review*, 79(2): 197-203.

Stock, J.H. and Yogo, M., 2005. 'Testing for weak instruments in linear IV regression,' in (Andrews, D.W. and Stock, J.H. eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*, 80-108. Cambridge University Press, Cambridge, MA.

Tether, B. S., 2002. Who co-operates for innovation, and why: an empirical analysis. *Research Policy*, *31*(6): 947-967.

Tobin, J., 1958. *Estimation of relationships for limited dependent variables*. *Econometrica: Journal of the Econometric Society*, 24-36.

Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica: *Journal of the Econometric Society*, 307-333.

Wallsten, S.J., 2000. The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *RAND Journal of Economics*, *31*(1): 82-100.

Whited, T.M., 1992. Debt, liquidity constraints, and corporate investment: Evidence from panel data. *Journal of Finance,* 47(4): 1425-1460.

Yu, F., Guo, Y., Le-Nguyen, K., Barnes, S.J. and Zhang, W., 2016. The impact of government subsidies and enterprises' R&D investment: A panel data study from renewable energy in China. *Energy Policy*, 89: 106-113.

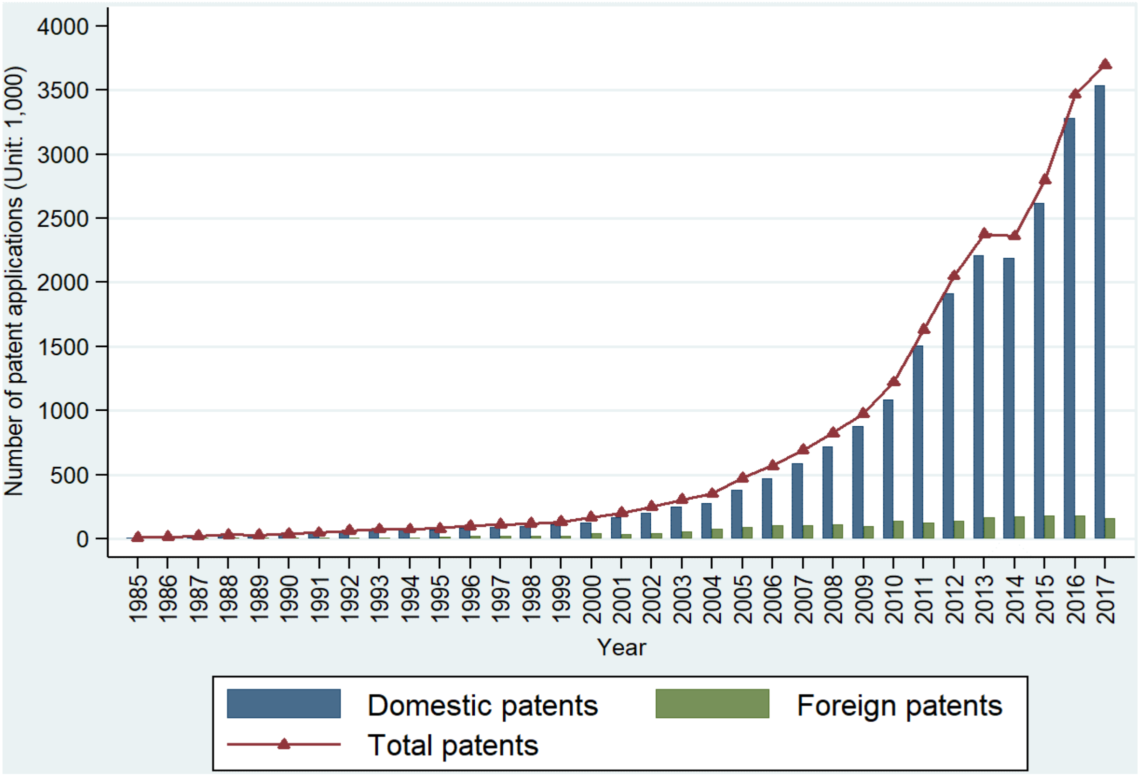

Figure 1. Number of China's patent applications from 1985 to 2017. Data Source: China's National Bureau of Statistics (NBS) – www.stats.gov.cn

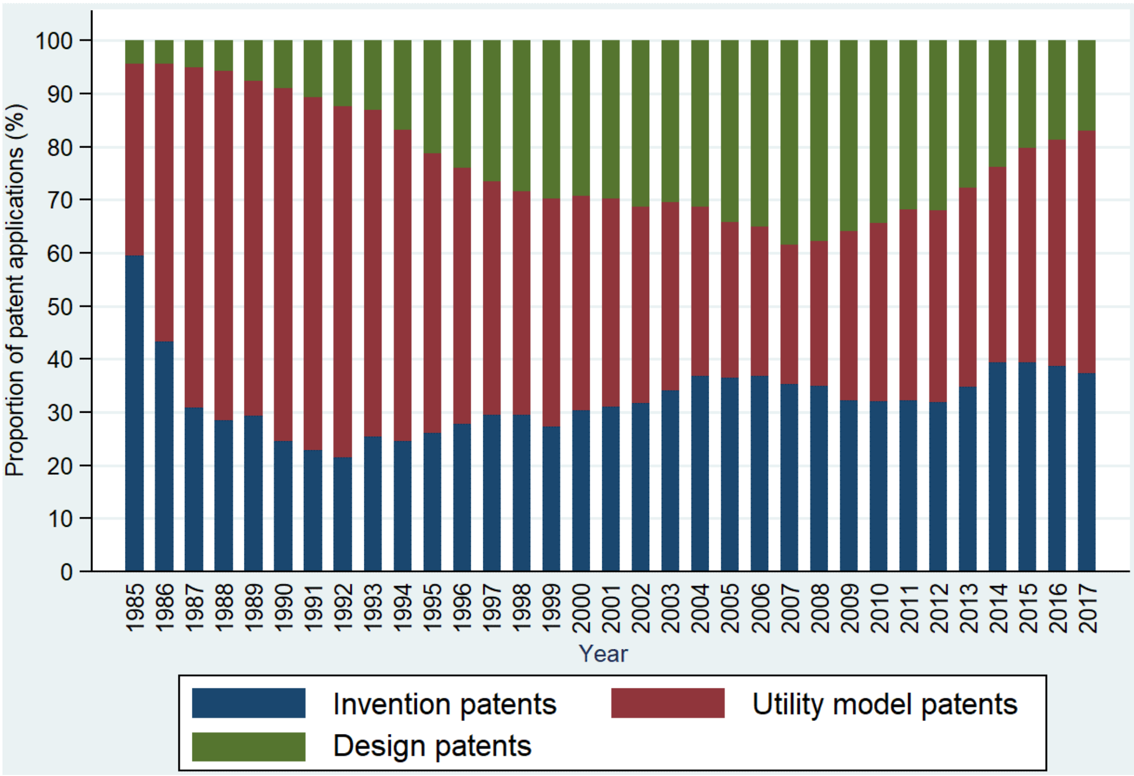

Figure 2. Proportion of three types of China's patent applications from 1985 to 2017. Data Source: China's National Bureau of Statistics (NBS) – www.stats.gov.cn

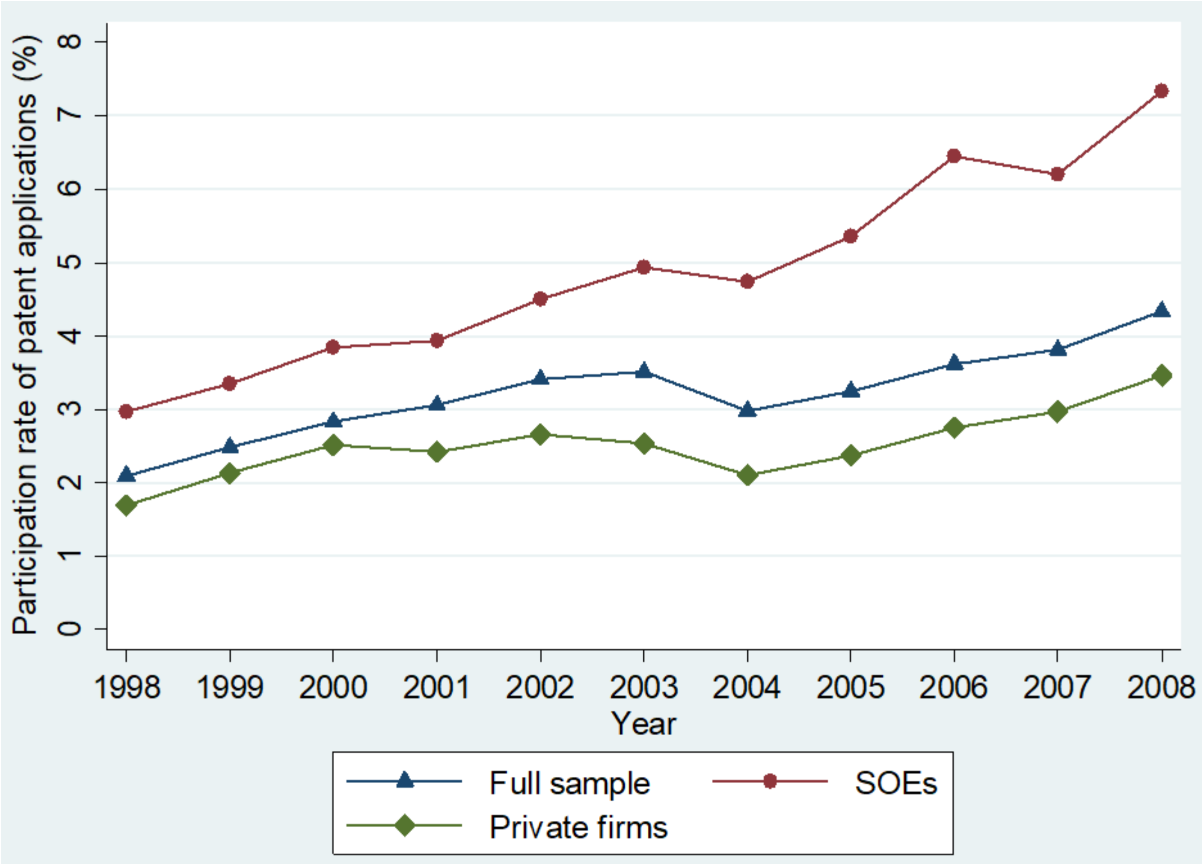

Figure 3. Participation rate of patent applications for firms in China from 1998 to 2008

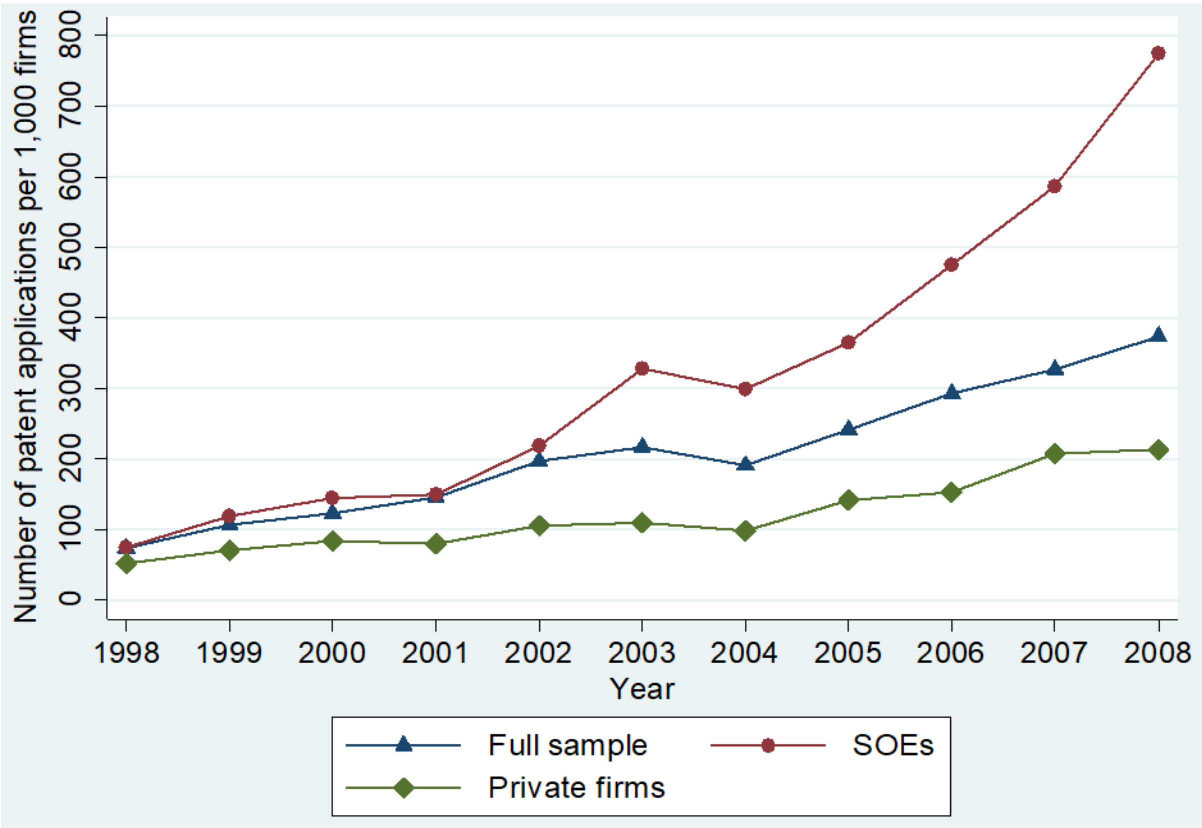

Figure 4. Number of patent applications per 1,000 firms in China from 1998 to 2008

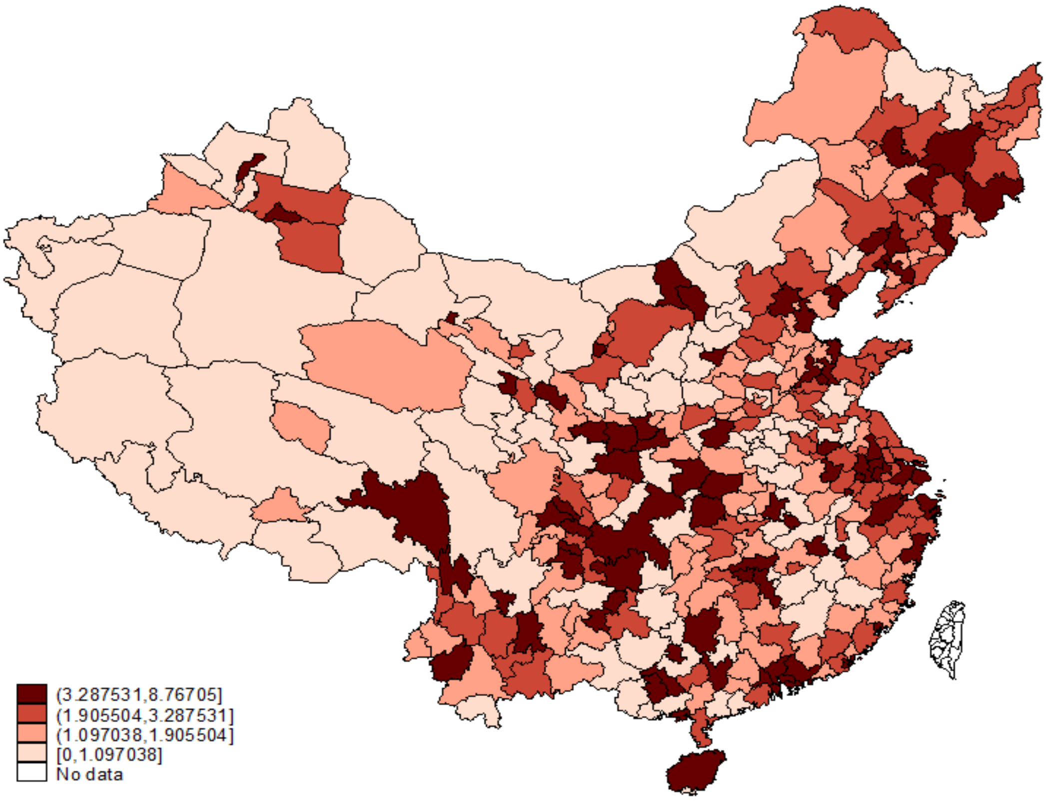

Figure 5. Average participation rate of patent applications for firms across prefecture-level administrative divisions in China from 1998 to 2008

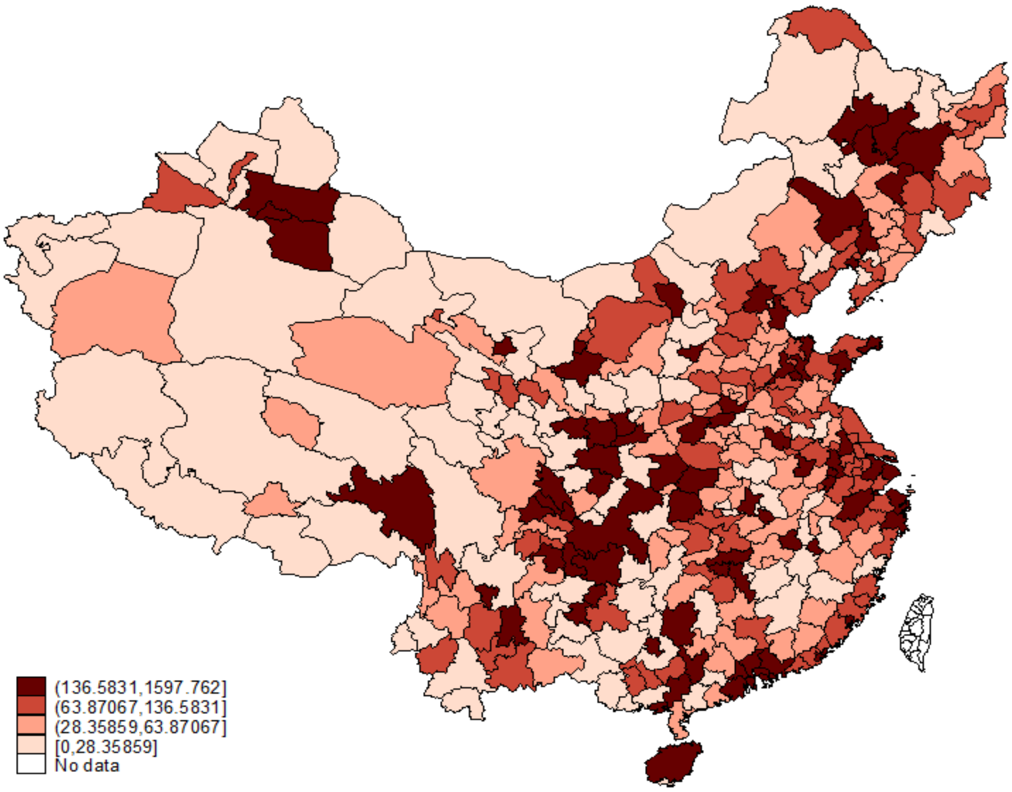

Figure 6. Average number of patent applications per 1,000 firms across prefecture-level administrative divisions in China from 1998 to 2008

Table 1

Complete definitions of regression variables.

$Log\ (Pat_{i,t} + 1)$	Natural logarithm of the number of patent applications plus one for firm i in the year t
$Log\ (Pat_{i,t-1} + 1)$	Natural logarithm of the number of patent applications plus one for firm i in the first lagged year of year t
$Log\ (Pat_{i,t-1} + 1)^2$	Squared natural logarithm of the number of patent applications plus one for firm i in the first lagged year of year t
$S_{i,t-1}$	The amount of sales to the amount of total assets for firm i in the first lagged year of year t
$Cf_{i,t-1}$	The amount of cash flows to the amount of total assets for firm i in the first lagged year of year t
$Dbt_{i,t-1}$	The amount of new long-term debts to the amount of total assets for firm i in the first lagged year of year t
$Sub_{i,t-1}$	The amount of total government subsidies to the amount of total assets for firm i in the first lagged year of year t
V_i	Firm fixed effects
V_t	Year fixed effects (2000 - 2008)
V_o	Ownership dummies (six types, SOE dummy is the benchmark)
V_j	Industry dummies (39 GB/T two-digit industry codes)
V_p	Geographical dummies (31 provincial administrative units except Hong Kong, Macao and Taiwan)
$e_{i,j,o,p,t}$	Idiosyncratic error term

Table 2

Correlation analysis of regression variables

	$Log\ (Pat_{i,t}+1)$	$Sub_{i,t-1}$	$Log\ (Pat_{i,t-1}+1)$	$Log\ (Pat_{i,t-1}+1)^2$	$S_{i,t-1}$	$Cf_{i,t-1}$	$Dbt_{i,t-1}$
$Log\ (Pat_{i,t}+1)$	1.0000***						
$Sub_{i,t-1}$	0.0188***	1.0000***					
$Log\ (Pat_{i,t-1}+1)$	0.6220***	0.0173***	1.0000***				
$Log\ (Pat_{i,t-1}+1)^2$	0.5991***	0.0109***	0.8816***	1.0000***			
$S_{i,t-1}$	-0.0645***	-0.0708***	-0.0630***	-0.0385***	1.0000***		
$Cf_{i,t-1}$	-0.0092***	-0.0167***	-0.0147***	-0.0069***	0.4864***	1.0000***	
$Dbt_{i,t-1}$	0.0100***	-0.0011	0.0065***	0.0051***	-0.0064***	-0.0066***	1.0000***

Notes: This table reports the correlation indexes of main regression variables in baseline Euler equation (1). ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

Table 3
Summary statistics - Sample means and medians (in parentheses)

	Full sample	Firms with patent applications	Firms without patent applications	SOEs	Private firms	*Diff1*	*Diff2*
Main regression variables							
Log (number of patent applications)	0.068	1.454	0.000	0.083	0.054	0.000	0.000
	(0.000)	(1.099)	(0.000)	(0.000)	(0.000)		
New product output value / total assets	2.050	7.530	1.785	2.527	2.105	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
R&D expenditure / total assets	0.098	0.501	0.080	0.113	0.095	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lag. Government subsidies / total assets	0.186	0.260	0.182	0.277	0.168	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lag. Log (number of patent applications)	0.059	0.760	0.024	0.074	0.044	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lag. Squared log (number of patent applications)	0.111	1.689	0.033	0.137	0.077	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lag. Sales / total assets	189.053	125.652	192.177	86.131	222.384	0.000	0.000
	(130.496)	(98.057)	(132.829)	(57.829)	(158.964)		
Lag. Cash flow / total assets	9.700	8.645	9.752	4.377	10.596	0.000	0.000
	(6.073)	(6.326)	(6.059)	(3.123)	(6.427)		
Lag. New long-term debt issue / total assets	0.076	0.319	0.064	0.171	0.131	0.000	0.105
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Other firm-level variables							
Real total assets	115.370	776.732	82.779	397.523	43.140	0.000	0.000
	(20.006)	(94.073)	(18.940)	(60.817)	(13.990)		
Age	11.648	14.647	11.501	26.197	9.643	0.000	0.000
	(8.000)	(9.000)	(8.000)	(24.000)	(7.000)		
Political affiliation	73.986	66.575	74.352	39.784	82.002	0.000	0.000
	(90.000)	(90.000)	(90.000)	(40.000)	(90.000)		
Percentage of state shares	8.205	10.231	8.105	93.134	0.272	0.000	0.000
	(0.000)	(0.000)	(0.000)	(100.00)	(0.000)		
Region	1.355	1.320	1.357	1.780	1.330	0.000	0.000
	(1.000)	(1.000)	(1.000)	(2.000)	(1.000)		
Observations	1,110,382	52,147	1,058,235	90,124	446,572		

Notes: Real total assets are expressed in millions of yuan. All other variables except Log (number of patent applications), age and political affiliation are shown in percentage terms. All monetary variables are deflated using provincial ex-factory producer price indices. The last two columns present the p-values associated with the mean-equality test between the group of firms with patent applications and the group of firms without patent applications (*Diff1*) and between the group of SOEs and the group of private firms (*Diff2*). Complete definitions of all the variables and classification standards are in Table 1 and Appendix D.

Table 4

Baseline Euler equation (1) for the full sample

	Random-effects Tobit			Pooled Tobit		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.193***	0.721***	0.238***	0.185***	0.686***	0.255***
	[0.021]	[0.080]	[0.026]	[0.019]	[0.071]	[0.026]
$Log\ (Pat_{i,t-1}+1)$	0.049***	0.184***	0.061***	0.100***	0.369***	0.137***
	[0.001]	[0.003]	[0.001]	[0.001]	[0.005]	[0.002]
$Log\ (Pat_{i,t-1}+1)^2$	-0.003***	-0.012***	-0.004***	-0.010***	-0.038***	-0.014***
	[0.000]	[0.001]	[0.000]	[0.001]	[0.002]	[0.001]
$S_{i,t-1}$	-0.009***	-0.032***	-0.011***	-0.009***	-0.033***	-0.012***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.032***	0.121***	0.040***	0.033***	0.124***	0.046***
	[0.002]	[0.007]	[0.002]	[0.002]	[0.007]	[0.002]
$Dbt_{i,t-1}$	0.015***	0.054***	0.018***	0.019***	0.071***	0.026***
	[0.003]	[0.010]	[0.003]	[0.003]	[0.010]	[0.004]
Rho	0.370	0.370	0.370			
Pseudo R2				0.226	0.226	0.226
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	337,637	337,637	337,637	337,637	337,637	337,637
Observations	1,110,382	1,110,382	1,110,382	1,110,382	1,110,382	1,110,382
Left-censored	1,058,235	1,058,235	1,058,235	1,058,235	1,058,235	1,058,235
Uncensored	52,147	52,147	52,147	52,147	52,147	52,147

Notes: This table reports marginal effects of baseline Euler equation (1) using the Random-effects Tobit and the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Pseudo R2 is McFadden's pseudo R-squared in the Pooled Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 5

Baseline Euler equation (1) for the sample of SOEs and private firms

	Probability		Truncated		Censored	
	(1)	(2)	(3)	(4)	(5)	(6)
	SOEs	Private firms	SOEs	Private firms	SOEs	Private firms
$Sub_{i,t-1}$	0.068	0.294***	0.196	1.237***	0.081	0.375***
	[0.074]	[0.030]	[0.213]	[0.132]	[0.088]	[0.039]
Diff1 $(\mathrm{p-value})$	(0.000)***		(0.000)***		(0.000)***	
$Log\ (Pat_{i,t-1} + 1)$	0.082***	0.062***	0.234***	0.260***	0.098***	0.079***
	[0.003]	[0.001]	[0.009]	[0.009]	[0.004]	[0.002]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.006***	-0.006***	-0.018***	-0.025***	-0.007***	-0.008***
	[0.001]	[0.000]	[0.002]	[0.002]	[0.001]	[0.000]
$S_{i,t-1}$	-0.013***	-0.007***	-0.036***	-0.030***	-0.015***	-0.009***
	[0.001]	[0.000]	[0.003]	[0.001]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.109***	0.024***	0.312***	0.100***	0.130***	0.030***
	[0.009]	[0.003]	[0.026]	[0.012]	[0.011]	[0.004]
$Dbt_{i,t-1}$	0.022**	0.020***	0.064**	0.083***	0.026**	0.025***
	[0.009]	[0.004]	[0.025]	[0.017]	[0.010]	[0.005]
Rho	0.273	0.234	0.273	0.234	0.273	0.234
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	32,418	177,573	32,418	177,573	32,418	177,573
Observations	95,650	435,205	95,650	435,205	95,650	435,205
Left-censored	90,015	418,145	90,015	418,145	90,015	418,145
Uncensored	5,635	17,060	5,635	17,060	5,635	17,060

Notes: This table reports marginal effects of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Diff1 (p-value) is the p-value for the difference in the marginal effects of $Sub_{i,t-1}$ between SOEs and private firms. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 6

Baseline Euler equation (1) for the heterogeneity of firms' financial constraints

	Size		Age		Political affiliation		State shares		SA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Small	Large	Young	Mature	Without	With	Without	With	Low	High
$Sub_{i,t-1}$	0.212***	0.152***	0.305***	0.203***	0.460***	0.044	0.256***	0.145*	0.173***	0.204***
	[0.044]	[0.008]	[0.035]	[0.037]	[0.035]	[0.039]	[0.027]	[0.086]	[0.009]	[0.042]
Diff1 (p − value)	(0.000)***		(0.000)***		(0.000)***		(0.000)***		(0.000)***	
$Log\ (Pat_{i,t-1} + 1)$	0.071***	0.173***	0.123***	0.150***	0.130***	0.144***	0.132***	0.170***	0.179***	0.072***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.004]	[0.003]	[0.003]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.013***	-0.016***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.016***	-0.017***	-0.013***
	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
$S_{i,t-1}$	-0.006***	-0.019***	-0.010***	-0.014***	-0.010***	-0.016***	-0.011***	-0.017***	-0.012***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.005***	0.045***	0.033***	0.062***	0.036***	0.070***	0.041***	0.135***	0.078***	0.003***
	[0.001]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.002]	[0.010]	[0.004]	[0.001]
$Dbt_{i,t-1}$	0.005***	0.033***	0.028***	0.025***	0.023***	0.031***	0.025***	0.038***	0.034***	0.009***
	[0.000]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.011]	[0.006]	[0.000]
Rho	0.174	0.232	0.212	0.234	0.209	0.249	0.221	0.261	0.222	0.181
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	195,972	209,831	231,066	185,465	232,662	159,139	313,605	41,707	198,370	202,027
Observations	457,705	652,677	520,124	589,009	635,312	475,070	982,444	124,176	658,374	452,008
Left-censored	448,993	609,242	499,797	557,344	608,397	449,838	938,790	115,800	614,440	443,795
Uncensored	8,712	43,435	20,327	31,665	26,915	25,232	43,654	8,376	43,934	8,213

Notes: This table only reports marginal effects in quantity of censored data of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Diff1 (p-value) is the p-value for the difference in the marginal effects of $Sub_{i,t-1}$ between two groups for one comparison. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 7
Baseline Euler equation (1) using the IV Tobit for the full sample

	$Sub_{i,t-1}$ is only instrumented by $Fin\_Inc_{c,t-1}$				$Sub_{i,t-1}$ is instrumented by $Fin\_Inc_{c,t-1}$ and $Med\_Sub_{c,t-1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-stage	Probability	Truncated	Censored	First-stage	Probability	Truncated	Censored
$Fin\_Inc_{c,t-1}$	0.003***				0.003***			
	[0.000]				[0.000]			
$Med\_Sub_{c,t-1}$					198.118***			
					[0.098]			
$Sub_{i,t-1}$		41.993***	153.064***	58.750***		7.591***	27.674***	10.619***
		[5.854]	[18.956]	[8.676]		[1.217]	[4.334]	[1.723]
$Log\ (Pat_{i,t-1} + 1)$	0.059***	0.102***	0.371***	0.142***	0.059***	0.102***	0.372***	0.143***
	[0.000]	[0.001]	[0.010]	[0.001]	[0.000]	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.010***	-0.010***	-0.038***	-0.014***	-0.010***	-0.010***	-0.038***	-0.014***
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.030***	-0.009***	-0.032***	-0.012***	-0.030***	-0.009***	-0.033***	-0.013***
	[0.000]	[0.001]	[0.005]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]
$Cf_{i,t-1}$	0.220***	0.034***	0.123***	0.047***	0.219***	0.033***	0.122***	0.047***
	[0.000]	[0.011]	[0.041]	[0.014]	[0.000]	[0.003]	[0.012]	[0.004]
$Dbt_{i,t-1}$	0.013	0.021***	0.076***	0.029***	0.013	0.021***	0.076***	0.029***
	[0.000]	[0.003]	[0.011]	[0.004]	[0.000]	[0.003]	[0.011]	[0.004]
F-statistics	418.100				418.190			
Adjusted R2	0.036				0.036			
Prob > chi2		0.000	0.000	0.000		0.000	0.000	0.000
Wald test of exogeneity (p−value)		0.000	0.000	0.000		0.000	0.000	0.000
Anderson−Rubin (p−value)		0.000	0.000	0.000		0.000	0.000	0.000
Firms	306,659	306,659	306,659	306,659	306,659	306,659	306,659	306,659
Observations	948,873	948,873	948,873	948,873	948,873	948,873	948,873	948,873
Left-censored	902,183	902,183	902,183	902,183	902,183	902,183	902,183	902,183
Uncensored	46,690	46,690	46,690	46,690	46,690	46,690	46,690	46,690

Notes: This table reports the estimation results of baseline Euler equation (1) using the IV Tobit. Columns (1) and (5) report coefficients (in percentage) of the first-stage results. Columns (2) to (4) and columns (6) to (8) report marginal effects of the second-stage results. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 8

The estimation results of the quasi-natural experiment for the subsample of firms in Suzhou

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treat * Post$	0.029**	0.032***	0.048***			0.001	0.005
	[0.012]	[0.012]	[0.009]			[0.013]	[0.010]
$Treat$	0.004						
	[0.011]						
$Post$	0.039***						
	[0.005]						
$Treat * Year$ 2000			0.022		0.022		
			[0.026]		[0.026]		
$Treat * Year$ 2001			0.016		0.016		
			[0.034]		[0.034]		
$Treat * Year$ 2002			0.033		0.033		
			[0.029]		[0.029]		
$Treat * Year$ 2003			-0.017		-0.017		
			[0.025]		[0.025]		
$Treat * Year$ 2004			0.019		0.019		
			[0.021]		[0.021]		
$Treat * Year$ 2005			0.024		0.024		
			[0.019]		[0.019]		
$Treat * Year$ 2006				0.042***	0.059***		
				[0.015]	[0.013]		
$Treat * Year$ 2007				0.051***	0.067***		
				[0.015]	[0.013]		
$Treat * Year$ 2008				0.005	0.022*		
				[0.015]	[0.013]		
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	0.334	0.357	0.358	0.356	0.357	0.168	0.349
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	8,740	8,740	8,740	8,740	8,740	4,576	8,740
Observations	30,180	30,180	30,180	30,180	30,180	12,992	30,180
Left-censored	28,362	28,362	28,362	28,362	28,362	12,421	28,362
Uncensored	1,818	1,818	1,818	1,818	1,818	571	1,818

Notes: This table only reports marginal effects in quantity for censored data of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroskedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported (except column (1) which does not cover the geographical effect and the year effect). Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. The Wald test of exogeneity is distributed as chi-square under the null hypothesis of exogeneity. Anderson-Rubin is under the null hypothesis that the minimum canonical correlation is zero. Complete definitions of all variables are in Table 1 and Appendix D.

Table 9

Augmented Euler equation (1) the full sample with contemporaneous terms

	(1)	(2)	(3)
	Probability	Truncated	Censored
$Sub_{i,t}$	0.191***	0.704***	0.229***
	[0.028]	[0.104]	[0.034]
$Sub_{i,t-1}$	0.084***	0.311***	0.101***
	[0.028]	[0.104]	[0.034]
SUM ($Sub_{i,t}$ and $Sub_{i,t-1}$)	0.275***	1.015***	0.331***
	[0.028]	[0.104]	[0.034]
$Log\ (Pat_{i,t-1} + 1)$	0.053***	0.196***	0.064***
	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.003***	-0.012***	-0.004***
	[0.000]	[0.001]	[0.000]
$S_{i,t}$	-0.005***	-0.019***	-0.006***
	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.005***	-0.018***	-0.006***
	[0.000]	[0.001]	[0.000]
$Cf_{i,t}$	0.020***	0.075***	0.024***
	[0.003]	[0.009]	[0.003]
$Cf_{i,t-1}$	0.020***	0.073***	0.024***
	[0.003]	[0.010]	[0.003]
$Dbt_{i,t}$	0.016***	0.058***	0.019***
	[0.003]	[0.011]	[0.004]
$Dbt_{i,t-1}$	0.018***	0.068***	0.022***
	[0.003]	[0.011]	[0.004]
Rho	0.335	0.335	0.335
Prob > chi2	0.000	0.000	0.000
Firms	287,452	287,452	287,452
Observations	868,294	868,294	868,294
Left-censored	828,868	828,868	828,868
Uncensored	39,426	39,426	39,426

Notes: This table reports marginal effects of augmented Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). SUM ($Sub_{i,t}$ and $Sub_{i,t-1}$) is the sum of the marginal effects of the contemporaneous subsidy variable $Sub_{i,t}$ and the lagged subsidy vairbale $Sub_{i,t-1}$. Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 10

Baseline Euler equation (1) for the full sample: using alternative measurements of innovation activities (new product output value/ total assets, labelled as Np, and R&D expenditure / total assets, labelled as Rd)

	New product output value			R&D expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.083***	0.047***	0.024***	0.406***	0.006***	0.004***
	[0.025]	[0.014]	[0.007]	[0.047]	[0.001]	[0.000]
$Np_{i,t-1}(Rd_{i,t-1})$	0.607***	0.346***	0.177***	27.790***	0.390***	0.253***
	[0.004]	[0.002]	[0.001]	[0.197]	[0.003]	[0.002]
${Np_{i,t-1}}^2(Rd_{i,t-1})^2$	-0.481***	-0.274***	-0.140***	-572.315***	-8.038***	-5.211***
	[0.004]	[0.003]	[0.001]	[5.977]	[0.086]	[0.058]
$S_{i,t-1}$	-0.010***	-0.006***	-0.003***	-0.014***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.018***	0.010***	0.005***	0.062***	0.001***	0.001***
	[0.002]	[0.001]	[0.001]	[0.004]	[0.000]	[0.000]
$Dbt_{i,t-1}$	-0.001	-0.001	-0.000	0.019***	0.000***	0.000***
	[0.003]	[0.002]	[0.001]	[0.006]	[0.000]	[0.000]
Rho	0.270	0.270	0.270	0.286	0.286	0.286
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	327,550	327,550	327,550	252,311	252,311	252,311
Observations	888,928	888,928	888,928	514,380	514,380	514,380
Left-censored	829,733	829,733	829,733	449,395	449,395	449,395
Uncensored	59,195	59,195	59,195	64,985	64,985	64,985

Notes: This table reports marginal effects of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Np_{i,t}$ or $Rd_{i,t}$ is a censored variable which takes its real value if the firm has new product output value or R&D expenditure (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 11

Additional robustness tests for the full sample

	(1) Invention patents	(2) Zero-inflated Poisson	(3) Log of financial variables	(4) Data excluding the year 2008
$Sub_{i,t-1}$	0.134***	0.162***	0.003***	0.193***
	[0.012]	[0.024]	[0.000]	[0.027]
$Log\ (Pat_{i,t-1}+1)$	0.062***	0.030***	0.084***	0.063***
	[0.001]	[0.001]	[0.001]	[0.001]
$Log\ (Pat_{i,t-1}+1)^2$	-0.006***	-0.005***	-0.011***	-0.004***
	[0.001]	[0.000]	[0.000]	[0.000]
$S_{i,t-1}$	-0.006***	-0.011***	0.013***	-0.010***
	[0.000]	[0.000]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.026***	0.030***	0.006***	0.035***
	[0.001]	[0.002]	[0.000]	[0.003]
$Dbt_{i,t-1}$	0.014***	0.011***	0.001***	0.017***
	[0.002]	[0.003]	[0.000]	[0.003]
Rho	0.234	0.190	0.203	0.228
Prob > chi2	0.000	0.000	0.000	0.000
Firms	337,637	335,620	305,876	297,534
Observations	1,110,382	1,089,180	782,094	905,590
Left-censored	1,088,763	1,055,302	751,291	865,272
Uncensored	21,619	33,878	30,803	40,318

Notes: This table reports estimation results of additional robustness tests. In the columns (1), (3) and (4) we report marginal effects in quantity of censored data and the dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). In column (2) we report marginal effects on expected value of number of patent applications with respect to the random effect and the dependent variable is the number of patent applications per firm ($Pat_{i,t}$). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit and Random-effects Poisson regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 12

Baseline Euler equation (1) for the full sample with industry-level EFD and High tech-intensiveness

	EFD			High tech-intensiveness		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.158***	0.583***	0.190***	0.146***	0.544***	0.179***
	[0.024]	[0.087]	[0.028]	[0.023]	[0.088]	[0.029]
$Sub_{i,t-1} * EFD_j$	-0.513***	-1.888***	-0.615***			
	[0.138]	[0.507]	[0.165]			
EFD_j	0.012***	0.045***	0.015***			
	[0.002]	[0.007]	[0.002]			
$Sub_{i,t-1} * High-tech_{j,t-1}$				0.292***	1.088***	0.359***
				[0.059]	[0.218]	[0.072]
$High-tech_{j,t-1}$				0.01***	0.060***	0.020***
				[0.001]	[0.004]	[0.001]
$Log\ (Pat_{i,t-1}+1)$	0.054***	0.198***	0.064***	0.049***	0.183***	0.060***
	[0.001]	[0.003]	[0.001]	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1}+1)^2$	-0.003***	-0.013***	-0.004***	-0.003***	-0.012***	-0.004***
	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.008***	-0.031***	-0.010***	-0.009***	-0.032***	-0.011***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.031***	0.113***	0.037***	0.032***	0.119***	0.039***
	[0.002]	[0.008]	[0.003]	[0.002]	[0.007]	[0.002]
$Dbt_{i,t-1}$	0.015***	0.054***	0.018***	0.015***	0.054***	0.018***
	[0.003]	[0.010]	[0.003]	[0.003]	[0.010]	[0.003]
Rho	0.332	0.332	0.332	0.371	0.371	0.371
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	292,722	292,722	292,722	337,637	337,637	337,637
Observations	878,713	878,713	878,713	1,110,382	1,110,382	1,110,382
Left-censored	838,638	838,638	838,638	1,058,235	1,058,235	1,058,235
Uncensored	40,075	40,075	40,075	52,147	52,147	52,147

Notes: This table reports marginal effects of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Table 13

Baseline Euler equation (1) for the full sample with city-level financial development and foreign direct investment

	Panel A: financial development								
	Loans			Deposits			Savings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Truncated	Censored	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.250***	0.902***	0.328***	0.252***	0.910***	0.331***	0.242***	0.871***	0.317***
	[0.027]	[0.098]	[0.036]	[0.027]	[0.097]	[0.035]	[0.026]	[0.094]	[0.034]
$Sub_{i,t-1} * Fin-dev_{c,t-1}$	-0.082*	-0.294*	-0.107**	-0.074**	-0.265**	-0.097**	-0.285**	-1.028**	-0.374**
	[0.044]	[0.160]	[0.058]	[0.030]	[0.108]	[0.039]	[0.118]	[0.426]	[0.155]
$Fin-dev_{c,t-1}$	0.010***	0.035***	0.013***	0.008***	0.027***	0.010***	0.002	0.006	0.002
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.005]	[0.002]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	0.240	0.240	0.240	0.239	0.239	0.239	0.238	0.238	0.238
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	277,534	277,534	277,534	277,534	277,534	277,534	277,534	277,534	277,534
Observations	784,847	784,847	784,847	784,847	784,847	784,847	784,847	784,847	784,847
Left-censored	745,600	745,600	745,600	745,600	745,600	745,600	745,600	745,600	745,600
Uncensored	39,247	39,247	39,247	39,247	39,247	39,247	39,247	39,247	39,247
	Panel B: foreign direct investment								
	New contracts signed			Agreed investment			Actual investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Truncated	Censored	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.225***	0.823***	0.280***	0.216***	0.792***	0.269***	0.214***	0.782***	0.265***
	[0.023]	[0.084]	[0.029]	[0.023]	[0.084]	[0.029]	[0.023]	[0.084]	[0.028]
$Sub_{i,t-1} * For-inv_{c,t-1}$	-0.030**	-0.108**	-0.037**	-0.508*	-1.858*	-0.631*	-1.011	-3.701	-1.256
	[0.012]	[0.044]	[0.015]	[0.281]	[1.028]	[0.349]	[0.631]	[2.308]	[0.783]
$For-inv_{c,t-1}$	0.004***	0.015***	0.005***	0.027***	0.099***	0.034***	0.051***	0.186***	0.063***
	[0.000]	[0.001]	[0.000]	[0.003]	[0.011]	[0.004]	[0.006]	[0.024]	[0.008]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	0.361	0.361	0.361	0.361	0.361	0.361	0.362	0.362	0.362
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	314,677	314,677	314,677	314,844	314,844	314,844	315,118	315,118	315,118
Observations	1,011,225	1,011,225	1,011,225	1,012,299	1,012,299	1,012,299	1,013,293	1,013,293	1,013,293
Left-censored	962,103	962,103	962,103	963,144	963,144	963,144	964,122	964,122	964,122
Uncensored	49,122	49,122	49,122	49,155	49,155	49,155	49,171	49,171	49,171

Notes: This table reports marginal effects of baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable which takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Outliers in all firm-level continuous variables are trimmed at the 1% and 99% levels. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time dummies, industry dummies, location dummies and ownership dummies are included in all specifications but not reported. Rho is the percent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 1 and Appendix D.

Appendix A. Description of the three types of patents in China

The three types of China's patents are different in applicable targets, protection periods and approval procedures. First, according to China's patent law, invention patents are defined as new technical proposals on products, methods or their improvements; utility model patents are defined as new technical proposals on product shape, product structure or their combination; design patents are defined as new aesthetic designs of product shape, product pattern, product colour or their combination. Second, the amendment to China's patent law in 1992 extends the protection duration for invention patents from 15 to 20 years and for utility model patents and design patents from 5 to 10 years, which is also a major requirement from TRIPS to ensure benefits of patent applications. Third, it usually takes about 2 to 3 years for the SIPO to process an invention patent application, while the corresponding approval cycle for a utility model patent application and a design patent application is about 6 months. Besides that, the approval procedures for an innovation patent must meet the high requirement of 'novelty, inventiveness, and practical applicability'. However, the approval procedures for a utility model patent and a design patent are simpler, and thus it is difficult to determine whether they have 'novelty, inventiveness, and practical applicability'.

Appendix B. NBS firm-level panel data

In principle, the sample coverage of the NBS firm-level data should be identical with that of China Statistical Yearbook, or the discrepancies are relatively small. Thus, we compare the NBS-firm level data with the China Statistical Yearbook 2009 to verify the data reliability, and Table A1 reports the comparison results. The statistics for all years expect 1998, 2004 and 2008 are identical, confirming that the NBS-firm level data in our paper are also the basis for the numbers reported in the China Statistical Yearbook. For year 1998, the number of firms in the NBS firm-level data is more than that recorded in the China Statistical Yearbook, while the discrepancy is quite small (only 38). Additionally, the data in 1998 is used to construct lagged values of the independent variables in our models, and thus the period of our estimation sample does not cover the year 1998. The data in 2004 contains the information of some SOEs that are not 'above-scale' enterprises, so the number of firms in 2004 of the NBS firm-level data is more than that recorded in the China Statistical Yearbook. In the section of our data process, we have dropped the observations with sales of less than 5 million Chinese Yuan to avoid the influence of no 'above-scale' enterprises. The number of firms in year 2008 is less 10,000 than that recorded in the China Statistical Yearbook, so we also delete the data in year 2008 to estimate again for robustness test and the results keep qualitatively consistent. Table A2 shows the structure of the unbalanced panel after data process.

Table A1. Comparison of the NBS firm-level data with the China Statistical Yearbook 2009

Year	NBS firm-level data	China Statistical Yearbook
1998	165,118	165,080
1999	162,033	162,033
2000	162,885	162,885
2001	171,256	171,256
2002	181,557	181,557
2003	196,222	196,222
2004	279,092	276,474
2005	271,835	271,835
2006	301,961	301,961
2007	336,768	336,768
2008	412,212	426,113
Total	2,640,939	2,652,184

Table A2. Structure of the unbalanced panel

Year	Number of observations	Percent (%)	Cumulative (%)
1998	123,544	5.21	5.21
1999	121,014	5.10	10.30
2000	125,585	5.29	15.59
2001	137,985	5.81	21.41
2002	150,861	6.36	27.76
2003	172,869	7.28	35.05
2004	262,145	11.04	46.09
2005	258,969	10.91	57.00
2006	290,526	12.24	69.24
2007	330,185	13.91	83.16
2008	399,805	16.84	100.00
Total	2,373,488	100.00	

Number of years per firm	Number of observations	Percent (%)	Cumulative (%)
1	196,037	8.26	8.26
2	216,454	9.12	17.38
3	257,418	10.85	28.22
4	242,812	10.23	38.45
5	419,360	17.67	56.12
6	228,102	9.61	65.73
7	157,465	6.63	72.37
8	168,976	7.12	79.49
9	106,038	4.47	83.96
10	111,920	4.72	88.67
11	268,906	11.33	100.00
Total	2,373,488	100.00	

Appendix C. China's industry classification standard and its revision in 2002

China's industry sector code is made up of four digits. The first two digits are GB/T two-digit sector codes, the first three digits are GB/T three-digit sector codes, and all four digits are GB/T four-digit sector codes. In 2002, China revised its industrial classification standard issued in 1994 to keep consistent with the regulations of the WTO. The revision of the industry classification in 2002 has little impact on two-digit codes but more on three-digit codes and four-digit codes. The adjustments to four-digit sector codes totally have four types: first, some sectors just change their codes; second, some sectors are broken down into new ones; third, some sectors are merged with others into a new sector; fourth, some sectors are broken down into new sectors some of which are merged with other sectors into a new one. We manually adjust all four-digit sector codes to the revision in 2002. After the adjustment, we extract the first three digits and first two digits respectively to get the adjusted three-digit sector codes and the adjusted two-digit sector codes. Finally, we get 525 GB/T four digit-sector codes, 191 GB/T three digit-sector codes and 39 GB/T two digit-sector codes. All industry dummy variables are constructed on the adjusted sector codes. We drop observations in the sectors that disappeared or transferred to other non-manufacturing sectors after the revision in 2002. The proportion of these observations in the transferred and disappeared is low, only approximately 0.290%.

Since we use the industry dummy variables based on GB/T two digit-code in our regression models, we show the detailed description of all two-digit sectors in Table A3. We can find all two-digit sectors keep the same codes after the revision in 2002 except the sector of timber and bamboo wood with the code of 12 (which is removed from the scope of manufacturing industries) and the sector of Waste Material Recycling Processing with the code of 43 (which is moved to the scope of manufacturing industries).

Table A3. Description of GB/T two-digit industries

Two-Digit Industry name	Two-Digit codes (1994-2002)	Two-Digit codes (1994-2002)
Coal Mining & Dressing	06	06
Petroleum & Natural Gas Extraction	07	07
Ferrous Metals Mining & Dressing	08	08
Non-Ferrous Metals Mining & Dressing	09	09
Non-metal Minerals Mining & Dressing	10	10
Mining of other Mineral	11	11
Timber and bamboo wood	12	/

Farm & Side-line Products Processing	13	13
Food Production	14	14
Beverage Manufacturing	15	15
Tobacco Processing	16	16
Textile Industry	17	17
Clothing, Shoes, Hats Manufacturing	18	18
Leather, Fur, Feathers Manufacturing	19	19
Timber Manufacturing	20	20
Furniture Manufacturing	21	21
Papermaking & Paper Products	22	22
Printing Industry	23	23
Cultural Educational & Sports Goods	24	24
Petroleum Processing & Coking	25	25
Chemical Raw Materials & Chemical Products	26	26
Medical & Pharmaceutical Products	27	27
Chemical Fibre	28	28
Rubber Products	29	29
Plastic Products	30	30
Non-metal Mineral Products	31	31
Ferrous Metal Smelting & Rolling Processing	32	32
Non-Ferrous Metal Smelting & Rolling Processing	33	33
Metal Products	34	34
Ordinary Machinery	35	35
Special Equipment	36	36
Transportation Equipment Manufacturing	37	37
Electric Equipment & Machinery	40	39
Electronic Communication Equipment Manufacturing	41	40
Instrument & Apparatus Manufacturing	42	41
Handicrafts & other Manufacturing	43	42
Waste Material Recycling Processing	/	43
Electricity, Heat Production & Supply	44	44
Gas Production & Supply	45	45
Water Production & Supply	46	46

Appendix D. Classification standards

Table A4. Description of classification standards

Ownership (based on the majority average paid-in capitals)	SOEs Private firms	At least 50% paid-in capitals are the state owned; At least 50% paid-in capitals are private (individuals) owned.
Size	Small Large	If a firm's real sales are in the lower half distribution of real sales of all firms with the same ownership type in the same GB/T Four-digit industry in a given year; If a firm's real sales are in the higher half distribution of real sales of all firms with the same ownership type in the same GB/T Four-digit industry in a given year.
Age	Young Mature	If a firm's age is in the lower half distribution of all firms' age with the same ownership type in the same GB/T Four-digit industry in a given year; If a firm's age is in the higher half distribution of all firms' age with the same ownership type in the same GB/T Four-digit industry in a given year.
Political affiliation	No With	If a firm has no political affiliation (Lishu = 90); If a firm is affiliated at a level of village, neighbourhood, township, town, sub-district, county, prefecture, province and central government (Lishu <90).
State Shares	No Yes	If a firm has no state shares; If a firm has some state shares.
Region	Coastal (Eastern) Central	If a firm is in the coastal regions, which include the 11 provinces (autonomous regions) or municipal cities: Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan; If a firm is in the central regions, which include the 8 provinces (autonomous regions) or municipal cities: Jilin, Heilongjiang, Shanxi, Henan, Anhui, Hubei, Jiangxi, Hunan.

	Western	If a firm is in the western regions, which include the 12 provinces (autonomous regions) or municipal cities: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

For firms' ownership, all firms are grouped into six categories based on the majority (at least 50%) of registered paid-in capital: state-owned enterprises (SOEs); foreign firms; private firms; collective firms; Hong Kong, Macao or Taiwan (HMT) firms; and mixed ownership firms. Specifically, we regard firms with the majority of state capitals as SOEs; firms with the majority of foreign capitals as foreign firms; firms with the majority of capitals from Hong Kong, Macao and Taiwan as HMT firms; firms with the majority of individual capitals as private firms; firms with the majority of capitals from collective investors as collective firms; firms with the majority of capitals from legal entities and firms without the majority of any type of capitals as mixed-ownership firms. Some papers group firms with the majority of capitals from legal entities into private firms (Ding et al., 2013; Guariglia et al., 2011); Guariglia & Liu, 2014). As one form of registered paid-in capitals, capitals from legal entities are a mixture of capitals from state-owned legal entities and private legal entities. However, the firms are invested mainly by state-owned legal entities should not be classified as SOEs. In this dataset, we cannot exactly distinguish which firms are invested mainly by state-owned legal entities and which firms are mainly invested by private legal entities since this dataset does not record it. Thus, to alleviate estimation bias, we only group firms with the majority of individual capitals into private firms and firms with the majority of state capitals into SOEs. For firms with the majority of capitals from legal entities, we have to classify them as one form of mixed-ownership firms. We also estimate if firms mainly invested by legal entities as private firms and all results keep consistent. Firms without the majority of any type of capitals is another form of mixed-ownership firms. For example, the firm with the legal person code of '613991812' in 2002 that has 43.7% of state capitals, 42.8% of individual capitals and 13.5% of foreign capitals is one mixed-ownership firm. This form of mixed-ownership firms makes up a small fraction of our sample, just around 1.6%. Since we compare the estimation results between SOEs and private firms in our main analysis, thus we only report the standards of SOEs and private firms in Table A4.

Appendix E. Distribution of the number of prefecture-level administrative divisions for firms' patent applications (detailed explanation of maps of Figure 5 and Figure 6)

Table A5

First. Average participation rate of firms' patent applications

Participation rate \ Region	Eastern (Coastal)	Central	Western	Total
(0 – 1.09%]	8	30	48	86
(1.09% - 1.87%]	24	34	27	85
(1.87% - 3.26%]	38	25	21	84
(3.26% - 8.77%]	31	21	34	86
Total	101	110	130	341

Average number of patent applications per 1,000 firms

Number \ Region	Eastern (Coastal)	Central	Western	Total
(0 – 27.67]	9	23	54	86
(27.67 - 62.71]	24	40	20	84
(62.71 - 136.56]	39	24	23	86
(136.56 - 1597.76]	29	23	33	85
Total	101	110	130	341

Appendix F. Overview of subsidy policies for all county-level cities of Suzhou during the period from July 2004 to April 2008

We obtain the data from the study of Lei et al. (2012) and show them in Table A6. We can find that the amount of subsidies for all types of patent applications in Zhangjiagang increased after June 2006. Specifically, subsidies for invention patent applications increased from 1,500 to 3,000 + 10,000 (the '+' means the reward for granted invention patent); subsidies for utility model patent applications increased from 1,000 to 1,500; subsidies for design patent applications increased from 500 to 1,000. As a comparison, subsidies for all types of patent applications across other five neighbouring county-level areas of Suzhou remained unchanged until April 2008 (the subsidy policy in Changshu changed after April 2008). The Suzhou county-level city is the combination of municipal districts of Suzhou prefecture-level city (in China, a municipal district of one prefecture-level administrative division is a county-level administrative division).

Table A6. Amount of subsidies (Unit: Chinese Yuan) for patent applications across county-level cities of Suzhou

County-level city	Before June 2006			After June 2006		
	Invention patents	Utility model patents	Design patents	Invention patents	Utility model patents	Design patents
Zhangjigang	1,500	1,000	500	3,000+10,000	1,500	1,000
Wujiang	2,000	1,000	800	unchanged		
Taicang	4,000+5,000	1,000	1,000	unchanged		
Suzhou (urban districts)	4,000	1,000	1,000	unchanged		
Kunshan	4,000	1,000	500	unchanged		
Changshu	2,000	1,000	1,000	unchanged		